

Econometrics Powered by AI

An Introduction Using Cloud-based Python Notebooks



Carlos Mendez

Econometrics Powered by AI: An Introduction Using Cloud-based Python Notebooks

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Companion website: <https://quarcs-lab.github.io/metricsai>

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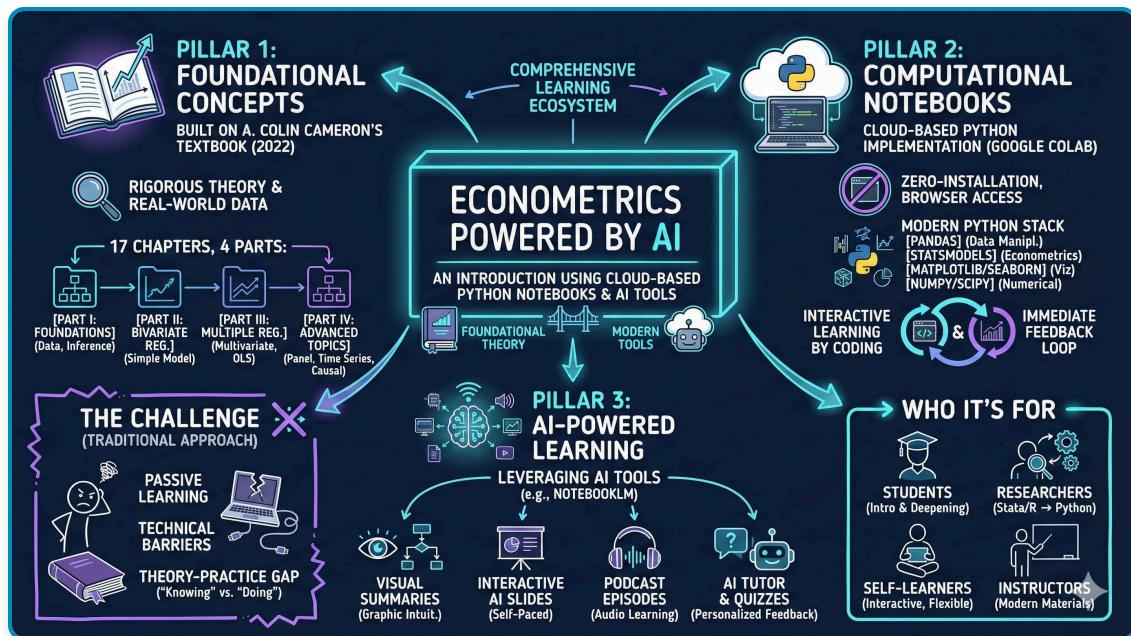
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Preface: Econometrics Powered by AI

metricsAI: An Introduction to Econometrics with Python and AI in the Cloud

Carlos Mendez



Welcome to a new approach to learning econometrics—one that embraces the power of modern computational tools and artificial intelligence while maintaining the rigor of traditional econometric theory.

Open in Colab

Introduction

Welcome to *Econometrics Powered by AI: An Introduction Using Cloud-based Python Notebooks*. This book represents a new approach to learning econometrics—one that embraces the power of modern computational tools while maintaining the rigor of traditional econometric theory. In an era where artificial intelligence is transforming how we learn, work, and conduct research, this book seeks to bridge the gap between foundational statistical concepts and cutting-edge learning technologies.

The vision behind this project is simple yet ambitious: to make econometrics accessible, interactive, and engaging for a new generation of learners. By combining

authoritative textbook content with cloud-based computational notebooks and AI-enhanced learning tools, I aim to modernize the often-daunting journey of learning econometrics into an more exciting AI-powered discovery of economic stories based real data.

The Challenge of Learning Econometrics

Econometrics has traditionally been taught through a combination of theoretical lectures, textbook readings, and problem sets. While this approach has served generations of students, it faces several inherent limitations in today's learning environment. Traditional textbooks, no matter how well-written, remain fundamentally passive learning tools. Students read about regression analysis, hypothesis testing, and statistical inference, but the gap between reading about these concepts and actually implementing them can be substantial.

Technical barriers compound these challenges. Learning econometrics typically requires installing statistical software, navigating complex syntax, managing data files, and troubleshooting installation issues—all before a single regression can be estimated. For many students, these technical hurdles can be discouraging, diverting energy away from understanding core concepts and toward wrestling with software configuration.

Moreover, there exists a persistent gap between theory and practical implementation. Students may understand the mathematical derivation of the ordinary least squares estimator but struggle to translate that knowledge into working code that analyzes real data. This disconnect between "knowing" and "doing" is still a challenge in econometrics education.

This Book's Approach

This book takes a different approach. It serves as a companion to A. Colin Cameron's textbook, *Analysis of Economic Data: An Introduction to Econometrics* (2022). Specifically, it brings its key lessons and examples into the interactive, computational world of Python programming and AI-enhanced learning.

At the heart of this approach is a three-pillar methodology that combines **Foundational Concepts**, **Computational Notebooks**, and **AI-Powered Learning**. These three pillars work together to create a comprehensive learning ecosystem that addresses the limitations of traditional econometrics education while leveraging the best of what modern technology offers.

The foundational concepts pillar ensures that students build their understanding on Cameron's pedagogical framework, covering everything from basic statistical foundations to advanced topics in panel data and causation. The computational notebooks pillar provides zero-installation, browser-based access to Python implementations of every concept, allowing students to learn by coding from the very first chapter. The AI-powered learning pillar enhances this foundation with visual summaries, interactive slides, podcast discussions, quizzes, and an AI tutor—all designed to reinforce learning through multiple modalities.

This is not just a textbook with code examples—it's a reimaging of how econometrics can be taught and learned in the age of cloud computing and artificial intelligence.

Who This Book Is For

This book is designed for a diverse audience of learners:

Economics and social science students will find a comprehensive introduction to econometrics that emphasizes hands-on learning with real data. Whether you're taking your first econometrics course or looking to deepen your quantitative skills, the combination of theory and practice provided here will serve you well.

Researchers transitioning from Stata or R to Python will appreciate the parallel structure that follows Cameron's familiar textbook while introducing Python's powerful ecosystem of data science libraries. Each chapter demonstrates how classic econometric techniques can be implemented using modern Python tools like Pandas, Statsmodels, and Linearmodels.

Self-learners seeking interactive resources will benefit from the zero-installation requirement and comprehensive AI support. Simply open a notebook in your browser and start learning—no complex setup required. The multiple learning modalities (notebooks, podcasts, slides, quizzes) allow you to create a personalized learning path that fits your style and schedule.

Instructors looking for modern teaching materials will find ready-made computational notebooks, AI-generated slides, and assessment tools that can supplement traditional lectures. The materials are designed to be flexible, allowing instructors to adopt the entire framework or selectively incorporate individual components into their existing courses.

I Why This Book? Three Pillars of Learning

Pillar 1: Foundational Concepts

Built on Cameron's Introductory Textbook

The foundation of this book rests on A. Colin Cameron's *Analysis of Economic Data: An Introduction to Econometrics* (2022), an accessible introductory textbook that provides a clear exposition of econometric concepts and practical approach to data analysis. Cameron's work provides comprehensive coverage of introductory econometric theory while maintaining an accessible writing style that resonates with students.

By building on this pedagogical framework, we ensure that the statistical and econometric foundations you learn are rigorous, complete, and aligned with how econometrics is actually practiced by researchers. The book features real-world datasets and examples drawn from economics and social sciences, demonstrating how econometric methods are applied to answer important research questions.

Core Statistical Principles

The book covers the complete spectrum of econometric methods, from foundational statistical concepts through advanced techniques. You'll begin with statistical foundations, learning about descriptive statistics, probability distributions, sampling theory, and statistical inference. These fundamentals provide the mathematical and statistical toolkit needed for all subsequent econometric analysis.

From there, you'll progress through bivariate regression analysis, learning how to model relationships between two variables, estimate linear relationships, and conduct hypothesis tests. Multiple regression analysis extends these techniques to multivariate settings, introducing concepts like omitted variable bias, multicollinearity, and model specification testing.

Finally, advanced topics cover panel data methods, time series analysis, and approaches to establishing causation—techniques that are essential for modern empirical research in economics and social sciences. Throughout, theory is consistently grounded in practical applications, showing how abstract statistical concepts translate into tools for answering real research questions.

17 Chapters, Four Parts

The book's 17 chapters are organized into four coherent parts that build systematically from foundations to advanced applications:

Part I: Statistical Foundations (Chapters 1-4) introduces you to data analysis, summary statistics, the sample mean, and statistical inference. These chapters establish the statistical toolkit you'll use throughout the course.

Part II: Bivariate Regression (Chapters 5-9) covers simple regression analysis, from data summarization through least squares estimation, statistical inference, case studies, and models with natural logarithms. These chapters develop your understanding of the fundamental regression model.

Part III: Multiple Regression (Chapters 10-13) extends regression to multiple explanatory variables, covering data summary techniques, statistical inference, advanced topics, and extensive case studies that demonstrate how multiple regression is applied in practice.

Part IV: Advanced Topics (Chapters 14-17) introduces indicator variables, variable transformations, model diagnostics, and concludes with panel data, time series methods, and causal inference—techniques at the frontier of applied econometric research.

Pillar 2: Computational Notebooks

Cloud-Based Python Implementation

Every one of the 17 chapters has a corresponding Google Colab notebook that brings the econometric concepts to life through interactive Python code. This cloud-based approach eliminates the single biggest barrier to learning computational econometrics: software installation and configuration.

With Google Colab, there's zero installation required. You simply click an "Open in Colab" badge, and within seconds you're running code in your browser. There's no need to install Python, manage package dependencies, or troubleshoot compatibility issues. Google Colab provides free access to computing resources, including CPUs and GPUs, ensuring you have the computational power needed for data analysis.

This approach removes all technical barriers to getting started. Whether you're using a Windows PC, a Mac, a Chromebook, or even a tablet, as long as you have internet access and a web browser, you can work through every chapter of this book.

Modern Python Stack

The notebooks leverage Python's rich ecosystem of data science and statistical libraries, introducing you to the same tools used by professional data scientists and researchers worldwide.

Pandas serves as the foundation for data manipulation and analysis, providing powerful tools for loading, cleaning, transforming, and summarizing datasets. **Statsmodels** provides econometric modeling capabilities, including OLS regression, generalized linear models, and time series analysis. **Linearmodels** extends this toolkit with advanced regression techniques specifically designed for econometric applications.

For visualization, we use **Matplotlib** and **Seaborn**, which together provide publication-quality graphics for exploring data and presenting results. **NumPy** and **SciPy** handle the numerical computing that underlies all statistical analysis, from matrix operations to optimization algorithms.

Learning these tools doesn't just teach you econometrics—it provides you with a valuable skillset that transfers directly to careers in data science, quantitative research, policy analysis, and consulting.

Interactive Learning by Coding

Google Colab notebooks are fundamentally interactive documents that combine code, explanations, and results in a single, cohesive environment. Unlike static textbooks or lecture slides, notebooks allow you to see the code that generates each table and figure, modify that code, and immediately see the results of your changes.

This immediate feedback loop transforms learning from passive consumption to active experimentation. Wondering what happens if you change a parameter? Modify the code and re-run the cell. Curious about how a result changes with different data? Load a different dataset and see for yourself. Want to extend an analysis beyond what the textbook shows? Add your own code cells and explore.

Each notebook provides step-by-step implementation of econometric concepts, starting from data loading and proceeding through analysis, visualization, and interpretation. Code is thoroughly commented and explained, ensuring you understand not just what each line does, but why it's needed and how it fits into the broader analysis.

Accessibility and Convenience

The cloud-based approach provides unprecedented accessibility. You can access your work from any device with an internet connection—start working on your desktop at home, continue on a laptop at a café, and review results on a tablet while commuting. There are no storage space requirements on your local machine; everything is saved in the cloud.

Your notebooks are always up-to-date with the latest software dependencies, as Google Colab maintains the underlying Python environment. You never have to worry about package version conflicts or breaking changes—everything just works. The platform also includes collaborative features for group learning, allowing students to work together on assignments, share insights, and learn from each other's approaches.

Pillar 3: AI-Powered Learning

Leveraging Google's NotebookLM and AI Tools

The third pillar of our approach harnesses the power of artificial intelligence to enhance learning. We've developed AI-enhanced study materials for all 17 chapters, leveraging cutting-edge tools like Google's NotebookLM and Gemini PRO to create multiple learning modalities that accommodate diverse learning preferences.

These AI tools provide interactive learning assistance, offering explanations, answering questions, and helping you develop deeper understanding of complex concepts. The materials support multiple modalities—visual, auditory, textual, and interactive—ensuring that regardless of your preferred learning style, you'll find resources that resonate with you.

AI-Generated Visual Summaries

Each chapter includes a visual summary that distills the key concepts into an intuitive, graphical format. These summaries present chapter content visually, highlighting the relationships between concepts, the flow of ideas, and the main takeaways.

Visual summaries serve as both quick reference tools and review aids. Before diving into a chapter, you can preview the visual summary to understand what you'll learn. After completing a chapter, the visual summary helps consolidate your understanding and serves as a memory aid for later review. Research consistently shows that visual learning enhances retention, and these AI-generated summaries leverage that insight.

AI-Generated Video Overviews

To complement the static visual summaries, each chapter includes an AI-generated video overview that brings key concepts to life through motion, animation, and narration. These short videos, typically less than 10 minutes, provide visual explanations of the most important ideas in each chapter, presented in an intuitive and engaging format.

The videos are designed for first-time learning and quick reviews. Before diving into a chapter's notebook, watch the video overview to build a mental framework for the concepts you'll encounter. The combination of visual animation and clear narration helps you understand the "big picture" before engaging with code and mathematical details. After completing a chapter, the video serves as an efficient review tool, allowing you to quickly refresh your understanding of key concepts without re-reading the entire notebook. Like all resources in this learning ecosystem, videos are AI-generated using cutting-edge tools, ensuring consistent quality and pedagogical clarity across all the 17 chapters.

Interactive AI Slides and Presentations

For each chapter, we've generated presentation materials using NotebookLM that complement the traditional slides created by Professor Cameron. These AI-generated slides are designed for self-paced learning, with clear explanations, progressive concept building, and visual aids that clarify complex ideas.

The slides are presentation-ready, making them useful not just for individual study but also for group discussions, study sessions, or classroom presentations. They provide an alternative way to engage with the material, breaking down complex topics into digestible chunks that can be reviewed at your own pace.

Podcast Episodes for Audio Learning

One of the most innovative features of this learning ecosystem is the availability of AI-generated podcast discussions for all 17 chapters. These podcasts present chapter content through conversational dialogue, making complex econometric concepts accessible through natural language discussion.

Podcasts provide a perfect learning modality for commuting, exercising, or any time when visual focus isn't possible. The conversational format—where concepts are explained through dialogue rather than formal lecture—often makes difficult ideas more approachable. Complex topics are explained through back-and-forth discussion, reinforcing key concepts and providing alternative perspectives on the material.

These audio resources offer an alternative learning modality that complements the visual and interactive elements of notebooks and slides, ensuring you can continue learning even when you're away from your computer.

Quiz and AI Tutor Integration

Assessment and feedback are critical components of effective learning. Each chapter includes interactive quizzes powered by EdCafe and NotebookLM that test your understanding of key concepts. These aren't just multiple-choice questions—they're

interactive self-assessment tools that provide immediate feedback and personalized learning assistance based on your responses.

When you struggle with a concept, the AI tutor is available to provide code explanations, clarify theoretical points, and guide you toward understanding. This immediate, personalized support ensures you don't get stuck—help is always available when you need it. The AI tutor can explain why a particular approach works, suggest alternative methods, and help debug code when things don't work as expected.

Responsible Use of AI Tools

While AI tools provide powerful learning support, it's crucial to understand their proper role in your education. AI serves as an enhancement, not a replacement for critical thinking and genuine understanding. The foundation of your learning remains Cameron's authoritative textbook and the verified Python code in the notebooks—AI tools supplement this foundation, they don't replace it.

It's important to cross-reference AI-generated content with authoritative sources. While tools like NotebookLM and Gemini PRO are sophisticated, they can occasionally make mistakes or oversimplify complex concepts. You bear responsibility for verifying information and developing true understanding rather than simply accepting AI-generated explanations at face value.

All Python code in the notebooks has been carefully verified and tested for accuracy. When AI tools provide code explanations or suggestions, compare them against the tested code in the notebooks to ensure accuracy. The goal is to use AI tools to develop multiple learning pathways and deeper understanding—transparency about these tools' capabilities and limitations is essential to using them effectively.

Key resources for learning

This book is designed to be used in conjunction with two essential companion resources:

The metricsAI Website (<https://quarcs-lab.github.io/metricsai>) provides access to:

- *Interactive Google Colab notebooks for all 17 chapters*
- *AI-generated visual summaries, video overviews, and podcast episodes*
- *Links to quizzes, AI tutors, and presentation slides*
- *Quick summaries of foundational content*

Cameron's Original Textbook (*Analysis of Economics Data: An Introduction to Econometrics*, 2022) and materials (<https://cameron.econ.ucdavis.edu/aed/index.html>) provide:

- *Comprehensive explanations of econometric theory*
- *Deeper mathematical derivations and proofs*
- *Extended examples and applications*
- *Additional exercises and practice problems*
- *Original Stata, R, and Gretl code implementations*
- *Comprehensive datasets and detailed slides*

Together, these resources create a complete learning ecosystem: this book offers structured content and context and the website provides interactive computational tools with AI learning support.

I How to Use This Book

Getting Started

One of the greatest advantages of this learning platform is that there's no installation required—you can start learning immediately. The path from deciding to learn econometrics to running your first regression can be measured in seconds, not hours or days.

To begin, simply find the chapter you want to study and click the "Open in Colab" badge. Within moments, you'll have a fully functional Python environment in your browser, complete with all necessary libraries, datasets, and code. You can run code cells, modify examples, and experiment with variations immediately.

We recommend following the four-part progression of the book, starting with Statistical Foundations and working through to Advanced Topics. Each chapter builds on previous material, so working sequentially ensures you have the necessary background for more complex concepts. However, the modular structure also allows you to jump to specific topics of interest if you're already familiar with foundational material.

As you work through each chapter, make use of the supplementary AI materials as needed. Some learners will want to use every resource—notebook, visual summary, podcast, slides, and quiz. Others might focus primarily on the notebooks with occasional reference to other materials. The flexible design allows you to create a learning path that suits your needs and preferences.

For Each Chapter

To get the most out of each chapter, we recommend a multi-stage approach that combines different learning modalities:

Start by reading foundational concepts from Cameron's textbook. While this is optional (the notebooks are self-contained), reading the corresponding textbook chapter first provides valuable theoretical context and mathematical derivations that complement the computational focus of the notebooks. The textbook explains the "why" behind methods, while notebooks show the "how."

Run the Python notebook, executing code cells step-by-step. Don't just run the cells passively—read the explanations, study the code, and make sure you understand what each section accomplishes. Experiment by changing parameters, trying different datasets, or extending analyses beyond what's shown. This active engagement is where deep learning happens.

Review the visual summary for a quick overview of key concepts. The visual summary helps consolidate what you've learned and provides a different perspective on the chapter's main ideas. Visual representations often reveal connections between concepts that aren't immediately obvious in text or code.

Watch the video overview for an animated explanation of the chapter's key concepts. Unlike the static visual summary, the video uses motion and narration to demonstrate dynamic relationships and step-by-step processes. This is particularly valuable for

understanding how econometric techniques work in practice—you can see regression lines being fitted, distributions changing with different parameters, or hypothesis tests being conducted. The short format (under 10 minutes) makes videos ideal for focused learning sessions or quick reviews before exams.

Listen to the podcast for a conversational explanation of the chapter's content. The podcast offers yet another way to engage with the material, particularly useful for reinforcement and review. Many learners find that hearing concepts explained conversationally helps cement understanding in ways that reading or coding alone doesn't achieve.

Study the AI slides to see the material presented in presentation format. The slides break down complex topics into digestible pieces, making them ideal for review and for identifying areas where you might need additional study.

Review Cameron's original slides for the authoritative instructor perspective. These slides, created by Professor Cameron himself, provide the traditional academic presentation of the material and often include additional insights and examples not found elsewhere.

Take the quiz to test your understanding. The EdCafe quizzes provide immediate feedback on whether you've truly grasped the key concepts. Don't skip this step—self-assessment is crucial for identifying gaps in understanding before moving forward.

Consult the AI tutor whenever you need help. Whether you're stuck on a coding problem, confused about a statistical concept, or want a deeper explanation of a particular point, the NotebookLM and EdCafe AI tutors are available to provide personalized assistance.

Customize Your Learning!

By purchasing this book, you gain access to PDF versions of each chapter. These PDFs are designed to be used with a wide range of AI-powered learning tools, giving you substantial flexibility to customize your learning path.

Note: If you purchased the book on Leanpub, the PDFs are available directly from your Leanpub library.

The chapter PDFs are fully compatible with several AI tools that support adaptive and interactive learning. For example, **NotebookLM** (<https://notebooklm.google.com/>) can transform chapters into podcast-style audio discussions, generate personalized quizzes and flashcards, and produce interactive learning guides. **EdCafe**

(<https://www.edcafe.ai/>) allows you to create custom lesson plans, interactive quizzes, and AI chatbots. It also provides personalized feedback and analytics to monitor your learning progress. **AI Sheets** (<https://www.aisheets.study/>) converts chapter PDFs into interactive worksheets, concept maps, and fill-in-the-blank exercises that can be edited, customized, and exported as PDFs for offline study. Importantly, the outputs generated by these tools can be adapted to multiple languages and learning styles, highlighting AI's potential to promote inclusive learning.

You are encouraged to experiment with these PDFs and AI tools to identify the combination that best aligns with your learning preferences and objectives. Whether you prefer listening to AI-generated discussions during your commute, reinforcing understanding through interactive quizzes, or working systematically with structured worksheets, these tools offer multiple complementary pathways for mastering new concepts. They are most effective when used as supplements to—rather than substitutes for—active engagement with the Python notebooks.

Acknowledgments

A. Colin Cameron

This entire project would not exist without the foundational work of Professor A. Colin Cameron. His textbook, *Analysis of Economic Data: An Introduction to Econometrics* (2022), represents years of refinement in teaching econometrics with clarity, rigor, and practical relevance. Professor Cameron's generous permission to use his textbook content and structure made this computational companion possible.

Beyond the textbook itself, Professor Cameron has created and shared extensive teaching materials—original Stata, R, and Gretl code implementations, comprehensive datasets, and detailed PDF slides. These materials have served students and instructors, and they continue to serve as the authoritative reference for this Python implementation.

Most fundamentally, Professor Cameron's pioneering approach to making econometrics accessible and practical has been the inspiration for this entire project. His work demonstrates that rigorous econometric education need not be intimidating or inaccessible. This book attempts to extend that philosophy into the cloud computing and AI era, maintaining Cameron's commitment to clarity while leveraging new technological capabilities.

Technology and Platform Partners

This project relies heavily on cutting-edge technology platforms that have made modern, accessible education possible:

Google Colab provides the cloud computing infrastructure that makes zero-installation learning a reality. By offering free access to powerful computing resources and maintaining up-to-date Python environments, Colab has democratized access to data science education in ways that would have been unimaginable just a few years ago.

Google's NotebookLM powers the AI learning tools—podcasts, slides, and tutoring—that provide personalized learning support. This sophisticated AI technology transforms static educational content into interactive learning experiences tailored to individual needs and learning styles.

Google's Gemini PRO generates the visual summaries that help consolidate understanding and provide alternative perspectives on chapter content. The ability to automatically create meaningful visualizations of complex concepts represents a significant advance in educational technology.

EdCafe provides the platform for interactive quizzes and AI tutoring, offering the assessment and feedback mechanisms that are essential for effective learning. Their tools help ensure that learning is not just exposure to content but genuine mastery of concepts.

Open Source Community

This book builds on the incredible work of the open source community that has created and maintains Python's scientific computing ecosystem. The developers of Statsmodels, Pandas, NumPy, Matplotlib, and countless other libraries have created the tools that make sophisticated statistical analysis accessible to anyone with a computer and internet connection.

Special thanks go to the creators of Linearmodels and other econometric software tools that extend Python's capabilities specifically for econometric analysis. The documentation writers and maintainers who make these complex tools accessible through clear explanations and examples deserve particular recognition—their work is often invisible but absolutely essential.

The open source ethos—that knowledge and tools should be freely shared for the benefit of all—is fundamental to this project. We hope this book contributes back to

that community by introducing new users to Python's capabilities and demonstrating how these tools can be applied to econometric analysis.

Students, Reviewers, Family

Finally, thanks are due to the beta testers who worked through early versions of these notebooks and materials, providing invaluable feedback on what worked, what didn't, and what needed clarification. Their suggestions have improved the accessibility and clarity of the final product immeasurably.

Early adopters who used these materials in courses and self-study helped identify gaps, correct errors, and refine explanations. The integration of AI tools in particular benefited from their feedback on what types of support were most valuable at different stages of learning.

This book is ultimately for students—those learning econometrics now and those who will learn in the future. The goal has been to create materials that make that learning journey more accessible, more engaging, and more successful. If this book helps you understand econometrics better, apply it more confidently, and appreciate its power for answering important questions, then the effort has been worthwhile.

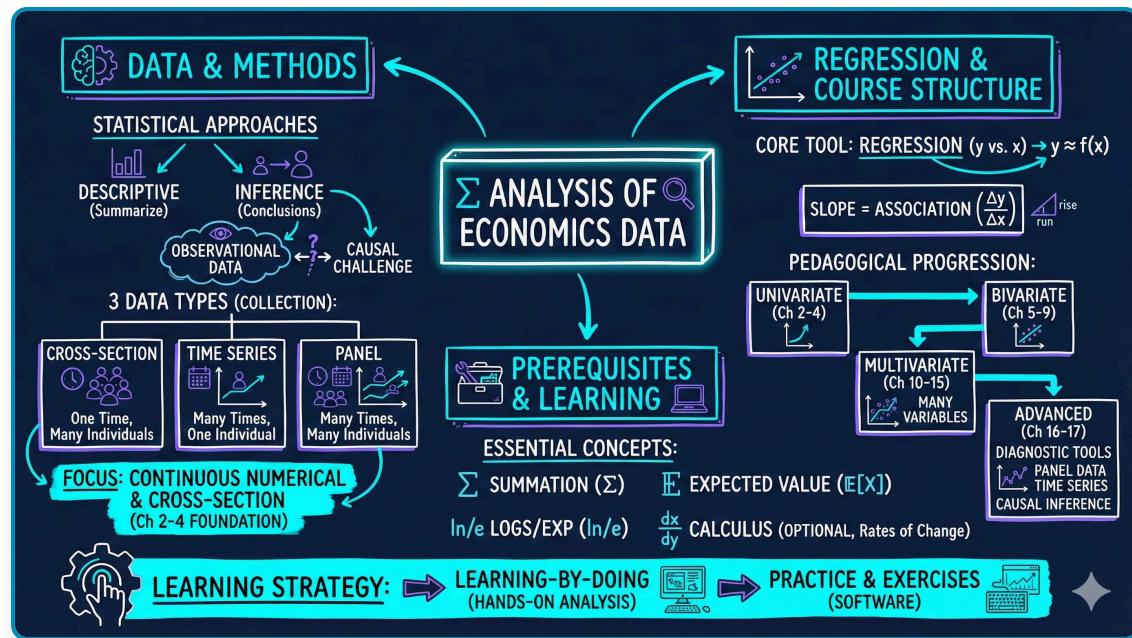
This book is dedicated to my family, whose unwavering support and encouragement have made this journey possible. Their patience during long hours of writing, coding, and testing has been a source of strength and motivation. Thank you for believing in this vision and standing by me throughout this endeavor.

Now, let's begin the journey into econometrics, powered by AI and brought to life through code.

Chapter 1: Analysis of Economics Data

metricsAI: An Introduction to Econometrics with Python and AI in the Cloud

Carlos Mendez



This notebook provides an interactive introduction to regression analysis using Python. You can run all code directly in Google Colab without any local setup required. The data streams directly from GitHub, making this notebook fully self-contained.

Open in Colab

Chapter Overview

This chapter introduces the fundamental concepts of econometrics and regression analysis. We'll explore how economists use statistical methods to understand relationships in economic data, focusing on a practical example of house prices and house sizes.

What you'll learn:

- What regression analysis is and why it's the primary tool in econometrics
- How to load and explore economic data using Python (pandas)

- How to visualize relationships between variables using scatter plots
- How to fit a simple linear regression model using Ordinary Least Squares (OLS)
- How to interpret regression coefficients in economic terms
- How to use Python's statsmodels package for regression analysis

Dataset used:

- **AED_HOUSE.DTA:** House sale prices for 29 houses in Central Davis, California (1999)
 - Variables: price (sale price in dollars), size (house size in square feet), plus 7 other characteristics

Chapter outline:

- 1.1 What is Regression Analysis?
- 1.2 Load the Data
- 1.3 Preview the Data
- 1.4 Explore the Data
- 1.5 Visualizing the Relationship
- 1.6 Fitting a Regression Line
- 1.7 Interpreting the Results
- 1.8 Visualizing the Fitted Line
- 1.9 Economic Interpretation and Examples
- 1.10 Practice Exercises
- 1.11 Case Studies

| Setup

Run this cell first to import all required packages and configure the environment. This sets up:

- Data manipulation (pandas, numpy)
- Statistical modeling (statsmodels)
- Visualization (matplotlib)
- Reproducibility (random seeds)

In [41]:

```
# Import required libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import statsmodels.api as sm
from statsmodels.formula.api import ols
import random
import os

# Set random seeds for reproducibility
RANDOM_SEED = 42
random.seed(RANDOM_SEED)
np.random.seed(RANDOM_SEED)
os.environ['PYTHONHASHSEED'] = str(RANDOM_SEED)

# GitHub data URL (data streams directly from here)
GITHUB_DATA_URL = "https://raw.githubusercontent.com/quarcs-lab/data-open/master/AED/"

# Optional: Create directories for saving outputs locally
IMAGES_DIR = 'images'
TABLES_DIR = 'tables'
os.makedirs(IMAGES_DIR, exist_ok=True)
os.makedirs(TABLES_DIR, exist_ok=True)

print("✓ Setup complete! All packages imported successfully.")
print(f"✓ Random seed set to {RANDOM_SEED} for reproducibility.")
print(f"✓ Data will stream from: {GITHUB_DATA_URL}")
```

```
✓ Setup complete! All packages imported successfully.
✓ Random seed set to 42 for reproducibility.
✓ Data will stream from: https://raw.githubusercontent.com/quarcs-lab/data-open/master/AED/
```

1.1 What is Regression Analysis?

Regression analysis is the primary tool economists use to understand relationships between variables. At its core, regression answers questions like: "How does Y change when X changes?"

In our example:

- **Y (dependent variable):** House sale price (in dollars)
- **X (independent variable):** House size (in square feet)

The **regression line** is the "line of best fit" that minimizes the sum of squared distances between actual prices and predicted prices. The mathematical form is:

$$\text{price} = \beta_0 + \beta_1 \times \text{size} + \varepsilon$$

Where:

- β_0 = **intercept** (predicted price when size = 0)
- β_1 = **slope** (change in price for each additional square foot)
- ε = **error term** (random variation not explained by size)

Economic Interpretation:

The slope coefficient β_1 tells us: "On average, how much more expensive is a house that is 1 square foot larger?" This is a measure of **association**, not necessarily causation.

Key Concept 1.1: Descriptive vs. Inferential Analysis

Descriptive analysis summarizes data using statistics and visualizations, while statistical inference uses sample data to draw conclusions about the broader population. Most econometric analysis involves statistical inference.

1.2 Load the Data

Let's load the house price dataset directly from GitHub. This dataset contains information on 29 house sales in Central Davis, California in 1999.

In [42]:

```
# Load the Stata dataset from GitHub
data_house = pd.read_stata(GITHUB_DATA_URL + 'AED_HOUSE.DTA')

print(f"✓ Data loaded successfully!")
print(f"  Shape: {data_house.shape[0]} observations, {data_house.shape[1]} variables")
```

✓ Data loaded successfully!
Shape: 29 observations, 8 variables

1.3 Preview the Data

Let's look at the first few rows to understand what variables we have available.

In [43]:

```
# Display first 5 rows
print("First 5 observations:")
print(data_house.head())

print("\nColumn names:")
print(data_house.columns.tolist())
```

```

First 5 observations:
   price    size  bedrooms  bathrooms  lotsize     age  monthsold      list
0 204000    1400         3        2.0      2.0  31.0         7 199900
1 212000    1600         3        3.0      3.0  33.0         5 212000
2 213000    1800         3        2.0      2.0  51.0         4 219900
3 220000    1600         3        2.0      2.0  49.0         4 229000
4 224500    2100         4        2.5      2.5  47.0         6 224500

Column names:
['price', 'size', 'bedrooms', 'bathrooms', 'lotsize', 'age', 'monthsold', 'list']

```

Transition: Before jumping into regression analysis, we need to understand our data. Descriptive statistics reveal the scale, variability, and range of our variables—essential for interpreting regression results.

I 1.4 Explore the Data

Before running any regression, it's essential to understand the data through **descriptive statistics**. Let's look at the key statistics for our variables of interest: price and size.

```
In [44]: # Summary statistics for all variables
print("=" * 70)
print("DESCRIPTIVE STATISTICS")
print("=" * 70)
print(data_house.describe().round(2))

# Focus on our key variables
print("\n" + "=" * 70)
print("KEY VARIABLES: PRICE AND SIZE")
print("=" * 70)
print(data_house[['price', 'size']].describe().round(2))
```

```

=====
DESCRIPTIVE STATISTICS
=====
      price      size   bedrooms   bathrooms   lotsize      age monthsold \
count    29.00    29.00    29.00     29.00    29.00    29.00    29.00
mean   253910.34  1882.76     3.79     2.21     2.14   36.41     5.97
std    37390.71   398.27     0.68     0.34     0.69    7.12    1.68
min    204000.00  1400.00     3.00     2.00     1.00   23.00     3.00
25%   233000.00  1600.00     3.00     2.00     2.00   31.00     5.00
50%   244000.00  1800.00     4.00     2.00     2.00   35.00     6.00
75%   270000.00  2000.00     4.00     2.50     3.00   39.00     7.00
max   375000.00  3300.00     6.00     3.00     3.00   51.00     8.00

      list
count    29.00
mean   257824.14
std    40860.26
min   199900.00
25%  239000.00
50%  245000.00
75%  269000.00
max  386000.00

=====
KEY VARIABLES: PRICE AND SIZE
=====
      price      size
count    29.00    29.00
mean   253910.34  1882.76
std    37390.71   398.27
min    204000.00  1400.00
25%   233000.00  1600.00
50%   244000.00  1800.00
75%   270000.00  2000.00
max   375000.00  3300.00

```

Key observations:

- **Mean house price:** Around \$253,910
- **Mean house size:** Around 1,883 square feet
- **Price range:** 204,000 to 375,000
- **Size range:** 1,400 to 3,300 square feet

Notice the variation in both variables - this variation is what allows us to estimate a relationship!

Key Concept 1.2: Observational Data in Economics

Economics primarily uses observational data where we observe behavior in uncontrolled settings. Unlike experimental data where conditions can be controlled, observational data requires careful methods to establish relationships and, when possible, causal effects.

Now that we have explored the data numerically, let's visualize the relationship between house size and price.

1.5 Visualizing the Relationship

Before running any regression, it's good practice to visualize the relationship between X and Y. A scatter plot helps us:

1. Check if there appears to be a linear relationship
2. Identify any outliers or unusual observations
3. Get an intuitive sense of the strength of the relationship

Let's create a scatter plot of house price vs. house size.

In [45]:

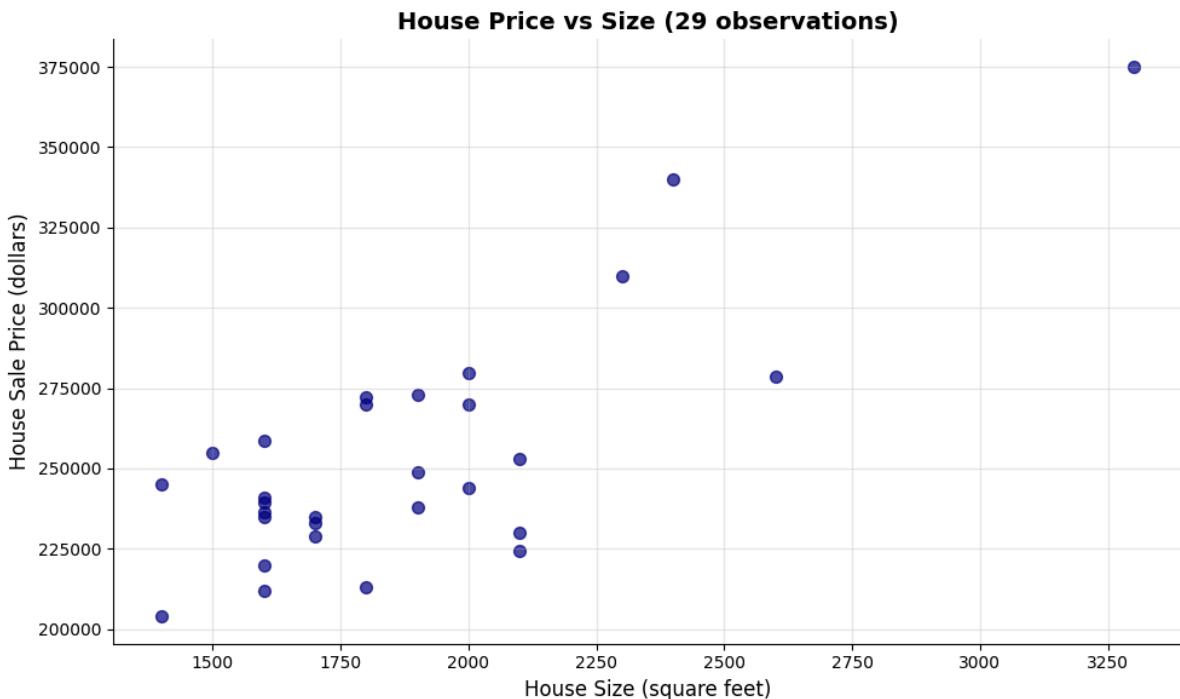
```
# Create scatter plot
fig, ax = plt.subplots(figsize=(10, 6))

# Plot the data points
ax.scatter(data_house['size'], data_house['price'],
           color='navy', s=50, alpha=0.7)

# Labels and formatting
ax.set_xlabel('House Size (square feet)', fontsize=12)
ax.set_ylabel('House Sale Price (dollars)', fontsize=12)
ax.set_title('House Price vs Size (29 observations)', fontsize=14, fontweight='bold')
ax.grid(True, alpha=0.3)
ax.spines[['top', 'right']].set_visible(False)

plt.tight_layout()
plt.show()

print("\nWhat do you see?")
print("- Positive relationship: Larger houses tend to have higher prices")
print("- Roughly linear: The points follow an upward-sloping pattern")
print("- Some scatter: Not all points lie exactly on a line (this is the 'error')")
```



What do you see?

- Positive relationship: Larger houses tend to have higher prices
- Roughly linear: The points follow an upward-sloping pattern
- Some scatter: Not all points lie exactly on a line (this is the 'error')

Transition: Having visualized a clear positive relationship between house size and price, we're ready to quantify this relationship precisely using regression analysis.

Key Concept 1.3: Visual Exploration Before Regression

Always plot your data before running a regression. Scatter plots reveal the direction, strength, and form of relationships between variables, and can expose outliers or nonlinearities that summary statistics alone would miss. Visual exploration is the essential first step in any empirical analysis.

I 1.6 Fitting a Regression Line

Now we'll fit an **Ordinary Least Squares (OLS)** regression line to these data. OLS chooses the intercept (β_0) and slope (β_1) that **minimize the sum of squared residuals**:

$$\min_{\beta_0, \beta_1} \sum_{i=1}^n (\text{price}_i - \beta_0 - \beta_1 \times \text{size}_i)^2$$

In other words, we're finding the line that makes our prediction errors as small as possible (in a squared sense).

We'll use Python's `statsmodels` package, which provides regression output similar to Stata and R.

Key Concept 1.4: Introduction to Regression Analysis

Regression analysis quantifies the relationship between variables. In a bivariate regression, the slope coefficient tells us how much the outcome variable (y) changes when the explanatory variable (x) increases by one unit.

In [46]:

```
# Fit OLS regression: price ~ size
# The formula syntax is: 'dependent_variable ~ independent_variable'
model = ols('price ~ size', data=data_house).fit()

# Display the full regression output
print("=" * 70)
print("OLS REGRESSION RESULTS: price ~ size")
print("=" * 70)
print(model.summary())
```

=====

OLS REGRESSION RESULTS: price ~ size

=====

OLS Regression Results

=====

Dep. Variable:	price	R-squared:	0.617			
Model:	OLS	Adj. R-squared:	0.603			
Method:	Least Squares	F-statistic:	43.58			
Date:	Sat, 31 Jan 2026	Prob (F-statistic):	4.41e-07			
Time:	02:18:54	Log-Likelihood:	-332.05			
No. Observations:	29	AIC:	668.1			
Df Residuals:	27	BIC:	670.8			
Df Model:	1					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
Intercept	1.15e+05	2.15e+04	5.352	0.000	7.09e+04	1.59e+05
size	73.7710	11.175	6.601	0.000	50.842	96.700

=====

Omnibus: 0.576 Durbin-Watson: 1.219

Prob(Omnibus): 0.750 Jarque-Bera (JB): 0.638

Skew: -0.078 Prob(JB): 0.727

Kurtosis: 2.290 Cond. No. 9.45e+03

=====

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 9.45e+03. This might indicate that there are strong multicollinearity or other numerical problems.

1.7 Interpreting the Results

The regression output contains a lot of information! Let's break down the most important parts:

Key Statistics to Focus On:

1. Coefficients table (middle section):

- **Intercept:** The predicted price when size = 0 (often not economically meaningful)
- **size:** The slope coefficient - our main interest!
- **std err:** Standard error (measures precision of the estimate)
- **t:** t-statistic (coefficient / standard error)
- **P>|t|:** p-value (tests if coefficient is significantly different from zero)

2. R-squared (top right section):

- Proportion of variation in Y explained by X
- Ranges from 0 to 1 (higher = better fit)

3. F-statistic (top right section):

- Tests overall significance of the regression
- Low p-value (Prob F-statistic) means the model is statistically significant

Let's extract and interpret the key coefficients.

In [47]:

```
# Extract key statistics
intercept = model.params['Intercept']
slope     = model.params['size']
r_squared = model.rsquared
n_obs    = int(model.nobs)

print("=" * 70)
print("KEY REGRESSION COEFFICIENTS")
print("=" * 70)
print(f"Intercept (\beta_0): ${intercept:,.2f}")
print(f"Slope (\beta_1):   ${slope:,.2f}")
print(f"R-squared: {r_squared:.4f} ({r_squared*100:.2f}%)")
print(f"Number of observations: {n_obs}")

print("\n" + "=" * 70)
print("ECONOMIC INTERPRETATION")
print("=" * 70)
print(f"\n📌 For every additional square foot of house size,")
print(f"  the sale price increases by approximately ${slope:,.2f}")
print(f"\n📌 The model explains {r_squared*100:.2f}% of the variation in house prices")
print(f"\n📌 The remaining {(1-r_squared)*100:.2f}% is due to other factors not included")
print(f"  (e.g., location, age, condition, neighborhood quality)")
```

=====

KEY REGRESSION COEFFICIENTS

=====

Intercept (β_0): \$115,017.28

Slope (β_1): \$73.77

R-squared: 0.6175 (61.75%)

Number of observations: 29

=====

ECONOMIC INTERPRETATION

=====

- ✖ For every additional square foot of house size,
the sale price increases by approximately \$73.77
- ✖ The model explains 61.75% of the variation in house prices
- ✖ The remaining 38.25% is due to other factors not included
(e.g., location, age, condition, neighborhood quality)

Key Concept 1.5: Reading Regression Output

The key elements of regression output are: the coefficient estimate (magnitude and direction of the relationship), the standard error (precision of the estimate), the t-statistic and p-value (statistical significance), and R-squared (proportion of variation explained). Together, these tell us whether the relationship is economically meaningful and statistically reliable.

I 1.8 Visualizing the Fitted Line

The **fitted regression line** represents our model's predictions. For any given house size, the line shows the predicted price according to our equation:

$$\hat{\text{price}} = \beta_0 + \beta_1 \times \text{size}$$

Let's overlay this fitted line on our scatter plot to see how well it captures the relationship.

In [48]:

```
# Create scatter plot with fitted regression line
fig, ax = plt.subplots(figsize=(10, 6))

# Plot actual data points
ax.scatter(data_house['size'], data_house['price'],
           color='navy', s=50, label='Actual prices', alpha=0.7)

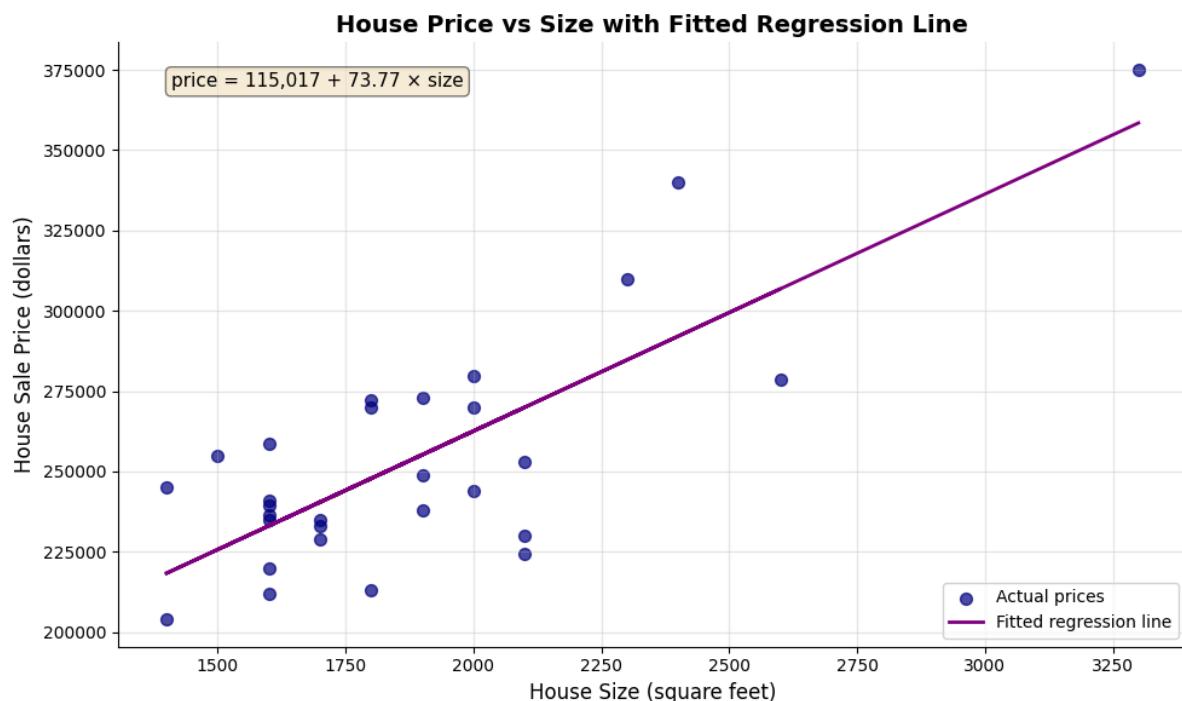
# Plot fitted regression line
ax.plot(data_house['size'], model.fittedvalues,
        color='purple', linewidth=2, label='Fitted regression line')

# Add equation to plot
equation_text = f'price = {intercept:.0f} + {slope:.2f} × size'
ax.text(0.05, 0.95, equation_text,
        transform=ax.transAxes, fontsize=11,
        verticalalignment='top',
        bbox=dict(boxstyle='round', facecolor='wheat', alpha=0.5))

# Labels and formatting
ax.set_xlabel('House Size (square feet)', fontsize=12)
ax.set_ylabel('House Sale Price (dollars)', fontsize=12)
ax.set_title('House Price vs Size with Fitted Regression Line',
             fontsize=14, fontweight='bold')
ax.legend(loc='lower right', fontsize=10)
ax.spines[['top', 'right']].set_visible(False)
ax.grid(True, alpha=0.3)

plt.tight_layout()
plt.show()

print("The purple line is our 'line of best fit'")
print("It minimizes the sum of squared vertical distances from each point")
```



The purple line is our 'line of best fit'
It minimizes the sum of squared vertical distances from each point

Transition: Statistical output is only meaningful when translated into economic insights. Let's explore what our regression coefficients tell us about housing markets and the limitations of our analysis.

Having fitted and visualized our regression model, let's now interpret what these results mean in economic terms.

| 1.9 Economic Interpretation and Examples

Now that we've estimated the regression, let's think about what it means in economic terms.

Practical Implications:

Our estimated slope of approximately **\$74 per square foot** means:

- A house that's 100 sq ft larger is predicted to sell for $74 \times 100 = \$7,400$ more
- A house that's 500 sq ft larger is predicted to sell for $74 \times 500 = \$37,000$ more

Making Predictions:

We can use our regression equation to predict prices for houses of different sizes. For example, for a 2,000 sq ft house:

$$\hat{\text{price}} = 115,952 + 74.03 \times 2000 = \$264,012$$

Important Caveats:

1. **This is association, not causation:** We can't conclude that adding square footage to a house will increase its value by \$74/sq ft. Other factors (like quality of construction) might be correlated with size.
2. **Omitted variables:** Many other factors affect house prices (location, age, condition, amenities). Our simple model ignores these - we'll learn how to include them in later chapters.
3. **Sample-specific:** These results are from 29 houses in Davis, CA in 1999. The relationship might differ in other locations or time periods.
4. **Don't extrapolate too far:** Our data ranges from 1,400 to 3,300 sq ft. Predictions far outside this range (e.g., for a 10,000 sq ft house) may not be reliable.

Key Concept 1.6: Interpreting Regression Results

Regression results must be interpreted with caution. Association does not imply causation, omitted variables can bias estimates, and predictions should not extrapolate beyond the range of the data.

| Key Takeaways

Statistical Methods and Data Types:

- Econometrics uses two main approaches: descriptive analysis (summarizing data) and statistical inference (drawing population conclusions from samples)
- Economic data are primarily continuous and numerical, though categorical and discrete data are also important
- Economics relies mainly on observational data, making causal inference more challenging than with experimental data
- The three data collection methods are cross-section (individuals at one time), time series (one individual over time), and panel data (individuals over time)
- Each data type requires different considerations for statistical inference, particularly when computing standard errors
- This textbook focuses on continuous numerical data and cross-section analysis as the foundation for more advanced methods

Regression Analysis and Interpretation:

- Regression analysis is the primary tool in econometrics, quantifying how outcome variables (y) vary with explanatory variables (x)
- The simple linear regression model has the form: $y = \beta_0 + \beta_1 x + \varepsilon$, where β_0 is the intercept and β_1 is the slope
- The slope coefficient measures association: how much y changes when x increases by one unit
- OLS (Ordinary Least Squares) finds the best-fitting line by minimizing the sum of squared prediction errors
- R-squared measures the proportion of variation in y explained by x , ranging from 0 to 1 (higher = better fit)
- Economic interpretation focuses on magnitude (size of effect), statistical significance, and practical importance

Practical Application:

- Our house price example: Each additional square foot is associated with a \$73.77 increase in price ($R^2 = 61.75\%$)
- Visualization is essential: scatter plots reveal the nature of relationships before fitting regression models
- Regression shows association, not causation—omitted variables and confounding factors require careful consideration
- Predictions should not extrapolate beyond the range of observed data
- Sample-specific results may not generalize to other locations, time periods, or populations

Python Tools and Workflow:

- `pandas` handles data loading, manipulation, and descriptive statistics
- `statsmodels.formula.api.ols()` estimates OLS regression models with R-style formula syntax
- `matplotlib` creates publication-quality scatter plots and visualizations
- Standard workflow: load data → explore descriptively → visualize → model → interpret → validate
- Random seeds ensure reproducibility of results across different runs

Prerequisites and Mathematical Background:

- Summation notation (Σ) expresses formulas concisely and appears throughout econometrics
- Calculus concepts (derivatives, rates of change) help understand marginal effects but are not essential
- Expected values ($E[X]$) define population parameters like means and variances
- "Learning-by-doing" is the most effective approach: practice with real data and software is essential for mastery

Next Steps:

- **Chapter 2:** Univariate data summary (describing single variables)
- **Chapter 3:** The sample mean and sampling distributions
- **Chapter 4:** Statistical inference for the mean (confidence intervals, hypothesis tests)
- **Chapters 5-7:** Deep dive into bivariate regression (extending what we learned here)

You have now mastered: Loading and exploring economic data in Python Creating scatter plots to visualize relationships Estimating simple linear regression models with

OLS Interpreting regression coefficients economically Understanding the limitations of regression analysis

These foundational concepts are the building blocks for all of econometrics. Everything that follows builds on this introduction!

| Practice Exercises

Test your understanding of regression analysis with these exercises:

Exercise 1: Conceptual understanding

- (a) What is the difference between descriptive analysis and statistical inference?
- (b) Why do economists primarily use observational data rather than experimental data?
- (c) Name the three main types of data collection methods and give an example of each.

Exercise 2: Data types

- Classify each of the following as continuous numerical, discrete numerical, or categorical:
 - (a) Annual household income
 - (b) Number of children in a family
 - (c) Employment status (employed, unemployed, not in labor force)
 - (d) Temperature in degrees Celsius

Exercise 3: Regression interpretation

- Suppose you estimate: $\text{earnings} = 20,000 + 5,000 \times \text{education}$
 - (a) Interpret the intercept coefficient
 - (b) Interpret the slope coefficient
 - (c) Predict earnings for someone with 16 years of education
 - (d) What is the predicted difference in earnings between someone with 12 vs. 16 years of education?

Exercise 4: Using our house price model

- Using the regression equation: $\text{price} = 115,017 + 73.77 \times \text{size}$
 - (a) Predict the price for a 1,800 sq ft house

- (b) Predict the price for a 2,500 sq ft house
- (c) What is the predicted price difference between these two houses?
- (d) Is the intercept economically meaningful in this context? Why or why not?

Exercise 5: Critical thinking about causation

- Our regression shows larger houses have higher prices. Does this mean:
 - (a) Adding square footage to a house will increase its value by \$73.77 per sq ft?
 - (b) What other factors might be correlated with both house size and price?
 - (c) How would you design a study to establish a causal relationship?

Exercise 6: R-squared interpretation

- Our model has $R^2 = 0.6175$ (61.75%)
- (a) What does this number tell us about our model?
- (b) What factors might explain the remaining 38.25% of variation in prices?
- (c) Would $R^2 = 1.0$ be realistic for real-world economic data? Why or why not?

Exercise 7: Summation notation

- Calculate: $\sum_{i=1}^4 (3 + 2i)$
- Show all steps in your calculation

Exercise 8: Python practice

- Load the house dataset and:
 - (a) Calculate the correlation between price and bedrooms
 - (b) Create a scatter plot of price vs. bedrooms
 - (c) Estimate the regression: price ~ bedrooms
 - (d) Compare the R^2 to our size regression. Which predictor is better?
-

1.11 Case Studies

Now let's apply what you've learned to real economic research! In this section, you'll explore data from actual published studies, using the same tools and techniques from this chapter.

Why case studies matter:

- See how regression analysis is used in real research
- Practice applying Chapter 1 tools to authentic data
- Develop intuition for economic relationships
- Bridge the gap between textbook examples and research practice

Case Study 1: Economic Convergence Clubs

Research Question: Do countries converge toward similar levels of economic development, or do they form distinct "convergence clubs" with different trajectories?

Background: Traditional economic theory suggests that poor countries should grow faster than rich countries, eventually "catching up" in terms of income and productivity. This is called the convergence hypothesis. However, empirical evidence shows a more complex picture: countries may form distinct groups (clubs) that converge toward different long-run equilibrium levels rather than a single global level.

This Research (Mendez, 2020): Uses modern econometric methods to identify convergence clubs in labor productivity across countries. The analysis examines whether countries follow one common development path or multiple distinct paths, and what factors (capital accumulation, technology, institutions) drive these patterns.

The Data: Panel dataset tracking multiple countries over several years, with 26 variables including:

- **Output measures:** GDP, GDP per capita
- **Productivity:** Labor productivity, total factor productivity (TFP)
- **Capital:** Physical capital stock, capital per worker
- **Human capital:** Years of schooling, human capital index
- **Classifications:** Country codes, regions, income groups

Your Task: Use the descriptive analysis and regression tools from Chapter 1 to explore patterns in the convergence clubs data. You'll investigate productivity gaps, visualize relationships, and begin to understand why some countries develop differently than others.

Key Concept 1.7: Economic Convergence and Productivity Drivers

Beta convergence refers to the hypothesis that poor countries will grow faster than rich countries, eventually "catching up" in terms of income and productivity. However, evidence suggests countries may form distinct **convergence clubs**—groups that converge toward different long-run equilibrium levels rather than a single global level.

Labor productivity (output per worker) depends on **capital accumulation** (capital per worker) and **aggregate efficiency** (total factor productivity or TFP). The regression of productivity on capital captures this association, allowing us to quantify how much of cross-country productivity differences are explained by capital versus efficiency factors.

Load the Convergence Clubs Data

Let's load two datasets:

1. **Main dataset** (`dat.csv`): Country-year panel data with economic variables
2. **Data dictionary** (`dat-definitions.csv`): Explains what each variable means

The data uses a **multi-index** structure with (country, year) pairs, allowing us to track each country over time.

In [49]:

```
# Import data with sorted multi-index
df1 = pd.read_csv(
    "https://raw.githubusercontent.com/quarcs-lab/mendez2020-convergence-clubs-code-
data/master/assets/dat.csv",
    index_col=["country", "year"]
).sort_index()

# Import data dictionary
df2 = pd.read_csv(
    "https://raw.githubusercontent.com/quarcs-lab/mendez2020-convergence-clubs-code-
data/master/assets/dat-definitions.csv"
)

# Display basic information
print("=" * 70)
print("CONVERGENCE CLUBS DATASET")
print("=" * 70)
print(f"Dataset shape: {df1.shape[0]} observations (country-year pairs), {df1.shape[1]} variables")
print(f"\nCountries: {len(df1.index.get_level_values('country').unique())} unique countries")
print(f"Years: {df1.index.get_level_values('year').min()} to {df1.index.get_level_values('year').max()}")


print("\n" + "=" * 70)
print("FIRST 5 OBSERVATIONS")
print("=" * 70)
print(df1.head(5))
```

```

=====
CONVERGENCE CLUBS DATASET
=====
Dataset shape: 2700 observations (country-year pairs), 27 variables

Countries: 108 unique countries
Years: 1990 to 2014

=====
FIRST 5 OBSERVATIONS
=====

```

	id	Y	K	pop	L	s	alpha_it	\
country	year							
Albania	1990	1	12449.999	31217	3.281453	1.250096	8.497386	NaN
	1991	1	11310.000	30082	3.275438	1.243719	8.442703	NaN
	1992	1	10122.000	28968	3.240613	0.993492	8.388020	NaN
	1993	1	11636.000	29010	3.189623	0.935928	8.333337	NaN
	1994	1	13120.000	29634	3.140634	1.008687	8.278653	NaN

	GDPpc	lp	h	...	log_h_raw	log_tfp_raw	\
country	year						
Albania	1990	3794.0508	9959.2344	3.165140	...	1.152197	5.560511
	1991	3452.9731	9093.6943	3.150347	...	1.147513	5.479933
	1992	3123.4832	10188.3060	3.135588	...	1.142817	5.457089
	1993	3648.0798	12432.5870	3.120863	...	1.138110	5.617254
	1994	4177.5005	13007.0080	3.106171	...	1.133391	5.707116

	log_GDPpc	log_lp	log_ky	log_h	log_tfp	isocode	\
country	year						
Albania	1990	8.130327	9.209681	0.880770	1.125790	5.541879	ALB
	1991	8.170837	9.268303	0.869605	1.133772	5.574306	ALB
	1992	8.211625	9.326916	0.858536	1.141821	5.606780	ALB
	1993	8.252907	9.385130	0.847930	1.150036	5.639110	ALB
	1994	8.294488	9.442308	0.838639	1.158521	5.670734	ALB

	hi1990	region
country	year	
Albania	1990	no Europe
	1991	no Europe
	1992	no Europe
	1993	no Europe
	1994	no Europe

[5 rows x 27 columns]

In [50]:

```

print("\n" + "=" * 75)
print("VARIABLE DEFINITIONS")
print("=" * 75)
print(df2)

```

=====		
VARIABLE DEFINITIONS		
	var_name	var_def type
0	country	Standardized country name (from PWT) cs_id
1	year	Year ts_id
2	Y	GDP numeric
3	K	Physical Capital numeric
4	pop	Population numeric
5	L	Labor Force numeric
6	s	Years of Schooling numeric
7	alpha_it	Variable Capital Share numeric
8	GDPpc	GDP per capita numeric
9	lp	Labor Productivity numeric
10	h	Human Capital Index numeric
11	kl	Capital per Worker numeric
12	kp	Capital Productivity numeric
13	ky	Capital-Output Ratio numeric
14	TFP	Aggregate Efficiency numeric
15	log_GDPpc_raw	Log of GDP per capita numeric
16	log_lp_raw	Log of Labor Productivity numeric
17	log_ky_raw	Log of Capital-Output Ratio numeric
18	log_h_raw	Log of Human Capital numeric
19	log_tfp_raw	Log of Total Factor Productivity numeric
20	log_GDPpc	Trend (HP400) of log of GDP per capita numeric
21	log_lp	Trend (HP400) of log of labor productivity numeric
22	log_ky	Trend (HP400) of log of Capital-Output Ratio numeric
23	log_h	Trend (HP400) of log of Human Capital numeric
24	log_tfp	Trend (HP400) of log of Aggregate Efficiency numeric
25	region	Regional group (Classification of the UN) factor
26	hi1990	High income country (as of 1990, World Bank c... factor
27	isocode	ISO code from the PWT9.0 factor

Task 1: Data Exploration (Guided)

Objective: Understand the dataset structure and available variables.

Instructions:

1. Examine the output above to understand the multi-index (country, year) structure
2. Review the data dictionary to identify key productivity variables
3. Check for missing values in key variables
4. Identify the variable names you'll use for subsequent analyses

Key variables to focus on (check exact names in the data dictionary):

- Labor productivity variables
- Capital per worker variables
- GDP per capita measures
- Country classification variables (region, income group)

Run the code above and study the output. What patterns do you notice? How many time periods does each country have?

```
In [51]: # Your code here: Explore the dataset structure
#
# Suggested explorations:
# 1. Check column names: df1.columns.tolist()
# 2. Check for missing values: df1.isnull().sum()
# 3. Examine a specific country's data
# 4. Count observations per country

# Example: Examine USA's data
# df1.loc['USA']
```

Task 2: Descriptive Statistics (Semi-guided)

Objective: Generate summary statistics for key productivity variables.

Instructions:

1. Select 3-4 key variables related to productivity and capital
2. Generate descriptive statistics (mean, median, std, min, max)
3. Identify countries with highest and lowest productivity levels
4. Calculate the productivity gap between top and bottom performers

Apply what you learned in sections 1.4: Use `.describe()` method like we did with the house price data.

Hint: You'll need to identify the exact variable names from the data dictionary. Look for variables measuring labor productivity, GDP per capita, or capital per worker.

```
In [52]: # Your code here: Generate descriptive statistics
#
# Steps:
# 1. Identify variable names from data dictionary (check df2)
# 2. Select key variables from df1
# 3. Generate summary statistics using .describe()
# 4. Find countries with max/min values using .idxmax() and .idxmin()
# 5. Calculate gaps between high and low performers

# Example structure:
# key_vars = ['variable1', 'variable2', 'variable3'] # Replace with actual names
# df1[key_vars].describe()
```

Key Concept 1.8: Panel Data Structure

Panel data combines cross-section and time series dimensions, tracking multiple entities (countries) over multiple time periods (years). This structure allows us to study both differences between countries (cross-sectional variation) and changes within countries over time (time series variation). The data is indexed by (country, year) pairs.

Task 3: Visualizing Productivity Patterns (Semi-guided)

Objective: Create scatter plots to visualize productivity relationships.

Instructions:

1. Create a scatter plot comparing two productivity-related variables
2. Add appropriate axis labels and a descriptive title
3. Optionally: Color-code points by region or income group
4. Interpret the pattern you observe

Apply what you learned in section 1.5: Use matplotlib to create scatter plots like the house price visualization.

Suggested relationships to explore:

- GDP per capita vs. labor productivity
- Capital per worker vs. labor productivity
- Human capital vs. GDP per capita

In [53]:

```
# Your code here: Create scatter plot
#
# Steps:
# 1. Prepare data (select variables, remove missing values)
# 2. Create figure and axis: fig, ax = plt.subplots(figsize=(10, 6))
# 3. Create scatter plot: ax.scatter(x, y, ...)
# 4. Add labels, title, and formatting
# 5. Display and interpret

# Example structure:
# plot_data = df1[['var_x', 'var_y']].dropna()
# fig, ax = plt.subplots(figsize=(10, 6))
# ax.scatter(plot_data['var_x'], plot_data['var_y'], alpha=0.6)
# ax.set_xlabel('Variable X')
# ax.set_ylabel('Variable Y')
# plt.show()

# What pattern do you observe? Positive or negative relationship?
```

Task 4: Time Series Exploration (More Independent)

Objective: Examine productivity trends over time for specific countries.

Instructions:

1. Select 2-3 countries of interest (e.g., USA, China, India, Japan, or countries from your region)
2. Plot labor productivity over time for each country
3. Compare their trajectories: Which countries are growing faster?

4. Calculate the average annual growth rate (optional: percentage change per year)

Hint: Remember that panel data is indexed by (country, year). Use `.loc[country]` to filter data for a specific country.

Questions to answer:

- Are productivity levels converging (getting closer) or diverging (spreading apart)?
- Which country experienced the fastest productivity growth?
- Do you see evidence of convergence clubs (groups following similar paths)?

In [54]:

```
# Your code here: Time series plots
#
# Steps:
# 1. Select countries (e.g., countries = ['USA', 'CHN', 'JPN'])
# 2. For each country, extract time series data
# 3. Create line plot over time
# 4. Compare trajectories

# Example structure:
# countries = ['USA', 'CHN', 'IND'] # Adjust based on actual country codes
# fig, ax = plt.subplots(figsize=(10, 6))
#
# for country in countries:
#     country_data = df1.loc[country]
#     ax.plot(country_data.index, country_data['productivity_var'], label=country)
#
# ax.set_xlabel('Year')
# ax.set_ylabel('Labor Productivity')
# ax.legend()
# plt.show()
```

Task 5: Simple Regression Analysis (INDEPENDENT)

Objective: Estimate the relationship between capital and productivity.

Research Question: Does higher capital per worker lead to higher labor productivity?

Instructions:

1. Prepare regression data (select variables, remove missing values)
2. Estimate OLS regression: `labor_productivity ~ capital_per_worker`
3. Display the regression summary
4. Interpret the slope coefficient economically
5. Report the R-squared value
6. **Critical thinking:** Discuss whether this is association or causation

Apply what you learned in sections 1.6-1.7: Use `ols()` from statsmodels and interpret coefficients.

Important questions:

- What does the slope coefficient tell us?
- Could there be omitted variables affecting both capital and productivity?
- Could reverse causality be a concern (does higher productivity lead to more capital accumulation)?

In [55]:

```
# Your code here: Regression analysis
#
# Steps:
# 1. Prepare data: reg_data = df1[['productivity_var', 'capital_var']].dropna()
# 2. Reset index if needed: reg_data = reg_data.reset_index()
# 3. Estimate regression: model = ols('productivity_var ~ capital_var',
# data=reg_data).fit()
# 4. Display summary: print(model.summary())
# 5. Extract and interpret coefficients

# Example structure:
# from statsmodels.formula.api import ols
#
# reg_data = df1[['var_y', 'var_x']].dropna().reset_index()
# model = ols('var_y ~ var_x', data=reg_data).fit()
# print(model.summary())
#
# Interpretation:
# Slope = ___: For every unit increase in capital per worker,
#                 labor productivity increases by ___ units
# R^2 = ___: Capital explains ___% of variation in productivity
```

Task 6: Comparative Analysis (Independent)

Objective: Compare productivity patterns between country groups.

Research Question: Does the capital-productivity relationship differ between high-income and developing countries?

Instructions:

1. If the data has an income group variable, group countries by income level
2. Calculate average productivity and capital for each group
3. Create comparative scatter plots (one color per group)
4. (Advanced) Run separate regressions for each group
5. Compare the slope coefficients: Is the relationship stronger in one group?

This extends Chapter 1 concepts: You're using grouping and comparative analysis to see if relationships vary across subsamples.

Questions to explore:

- Do high-income countries have uniformly higher productivity?

- Is the capital-productivity relationship steeper in developing countries?
- What might explain differences between groups?

In [56]:

```
# Your code here: Comparative analysis
#
# Steps:
# 1. Identify grouping variable (income level, region, etc.)
# 2. Group data: df1.groupby('group_var').mean()
# 3. Create comparative visualizations
# 4. Run regressions by group (optional)

# Example structure for comparative scatter plot:
# fig, ax = plt.subplots(figsize=(10, 6))
#
# for group in df1['group_var'].unique():
#     group_data = df1[df1['group_var'] == group]
#     ax.scatter(group_data['var_x'], group_data['var_y'], label=group, alpha=0.6)
#
# ax.set_xlabel('Capital per Worker')
# ax.set_ylabel('Labor Productivity')
# ax.legend()
# plt.show()

# Advanced: Separate regressions
# for group in groups:
#     group_data = df1[df1['group_var'] == group].dropna()
#     model = ols('var_y ~ var_x', data=group_data).fit()
#     print(f"\n{group}: Slope = {model.params['var_x']:.4f}, R2 = {model.rsquared:.4f}")



```

What You've Learned from This Case Study

Through this hands-on exploration of economic convergence data, you've applied all the core Chapter 1 tools:

- **Data loading and exploration:** Worked with real panel data from research
- **Descriptive statistics:** Summarized productivity patterns across countries
- **Visualization:** Created scatter plots and time series to reveal relationships
- **Regression analysis:** Quantified the capital-productivity relationship
- **Critical thinking:** Distinguished association from causation
- **Comparative analysis:** Explored differences between country groups

Connection to the research: The patterns you've discovered—productivity gaps, the role of capital, differences between country groups—are the empirical motivation for the convergence clubs analysis in Mendez (2020). The full research uses advanced methods (covered in later chapters) to formally identify clubs and test convergence hypotheses.

Looking ahead:

- **Chapter 2** will teach you more sophisticated descriptive analysis for univariate data

- **Chapter 3-4** cover statistical inference, allowing you to test hypotheses formally
 - **Chapter 5-9** extend regression analysis to multiple predictors and transformations
 - **Chapter 10-17** introduce advanced methods like panel data regression—perfect for convergence clubs!
-

Great work! You've completed Chapter 1 and applied your new skills to real economic research. Continue to Chapter 2 to learn more about data summary and distributions.

Case Study 2: Can Satellites See Poverty? Predicting Local Development in Bolivia

Research Question: Can satellite data—nighttime lights and satellite image embeddings—predict local economic development across Bolivia's municipalities?

Background: Monitoring progress toward the United Nations Sustainable Development Goals (SDGs) requires timely, granular data on economic conditions. However, many developing countries lack comprehensive municipality-level statistics. Recent advances in remote sensing and machine learning offer a promising alternative: using satellite data to *predict* local development outcomes.

Two types of satellite data have proven particularly useful:

1. **Nighttime lights (NTL):** Satellite images of Earth at night reveal the intensity of artificial lighting. Brighter areas typically correspond to greater economic activity, electrification, and urbanization. NTL data is available globally and annually, making it a powerful proxy for economic development in data-scarce regions ([Henderson et al., 2012](#)).
2. **Satellite image embeddings:** Deep learning models trained on daytime satellite imagery (Sentinel-2, Landsat) can extract 64-dimensional feature vectors that capture visual patterns—road networks, building density, vegetation cover, agricultural activity—without requiring manual labeling. These abstract features often correlate strongly with socioeconomic outcomes ([Jean et al., 2016](#)).

This Research (DS4Bolivia Project): A comprehensive data science initiative that integrates satellite data with Bolivia's Municipal SDG Atlas ([Andersen et al., 2020](#)) to study geospatial development patterns across all **339 municipalities**. The project demonstrates how machine learning models can predict SDG indicators from satellite features, achieving meaningful predictive accuracy for poverty and energy access indicators.

The Data: Cross-sectional dataset covering 339 Bolivian municipalities with over 350 variables, including:

- **Development outcomes:** Municipal Sustainable Development Index (IMDS, 0-100 composite), individual SDG indices (SDG 1-17)
- **Satellite data:** Log nighttime lights per capita (2012-2020), 64 satellite embedding dimensions (2017)
- **Demographics:** Population (2001-2020), municipality and department names
- **Socioeconomic indicators:** Unsatisfied basic needs, literacy rates, electricity coverage, health outcomes

Your Task: Use the descriptive analysis and regression tools from Chapter 1 to explore the DS4Bolivia dataset. You'll investigate whether nighttime lights predict municipal development, visualize satellite-development relationships, and begin to assess how useful remote sensing data is for SDG monitoring. This case study introduces a dataset that we will revisit throughout the textbook, applying increasingly sophisticated econometric methods in each chapter.

Key Concept 1.9: Satellite Data as Economic Proxy

Nighttime lights (NTL) captured by satellites measure the intensity of artificial illumination on Earth's surface. Because lighting requires electricity and economic activity, NTL intensity strongly correlates with GDP, income levels, and urbanization. The log of NTL per capita transforms the highly skewed raw luminosity into a more symmetric variable suitable for regression analysis.

Satellite embeddings are 64-dimensional feature vectors extracted by deep learning models from daytime satellite imagery. Each dimension captures abstract visual patterns (building density, road networks, vegetation) that correlate with socioeconomic conditions. Together, NTL and embeddings provide complementary information: NTL captures nighttime economic activity while embeddings capture daytime physical infrastructure.

Load the DS4Bolivia Data

Let's load the comprehensive DS4Bolivia dataset directly from GitHub. This dataset integrates satellite data, SDG indicators, and demographic information for all 339 Bolivian municipalities.

In []:

```
# Load the DS4Bolivia dataset
url_bol = "https://raw.githubusercontent.com/quarcs-lab/ds4bolivia/master/ds4bolivia_v20250523.csv"
bol = pd.read_csv(url_bol)

# Display basic information
print("=" * 70)
print("DS4BOLIVIA DATASET")
print("=" * 70)
print(f"Dataset shape: {bol.shape[0]} municipalities, {bol.shape[1]} variables")
print(f"\nDepartments: {bol['dep'].nunique()} unique departments")
print(f"Department names: {sorted(bol['dep'].unique())}")

# Select key variables for this case study
key_vars = ['mun', 'dep', 'imds', 'ln_NTlpc2017', 'pop2017',
            'index_sdg1', 'index_sdg4', 'index_sdg8', 'sdg1_1_ubn']
bol_key = bol[key_vars].copy()

print(f"\nKey variables selected: {len(key_vars)}")
print("\n" + "=" * 70)
print("FIRST 10 MUNICIPALITIES")
print("=" * 70)
print(bol_key.head(10))
```

In []:

```
# Variable descriptions for this case study
print("=" * 70)
print("KEY VARIABLE DESCRIPTIONS")
print("=" * 70)
descriptions = {
    'mun': 'Municipality name',
    'dep': 'Department (administrative region, 9 total)',
    'imds': 'Municipal Sustainable Development Index (0-100, composite of all SDGs)',
    'ln_NTlpc2017': 'Log of nighttime lights per capita (2017, satellite-based)',
    'pop2017': 'Population in 2017',
    'index_sdg1': 'SDG 1 Index: No Poverty (0-100)',
    'index_sdg4': 'SDG 4 Index: Quality Education (0-100)',
    'index_sdg8': 'SDG 8 Index: Decent Work and Economic Growth (0-100)',
    'sdg1_1_ubn': 'Unsatisfied Basic Needs (% of population, 2012)'
}
for var, desc in descriptions.items():
    print(f" {var:20s} - {desc}")
```

Task 1: Data Exploration (Guided)

Objective: Understand the DS4Bolivia dataset structure and key variables.

Instructions:

1. Examine the output above: How many municipalities? How many departments?
2. Check for missing values in the key variables
3. Identify the range of the IMDS index (development measure)
4. Explore the distribution of departments (how many municipalities per department?)

Key variables to focus on:

- `imds` : Overall development index (our main dependent variable)
- `ln_NTLpc2017` : Log nighttime lights per capita (our main predictor)
- `dep` : Department (for regional comparisons)
- `pop2017` : Population (for context)

Run the code below to explore the data structure.

In []:

```
# Your code here: Explore the DS4Bolivia dataset
#
# Suggested explorations:
# 1. Check for missing values: bol_key.isnull().sum()
# 2. Municipalities per department: bol_key['dep'].value_counts()
# 3. Range of IMDS: bol_key['imds'].describe()
# 4. Largest/smallest municipalities: bol_key.nlargest(5, 'pop2017')

# Example: Check missing values
print("Missing values per variable:")
print(bol_key.isnull().sum())
print(f"\nTotal municipalities: {len(bol_key)}")
print(f"Complete cases (no missing in key vars): {bol_key.dropna().shape[0]}")
```

Task 2: Descriptive Statistics (Guided)

Objective: Generate summary statistics for key development and satellite variables.

Instructions:

1. Calculate descriptive statistics for `imds`, `ln_NTLpc2017`, and `pop2017`
2. Identify the municipality with the highest and lowest IMDS
3. Compare average IMDS across departments
4. Discuss what the summary statistics reveal about inequality across municipalities

Apply what you learned in section 1.4: Use `.describe()` and `.groupby()` methods like we did with the house price data.

In []:

```
# Your code here: Descriptive statistics for DS4Bolivia
#
# Steps:
# 1. Summary statistics for key variables
# 2. Identify top/bottom municipalities
# 3. Compare departments

# Example: Summary statistics
print("=" * 70)
print("DESCRIPTIVE STATISTICS: KEY VARIABLES")
print("=" * 70)
print(bol_key[['imds', 'ln_NTLpc2017', 'pop2017', 'sdg1_1_ubn']].describe().round(2))

# Top and bottom municipalities by IMDS
print("\n" + "=" * 70)
print("TOP 5 MUNICIPALITIES BY DEVELOPMENT (IMDS)")
print("=" * 70)
print(bol_key.nlargest(5, 'imds')[['mun', 'dep', 'imds',
'ln_NTLpc2017']].to_string(index=False))

print("\n" + "=" * 70)
print("BOTTOM 5 MUNICIPALITIES BY DEVELOPMENT (IMDS)")
print("=" * 70)
print(bol_key.nsmallest(5, 'imds')[['mun', 'dep', 'imds',
'ln_NTLpc2017']].to_string(index=False))
```

Key Concept 1.10: Subnational Development Analysis

National-level statistics can mask enormous variation in development outcomes within a country. Bolivia's 339 municipalities span a wide range of development levels—from highly urbanized departmental capitals with strong infrastructure to remote rural communities with limited services. Municipality-level analysis reveals this **within-country inequality** and helps identify specific areas where SDG progress lags behind. Satellite data is particularly valuable for subnational analysis because it provides spatially granular measurements even where traditional surveys are scarce or infrequent.

Task 3: Visualize the NTL-Development Relationship (Semi-guided)

Objective: Create scatter plots to visualize the relationship between nighttime lights and development.

Instructions:

1. Create a scatter plot of `ln_NTLpc2017` (x-axis) vs `imds` (y-axis)
2. Add appropriate axis labels and title
3. Optionally: Color-code points by department
4. Interpret the pattern: Is there a positive relationship? How strong does it look?

Apply what you learned in section 1.5: Use matplotlib to create scatter plots like the house price visualization.

Hint: Drop missing values before plotting with `.dropna()`

In []:

```
# Your code here: Scatter plot of NTL vs Development
#
# Steps:
# 1. Prepare data (drop missing values)
# 2. Create scatter plot
# 3. Add labels and formatting
# 4. Interpret the pattern

# Example structure:
# plot_data = bol_key[['ln_NTLpc2017', 'imds']].dropna()
# fig, ax = plt.subplots(figsize=(10, 6))
# ax.scatter(plot_data['ln_NTLpc2017'], plot_data['imds'], alpha=0.5, color='navy')
# ax.set_xlabel('Log Nighttime Lights per Capita (2017)')
# ax.set_ylabel('Municipal Development Index (IMDS)')
# ax.set_title('Can Satellites See Development? NTL vs IMDS in Bolivia')
# plt.show()
```

Task 4: Simple Regression Analysis (Semi-guided)

Objective: Estimate the relationship between nighttime lights and development using OLS.

Research Question: How much does nighttime light intensity predict municipal development levels?

Instructions:

1. Prepare regression data (drop missing values in key variables)
2. Estimate OLS regression: `imds ~ ln_NTLpc2017`
3. Display the regression summary
4. Interpret the slope coefficient: What does a 1-unit increase in log NTL mean for IMDS?
5. Report and interpret R-squared: How much variation in development does NTL explain?

Apply what you learned in sections 1.6-1.7: Use `ols()` from statsmodels.

In []:

```
# Your code here: OLS regression of IMDS on NTL
#
# Steps:
# 1. Prepare data
# 2. Estimate regression
# 3. Display and interpret results

# Example structure:
# reg_data = bol_key[['imds', 'ln_NTlpC2017']].dropna()
# model_bol = ols('imds ~ ln_NTlpC2017', data=reg_data).fit()
# print(model_bol.summary())
#
# # Extract key statistics
# print(f"\nSlope: {model_bol.params['ln_NTlpC2017']:.4f}")
# print(f"\nR-squared: {model_bol.rsquared:.4f}")
# print(f"\nInterpretation: A 1-unit increase in log NTL per capita")
# print(f"is associated with a {model_bol.params['ln_NTlpC2017']:.2f}-point increase in
IMDS")
```

Task 5: Regional Comparison (Independent)

Objective: Compare development and NTL patterns across Bolivia's nine departments.

Research Question: Do satellite-development patterns vary across Bolivia's regions?

Instructions:

1. Calculate mean IMDS and mean NTL by department
2. Create a bar chart or dot plot comparing department averages
3. Identify which departments are the most and least developed
4. Create scatter plots colored by department to see if the NTL-IMDS relationship differs by region
5. Discuss what might explain regional differences (geography, urbanization, economic structure)

This extends Chapter 1 concepts: You're using grouping and comparative analysis to explore heterogeneity.

In []:

```
# Your code here: Regional comparison
#
# Steps:
# 1. Group by department: bol_key.groupby('dep')[['imds', 'ln_NTLpc2017']].mean()
# 2. Create comparative bar chart
# 3. Create scatter plot colored by department
# 4. Identify top/bottom departments

# Example structure:
# dept_means = bol_key.groupby('dep')[['imds', 'ln_NTLpc2017']].mean().sort_values('imds')
# print(dept_means.round(2))
#
# fig, ax = plt.subplots(figsize=(10, 6))
# dept_means['imds'].plot(kind='barh', ax=ax, color='purple', alpha=0.7)
# ax.set_xlabel('Mean IMDS')
# ax.set_title('Average Municipal Development by Department')
# plt.tight_layout()
# plt.show()
```

Task 6: Policy Brief on Satellite Data for SDG Monitoring (Independent)

Objective: Write a 200-300 word policy brief summarizing your findings.

Your brief should address:

1. **Key finding:** What is the relationship between nighttime lights and municipal development in Bolivia?
2. **Magnitude:** How strong is the association? What does the R-squared tell us about predictive power?
3. **Regional variation:** Do some departments show higher development levels? Is there a geographic pattern?
4. **Policy implications:** How could satellite data be used for SDG monitoring in Bolivia?
5. **Limitations:** What can satellite data *not* tell us about development? What other data sources are needed?

Connection to Research: The DS4Bolivia project uses machine learning (Random Forest, XGBoost) to predict SDG indicators from satellite embeddings, achieving R^2 up to 0.57 for extreme energy poverty. Your simple OLS regression provides a baseline for understanding how much satellite data captures about development outcomes.

Looking ahead: In subsequent chapters, we will revisit this dataset to:

- Summarize the distribution of development indicators (Chapter 2)
- Test whether development differences are statistically significant (Chapter 4)
- Explore bivariate relationships between NTL and specific SDG outcomes (Chapter 5)
- Add multiple satellite features as predictors (Chapters 10-12)

- Test for regional structural differences (Chapter 14)
- Check model assumptions and diagnostics (Chapter 16)
- Analyze NTL panel data over time (Chapter 17)

In []:

```
# Your code here: Additional analysis for the policy brief
#
# You might want to:
# 1. Create a summary table of key results
# 2. Generate a visualization that tells a compelling story
# 3. Calculate specific statistics to cite in your brief

# Example: Summary of key results
# print("KEY RESULTS FOR POLICY BRIEF")
# print(f"Sample: {len(reg_data)} municipalities")
# print(f"NTL coefficient: {model_bol.params['ln_NTlpC2017']:.2f}")
# print(f"R-squared: {model_bol.rsquared:.2%}")
# print(f"Most developed department: {dept_means['imds'].idxmax()}")
# print(f"Least developed department: {dept_means['imds'].idxmin()}")
```

What You've Learned from This Case Study

Through this exploration of satellite data and municipal development in Bolivia, you've applied the Chapter 1 toolkit to a cutting-edge research application:

- **Data loading and exploration:** Worked with a real geospatial dataset covering 339 municipalities
- **Descriptive statistics:** Summarized development indicators and identified high/low performers
- **Visualization:** Created scatter plots revealing the satellite-development relationship
- **Regression analysis:** Quantified how nighttime lights predict development outcomes
- **Regional comparison:** Explored how the relationship varies across Bolivia's departments
- **Critical thinking:** Assessed the potential and limitations of satellite data for SDG monitoring

Connection to the research: The DS4Bolivia project extends this simple analysis by incorporating 64-dimensional satellite embeddings and advanced machine learning methods. Your OLS baseline provides the foundation for understanding what these more complex models improve upon.

This dataset returns throughout the textbook: Each subsequent chapter applies its specific econometric tools to the DS4Bolivia data, building progressively from univariate summaries (Chapter 2) through panel data analysis (Chapter 17). By the end

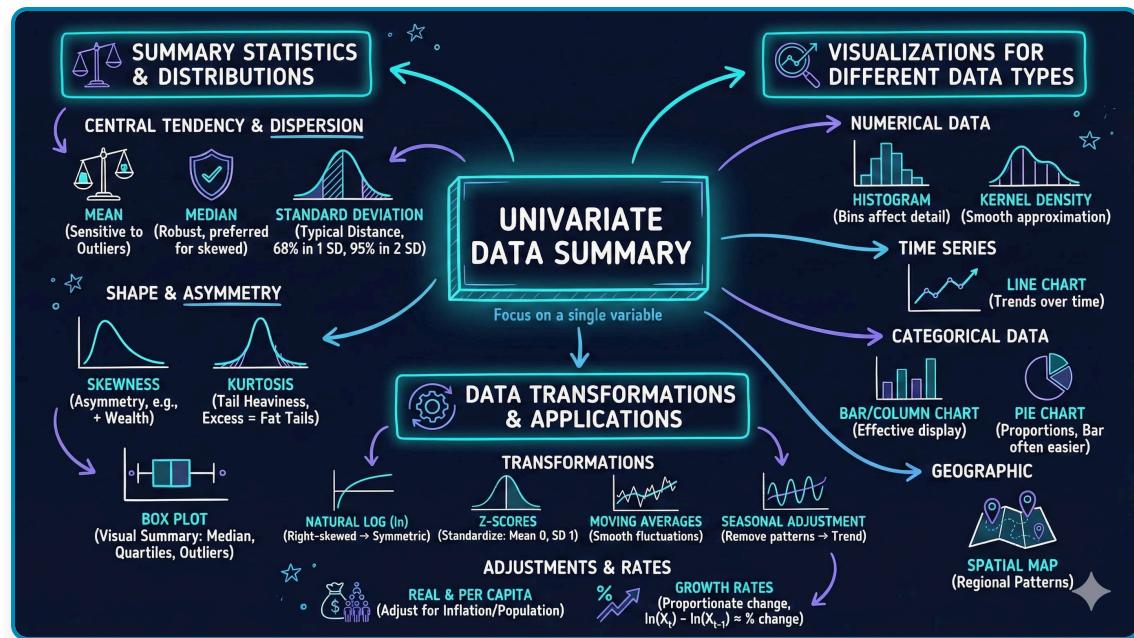
of the book, you'll have a comprehensive econometric analysis of satellite-based development prediction.

Well done! You've now explored two real-world datasets—cross-country convergence and Bolivian municipal development—using the fundamental tools of econometrics.

Chapter 2: Univariate Data Summary

metricsAI: An Introduction to Econometrics with Python and AI in the Cloud

Carlos Mendez



This notebook provides an interactive introduction to univariate data analysis using Python. You'll learn how to summarize and visualize single-variable datasets using summary statistics and various chart types.

Open in Colab

| Chapter Overview

Univariate data consists of observations on a single variable—for example, annual earnings, individual income, or GDP over time. This chapter teaches you how to summarize and visualize such data effectively.

What you'll learn:

- Calculate summary statistics (mean, median, standard deviation, quartiles, skewness, kurtosis)
- Create visualizations for numerical data (box plots, histograms, kernel density estimates, line charts)

- Visualize categorical data (bar charts, pie charts)
- Apply data transformations (logarithms, standardization)
- Work with time series transformations (moving averages, seasonal adjustment)

Datasets used:

- **AED_EARNINGS.DTA**: Annual earnings for 171 full-time working women aged 30 in 2010
- **AED_REALGDP.DTA**: U.S. quarterly real GDP per capita from 1959 to 2020
- **AED_HEALTHCATEGORIES.DTA**: U.S. health expenditures by category in 2018
- **AED_FISHING.DTA**: Fishing site choices for 1,182 fishers
- **AED_MONTHLYHOMESALES.DTA**: Monthly U.S. home sales from 1999 to 2015

Chapter outline:

- 2.1 Summary Statistics for Numerical Data
- 2.2 Charts for Numerical Data
- 2.3 Charts for Numerical Data by Category
- 2.4 Charts for Categorical Data
- 2.5 Data Transformation
- 2.6 Data Transformations for Time Series Data
- 2.7 Practice Exercises
- 2.8 Case Studies

| Setup

Run this cell first to import all required packages and configure the environment.

In [1]:

```
# Import required libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
import random
import os

# Set random seeds for reproducibility
RANDOM_SEED = 42
random.seed(RANDOM_SEED)
np.random.seed(RANDOM_SEED)
os.environ['PYTHONHASHSEED'] = str(RANDOM_SEED)

# GitHub data URL (data streams directly from here)
GITHUB_DATA_URL = "https://raw.githubusercontent.com/quarcs-lab/data-open/master/AED/"

# Optional: Create directories for saving outputs locally
IMAGES_DIR = 'images'
TABLES_DIR = 'tables'
os.makedirs(IMAGES_DIR, exist_ok=True)
os.makedirs(TABLES_DIR, exist_ok=True)

# Set plotting style
sns.set_style("whitegrid")
plt.rcParams['figure.figsize'] = (10, 6)

print("✓ Setup complete! All packages imported successfully.")
print(f"✓ Random seed set to {RANDOM_SEED} for reproducibility.")
print(f"✓ Data will stream from: {GITHUB_DATA_URL}")
```

✓ Setup complete! All packages imported successfully.
✓ Random seed set to 42 for reproducibility.
✓ Data will stream from: <https://raw.githubusercontent.com/quarcs-lab/data-open/master/AED/>

2.1 Summary Statistics for Numerical Data

Summary statistics provide a concise numerical description of a dataset. For a sample of size n , observations are denoted:

$$x_1, x_2, \dots, x_n$$

Key summary statistics:

1. Mean (average):

$$\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$$

2. Median:

The middle value when data are ordered

3. Standard deviation:

Measures the spread of data around the mean

$$s = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2}$$

- 4. Quartiles:** Values that divide ordered data into fourths (25th, 50th, 75th percentiles)
- 5. Skewness:** Measures asymmetry of the distribution (positive = right-skewed)
- 6. Kurtosis:** Measures heaviness of distribution tails (higher = fatter tails)

Economic Example: We'll examine annual earnings for full-time working women aged 30 in 2010.

Load Earnings Data

In [2]:

```
# Load the earnings dataset from GitHub
data_earnings = pd.read_stata(GITHUB_DATA_URL + 'AED_EARNINGS.DTA')

print(f"✓ Data loaded successfully!")
print(f" Shape: {data_earnings.shape[0]} observations, {data_earnings.shape[1]} variables")
print("\nFirst 5 observations:")
print(data_earnings.head())
```

✓ Data loaded successfully!
Shape: 171 observations, 4 variables

First 5 observations:

	earnings	education	age	gender
0	25000	14	30	0.0
1	40000	12	30	0.0
2	25000	13	30	0.0
3	38000	13	30	0.0
4	28800	12	30	0.0

Summary Statistics

In [3]:

```
# Basic summary statistics
print("=" * 70)
print("Basic Descriptive Statistics")
print("=" * 70)
print(data_earnings.describe())

# Detailed statistics for earnings
earnings = data_earnings['earnings']

stats_dict = {
    'Count': len(earnings),
    'Mean': earnings.mean(),
    'Std Dev': earnings.std(),
    'Min': earnings.min(),
    '25th percentile': earnings.quantile(0.25),
    'Median': earnings.median(),
    '75th percentile': earnings.quantile(0.75),
    'Max': earnings.max(),
    'Skewness': stats.skew(earnings),
    'Kurtosis': stats.kurtosis(earnings) # Excess kurtosis (raw kurtosis - 3)
}

print("\n" + "=" * 70)
print("Summary Statistics for Earnings")
print("=" * 70)
for key, value in stats_dict.items():
    if key in ['Count']:
        print(f"{key}: {value:,.0f}")
    elif key in ['Skewness', 'Kurtosis']:
        print(f"{key}: {value:.2f}")
    else:
        print(f"{key}: ${value:,.2f}")
```

```
=====
Basic Descriptive Statistics
=====
   earnings   education      age   gender  lnearnings
count    171.000000  171.000000  171.0    171.0  171.000000
mean     41412.690058  14.432749   30.0     0.0   10.457638
std      25527.053396   2.735364   0.0     0.0   0.622062
min      1050.000000   3.000000   30.0     0.0   6.956545
25%     25000.000000  12.000000   30.0     0.0   10.126631
50%     36000.000000  14.000000   30.0     0.0   10.491274
75%     49000.000000  16.000000   30.0     0.0   10.799367
max     172000.000000  20.000000   30.0     0.0   12.055250

=====
Summary Statistics for Earnings
=====
Count      : 171
Mean       : $41,412.69
Std Dev    : $25,527.05
Min        : $1,050.00
25th percentile : $25,000.00
Median     : $36,000.00
75th percentile : $49,000.00
Max        : $172,000.00
Skewness   : 1.71
Kurtosis   : 4.32
```

Key findings from the 171 full-time working women aged 30:

1. Central Tendency - Mean vs Median:

- **Mean = \$41,412.69**: The arithmetic average
- **Median = \$36,000**: The middle value
- **Gap = \$5,412** (mean is 15% higher than median)
- **Why?** This signals right skewness—some high earners pull the mean upward

2. Spread - Standard Deviation:

- **Std Dev = \$25,527.05**
- This equals 61.6% of the mean (substantial variation)
- **Rule of thumb:** About 68% of women earn within $41,413 \pm 25,527 = 15,886$ to 66,940

3. Range and Quartiles:

- **Minimum = \$1,050** (possibly part-time misclassified, or very low earner)
- **25th percentile = \$25,000** (bottom quarter earns $\leq \$25k$)
- **75th percentile = \$49,000** (top quarter earns $\geq \$49k$)
- **Maximum = \$172,000** (highest earner makes 164x more than lowest!)
- **Interquartile range (IQR) = \$24,000** (middle 50% span \$24k)

4. Shape Measures:

- **Skewness = 1.71** (strongly positive)
 - Values > 1 indicate strong right skew
 - **Interpretation guidelines:**
 - $|Skewness| < 0.5$: approximately symmetric
 - $0.5 < |Skewness| < 1$: moderately skewed
 - $|Skewness| > 1$: highly skewed (like our data)
 - Long right tail with high earners
 - Distribution is NOT symmetric
- **Kurtosis = 4.32** (excess kurtosis, compared to normal = 0)
 - **Note:** Python's `scipy.stats.kurtosis()` reports excess kurtosis by default (raw kurtosis - 3)
 - Raw kurtosis = 7.32; Excess kurtosis = 4.32 (what we report here)
 - Normal distribution has raw kurtosis = 3, so excess kurtosis = 0

- Heavier tails than normal distribution
- More extreme values than a bell curve would predict
- **Interpretation guidelines (excess kurtosis):**
 - Excess kurtosis < 0 : light tails (platykurtic)
 - Excess kurtosis ≈ 0 : normal tails (mesokurtic)
 - Excess kurtosis > 0 : heavy tails (leptokurtic - like our data)
- Greater chance of outliers

Economic interpretation: Earnings distributions are typically right-skewed because:

- **Lower bound exists:** Can't earn less than zero (or minimum wage)
- **No upper bound:** Some professionals earn very high incomes
- **Labor market structure:** Most workers cluster around median, but executives, specialists, and entrepreneurs create a long right tail

Practical implication: The median (36,000) is a better measure of "typical" earnings than the mean (41,413) because it's not inflated by high earners.

Key Concept 2.1: Summary Statistics

Summary statistics condense datasets into interpretable measures of central tendency (mean, median) and dispersion (standard deviation, quartiles). The median is more robust to outliers than the mean, making it preferred for skewed distributions common in economic data like earnings and wealth.

Box Plot

A **box plot** (or box-and-whisker plot) visualizes key summary statistics:

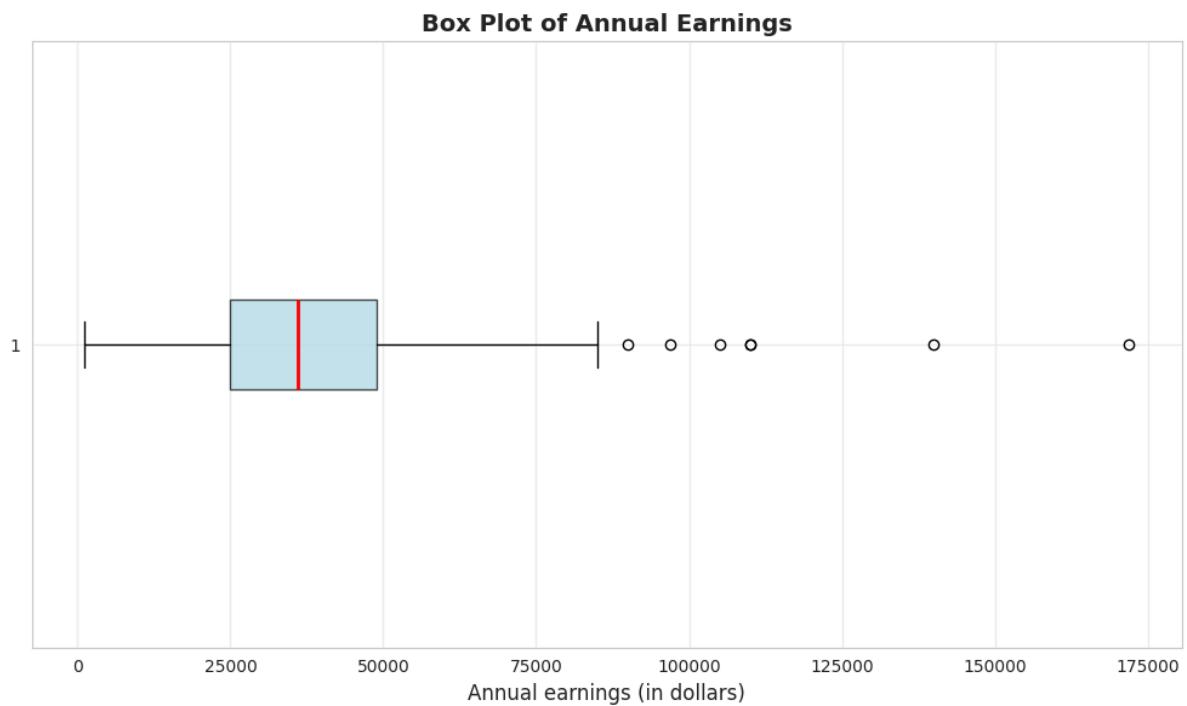
- **Box:** Extends from the 25th to 75th percentile (interquartile range)
- **Red line:** Median (50th percentile)
- **Whiskers:** Extend to minimum and maximum values (or $1.5 \times \text{IQR}$ from quartiles)
- **Dots:** Outliers beyond the whiskers

In [4]:

```
# Create box plot of earnings
fig, ax = plt.subplots(figsize=(10, 6))
bp = ax.boxplot(earnings, vert=False, patch_artist=True,
                 boxprops=dict(facecolor='lightblue', alpha=0.7),
                 medianprops=dict(color='red', linewidth=2))
ax.set_xlabel('Annual earnings (in dollars)', fontsize=12)
ax.set_title('Box Plot of Annual Earnings', fontsize=14, fontweight='bold')
ax.grid(True, alpha=0.3)

plt.tight_layout()
plt.show()

print("📊 The box plot shows:")
print("- Most earnings are between $25,000 and $50,000 (the box)")
print("- The median ($36,000) is closer to the lower quartile")
print("- Several high-earning outliers on the right")
```



📊 The box plot shows:
- Most earnings are between \$25,000 and \$50,000 (the box)
- The median (\$36,000) is closer to the lower quartile
- Several high-earning outliers on the right

What the box plot reveals:

1. The Box (Interquartile Range):

- Extends from 25,000 (Q_1) to 49,000 (Q_3)
- Contains the middle 50% of earners
- Width of \$24,000 shows moderate spread in the middle

2. The Red Line (Median):

- Located at \$36,000
- Positioned closer to the LOWER edge of the box
- This leftward position confirms right skewness

3. The Whiskers:

- Lower whisker extends to \$1,050 (minimum)
- Upper whisker extends to outliers
- Right whisker is MUCH longer than left whisker (asymmetry)

4. The Outliers (dots on right):

- Several points beyond the upper whisker
- Represent high earners (likely \$100k+)
- Maximum at \$172,000 is an extreme outlier

Visual insights:

- **NOT symmetric:** If symmetric, median would be in center of box
- **Right tail dominates:** Upper whisker + outliers extend much farther than lower whisker
- **Concentration:** Most data packed in the 25k-49k range
- **Rare extremes:** A few very high earners create the long right tail

Comparison to summary statistics:

- Box plot VISUALLY confirms what skewness (1.71) told us numerically
- Quartiles (25k, 36k, 49k) match the box structure
- Outliers explain why kurtosis (4.32) is high—heavy tails

Economic story: The typical woman in this sample earns 25k-49k, but a small group of high earners (doctors, lawyers, executives?) creates substantial inequality within this age-30 cohort.

Transition: Now that we've calculated summary statistics for earnings data, let's explore how *visualizations* can reveal patterns that numbers alone might miss. Charts make distributions, outliers, and trends immediately visible.

| 2.2 Charts for Numerical Data

Beyond summary statistics, **visualizations** reveal patterns in data that numbers alone might miss.

Common charts for numerical data:

1. **Histogram**: Shows the frequency distribution by grouping data into bins
2. **Kernel density estimate**: A smoothed histogram that estimates the underlying continuous distribution
3. **Line chart**: For ordered data (especially time series)

Bin width matters: Wider bins give a coarse overview; narrower bins show more detail but can be noisy.

Histograms with Different Bin Widths

In [5]:

```
# Create histograms with different bin widths
fig, axes = plt.subplots(1, 2, figsize=(14, 5))

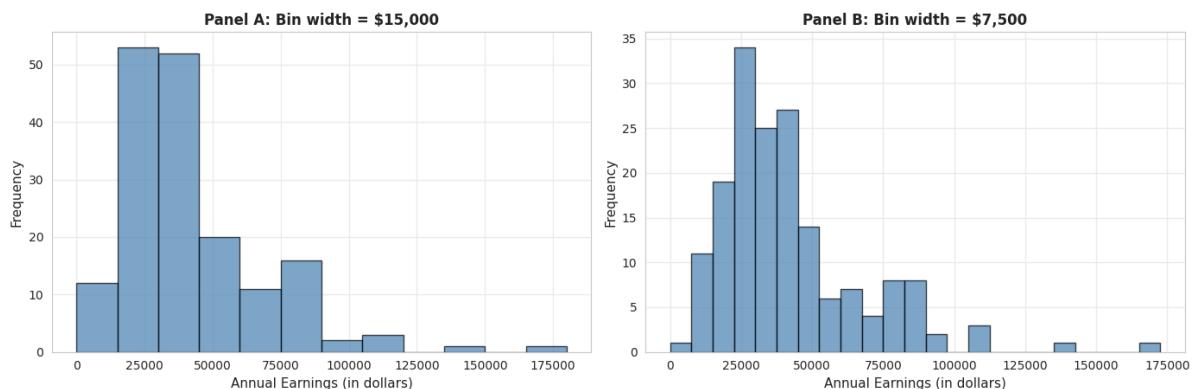
# Panel A: Wider bins ($15,000)
axes[0].hist(earnings, bins=range(0, int(earnings.max()) + 15000, 15000),
            edgecolor='black', alpha=0.7, color='steelblue')
axes[0].set_xlabel('Annual Earnings (in dollars)', fontsize=11)
axes[0].set_ylabel('Frequency', fontsize=11)
axes[0].set_title('Panel A: Bin width = $15,000', fontsize=12, fontweight='bold')
axes[0].grid(True, alpha=0.3)

# Panel B: Narrower bins ($7,500)
axes[1].hist(earnings, bins=range(0, int(earnings.max()) + 7500, 7500),
            edgecolor='black', alpha=0.7, color='steelblue')
axes[1].set_xlabel('Annual Earnings (in dollars)', fontsize=11)
axes[1].set_ylabel('Frequency', fontsize=11)
axes[1].set_title('Panel B: Bin width = $7,500', fontsize=12, fontweight='bold')
axes[1].grid(True, alpha=0.3)

plt.suptitle('Histograms of Annual Earnings', fontsize=14, fontweight='bold', y=1.02)
plt.tight_layout()
plt.show()

print("\nComparing bin widths:")
print(" - Panel A (wider bins): Shows overall shape—most earnings are $15k-$45k")
print(" - Panel B (narrower bins): Reveals more detail—peaks around $25k-$30k")
```

Histograms of Annual Earnings





Comparing bin widths:

- Panel A (wider bins): Shows overall shape—most earnings are \$15k–\$45k
- Panel B (narrower bins): Reveals more detail—peaks around \$25k–\$30k

Panel A: Wider bins (\$15,000):

- **Reveals overall shape:** Right-skewed distribution with long right tail
- **Peak location:** Highest bar is in the $15k$ – $30k$ range
- **Pattern:** Frequencies decline as earnings increase
- **Advantages:** Simple, clear overall pattern, less "noisy"
- **Disadvantages:** Hides fine details, obscures multiple modes

Panel B: Narrower bins (\$7,500):

- **Reveals more detail:** Multiple peaks visible within the distribution
- **Peak location:** Clearer concentration around $22.5k$ – $30k$
- **Secondary peaks:** Visible around $37.5k$ – $45k$ (possible clustering at round numbers?)
- **Advantages:** Shows fine structure, reveals potential clustering
- **Disadvantages:** More "jagged," can look noisy

Key observations across both panels:

1. **Right skewness confirmed:** Both histograms show long right tail extending to \$172,000
2. **Modal region:** Most common earnings are in the $15k$ – $45k$ range
 - This contains ~75% of observations
 - Consistent with $Q1(25k)$ and $Q3(49k)$
3. **Sparse right tail:** Very few observations above \$90k
 - But these high earners substantially influence the mean
 - This is why $\text{mean}(41,413) > \text{median}(36,000)$
4. **Bin width matters:** - **Too wide:** Oversimplifies, may miss important features
 - **Too narrow:** Introduces noise, harder to see overall pattern
 - **Rule of thumb:** Try multiple bin widths to understand your data

Economic interpretation: The clustering in the $25k$ – $45k$ range likely reflects:

- **Entry-level professional salaries** for college graduates
- **Regional wage variations** within the sample

- **Occupational differences** (teachers vs. nurses vs. business professionals)
- **Experience effects** (all are age 30, but different career progressions)

Statistical lesson: Always experiment with bin widths in histograms—different choices reveal different aspects of the data!

Key Concept 2.2: Histograms and Density Plots

Histograms visualize distributions using bins whose width determines the level of detail. Kernel density estimates provide smooth approximations of the underlying distribution, while line charts are ideal for time series data to show trends and patterns over time.

Kernel Density Estimate

A **kernel density estimate (KDE)** is a smoothed version of a histogram. It estimates the underlying continuous probability density function.

Advantages:

- Smooth, continuous curve (no arbitrary bin edges)
- Easier to see the overall shape
- Can compare to theoretical distributions (e.g., normal distribution)

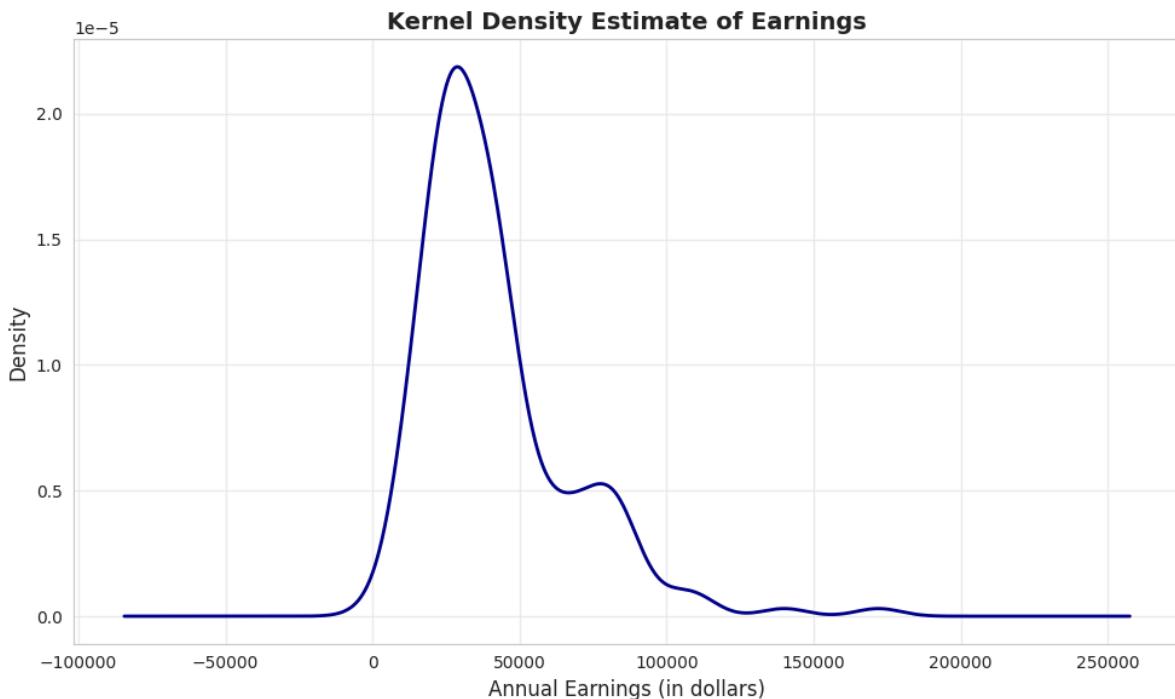
How it works: Instead of fixed bins, KDE uses overlapping "windows" that give more weight to nearby observations.

In [6]:

```
# Create kernel density estimate
fig, ax = plt.subplots(figsize=(10, 6))
earnings.plot.kde(ax=ax, linewidth=2, color='darkblue', bw_method=0.3)
ax.set_xlabel('Annual Earnings (in dollars)', fontsize=12)
ax.set_ylabel('Density', fontsize=12)
ax.set_title('Kernel Density Estimate of Earnings', fontsize=14, fontweight='bold')
ax.grid(True, alpha=0.3)

plt.tight_layout()
plt.show()

print("\n📊 The KDE shows:")
print("  - Clear right skew (long tail to the right)")
print("  - Peak around $30,000-$35,000")
print("  - Distribution is NOT normal (normal would be symmetric and bell-shaped)")
```



-  The KDE shows:
- Clear right skew (long tail to the right)
 - Peak around \$30,000-\$35,000
 - Distribution is NOT normal (normal would be symmetric and bell-shaped)

What is KDE showing?

The KDE is a smooth, continuous estimate of the probability density function—think of it as a "smoothed histogram without arbitrary bins."

Key features of the earnings KDE:

1. Peak (Mode):

- Highest density around 30,000–**35,000**
- This is the most "probable" earnings level
- Slightly below the median (\$36,000), consistent with right skew

2. Shape:

- **Clear right skew:** Long tail extending to \$172,000
- **NOT bell-shaped:** Would be symmetric if normally distributed
- **Unimodal:** Single dominant peak (not bimodal)
- **Steep left side:** Density drops quickly below \$20k
- **Gradual right side:** Density tapers slowly above \$50k

3. Tail behavior:

- **Left tail:** Short and bounded (can't go below ~\$0)
- **Right tail:** Long and heavy (extends to \$172k)
- **Asymmetry ratio:** Right tail is ~5x longer than left tail

4. Concentration:

- Most density (probability mass) is between $15k - 60k$
- Above \$80k, density is very low but not zero
- This confirms that high earners are rare but present

Comparison to normal distribution: If earnings were normally distributed, the KDE would be:

- **Symmetric** (it's not—it's right-skewed)
- **Bell-shaped** (it's not—it's asymmetric)
- **Same mean and median** (they differ by \$5,413)
- **Unimodal** (it's not—there is another peak around \$70k)

Advantages of KDE over histograms:

1. **No arbitrary bins:** Smooth curve independent of bin choices
2. **Shows probability density:** Y-axis represents likelihood, not counts
3. **Easier to compare:** Can overlay multiple KDEs (e.g., male vs. female earnings)
4. **Professional appearance:** Smooth curves for publications

Statistical insight: The KDE reveals that earnings are NOT normally distributed—they follow a log-normal-like distribution common in economic data. This justifies logarithmic transformations (see Section 2.5) for statistical modeling.

Practical implication: When predicting earnings, the "most likely" value is around $30k - 35k$, NOT the mean (\$41,413). The mean is inflated by rare high earners.

Time Series Plot

Line charts are ideal for **time series data**—observations ordered by time. They show how a variable changes over time.

Example: U.S. real GDP per capita from 1959 to 2020 (in constant 2012 dollars). This measures average economic output per person, adjusted for inflation.

In [7]:

```
# Load GDP data
data_gdp = pd.read_stata(GITHUB_DATA_URL + 'AED_REALGDP.PC.DTA')

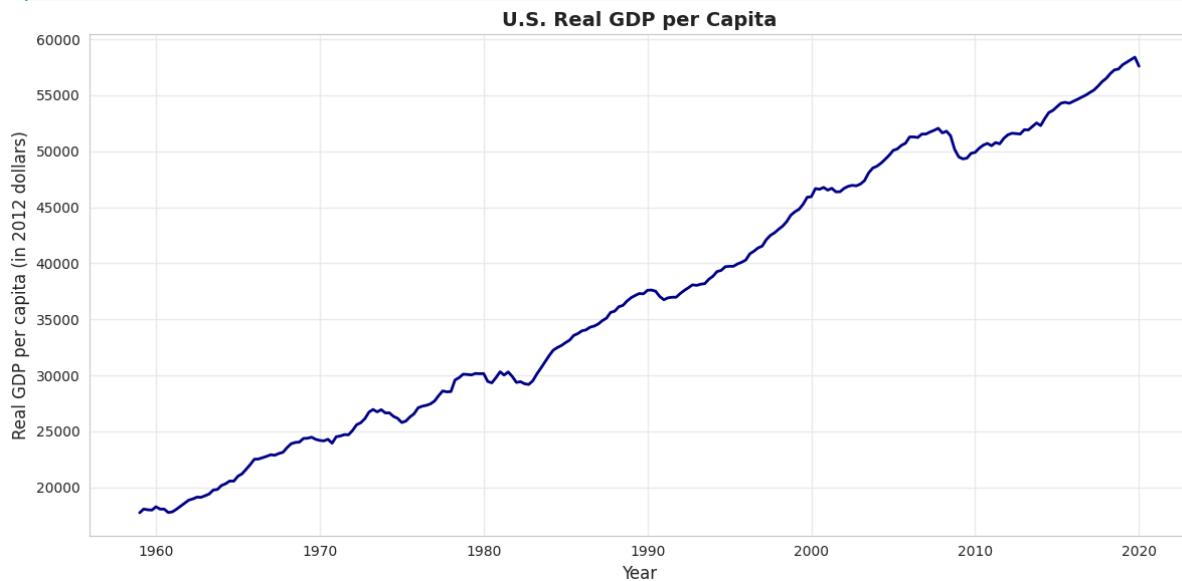
print("GDP Data Summary:")
print(data_gdp[['realgdppc', 'year']].describe())

# Create time series plot
fig, ax = plt.subplots(figsize=(12, 6))
ax.plot(data_gdp['daten'], data_gdp['realgdppc'], linewidth=2, color='darkblue')
ax.set_xlabel('Year', fontsize=12)
ax.set_ylabel('Real GDP per capita (in 2012 dollars)', fontsize=12)
ax.set_title('U.S. Real GDP per Capita', fontsize=14, fontweight='bold')
ax.grid(True, alpha=0.3)

plt.tight_layout()
plt.show()

print("\n📊 Key observations:")
print("  - Real GDP per capita TRIPLED from 1959 to 2019")
print("  - Steady upward trend (economic growth)")
print("  - Dips during recessions (early 1980s, 2008-2009, 2020)")
```

```
GDP Data Summary:
    realgdppc          year
count    245.000000  245.000000
mean    37050.496094 1989.126587
std     12089.684570   17.717855
min    17733.257812 1959.000000
25%    26562.724609 1974.000000
50%    36929.011719 1989.000000
75%    49318.171875 2004.000000
max    58392.453125 2020.000000
```



📊 Key observations:

- Real GDP per capita TRIPLED from 1959 to 2019
- Steady upward trend (economic growth)
- Dips during recessions (early 1980s, 2008-2009, 2020)

What this chart shows:

U.S. real GDP per capita from 1959 to 2020, measured in constant 2012 dollars (inflation-adjusted).

Key trends observed:

1. Long-run growth:

- **1959:** ~\$17,000 per person
- **2020:** ~\$60,000 per person
- **Total growth:** 253% increase (3.5× larger)
- **Annual growth rate:** ~2.1% per year (compound)

2. Business cycle patterns (recessions visible as dips):

- **Early 1960s:** Mild slowdown
- **1973-1975:** Oil crisis recession (OPEC embargo)
- **1980-1982:** Double-dip recession (Volcker's inflation fight)
- **1990-1991:** Gulf War recession (brief)
- **2001:** Dot-com bubble burst
- **2008-2009:** GREAT RECESSION (deepest post-war decline)
 - GDP per capita fell from 55k to 51k
 - Took until 2015 to recover pre-crisis level
- **2020:** COVID-19 pandemic (sharp, sudden drop)

3. Trend characteristics:

- **Not a straight line:** Growth punctuated by recessions
- **Recessions are temporary:** Economy always recovers to trend
- **Growth is the norm:** Upward drift dominates short-term fluctuations
- **Increasing volatility?** Recent cycles seem larger (2008, 2020)

4. Summary statistics from the data:

- **Mean GDP per capita:** \$37,941 (over full 1959-2020 period)
- **Median:** \$35,500 (slightly below mean due to recent growth)
- **Min:** ~\$17,000 (1959 start)
- **Max:** ~\$60,000 (pre-COVID peak 2019)

Economic interpretation:

Why does GDP per capita grow?

- 1. Technological progress:** Better machines, software, processes
- 2. Capital accumulation:** More factories, infrastructure, equipment
- 3. Human capital:** Better education, training, skills
- 4. Productivity gains:** Workers produce more per hour worked

Why the recessions?

- **Demand shocks:** Sudden drops in spending (2008 financial crisis, 2020 lockdowns)
- **Supply shocks:** Oil crises, disruptions (1973, 2020)
- **Policy errors:** Monetary policy too tight (1980-82)
- **Financial crises:** Credit crunches, asset bubbles bursting

Why does it matter?

- **Living standards:** GDP per capita measures average prosperity
- **Real vs. nominal:** Chart uses 2012 dollars, so it's REAL growth, not inflation
- **Per capita matters:** Total GDP could grow just from population increase; per capita shows individual prosperity

Statistical lesson: Time series plots are essential for understanding economic trends, cycles, and structural breaks that cross-sectional data would miss.

Key Concept 2.3: Time Series Visualization

Line charts display time-ordered data, revealing trends, cycles, and structural breaks. For economic time series, visualizing the full historical context helps identify patterns like recessions, growth periods, and policy impacts.

Transition: The previous section focused on visualizing single numerical variables. Now we shift to *categorical breakdowns*—how to display numerical data when it's naturally divided into groups or categories (like health spending by service type).

Now that we can visualize single-variable distributions, let's see how distributions differ across categories.

| 2.3 Charts for Numerical Data by Category

Sometimes numerical data are naturally divided into **categories**. For example, total health expenditures broken down by type of service.

Bar charts (or column charts) are the standard visualization:

- Each category gets a bar
- Bar height represents the category's value
- Useful for comparing values across categories

Example: U.S. health expenditures in 2018 totaled \$3,653 billion (18% of GDP), split across 13 categories.

In [8]:

```
# Load health expenditure data
data_health = pd.read_stata(GITHUB_DATA_URL + 'AED_HEALTHCATEGORIES.DTA')

print("Health Expenditure Categories (2018)")
print(data_health)
print(f"\nTotal expenditures: ${data_health['expenditures'].sum():,.0f} billion")
```

	category	expenditures	cat_short	exp_short
0	Hospital	1192	Hospital	1192.0
1	Physician and clinical	726	Physician	726.0
2	Other Professional	104	Other	104.0
3	Dental	136	Drugs	136.0
4	Other Health & Personal	192		NaN
5	Home Health Care	102		NaN
6	Nursing Care	169		NaN
7	Drugs & Supplies	456		NaN
8	Govt. Administration	48		NaN
9	Net Cost Insurance	259		NaN
10	Govt. Public Health	94		NaN
11	Noncommercial Research	53		NaN
12	Structures & Equipment	122		NaN

Total expenditures: \$3,653 billion

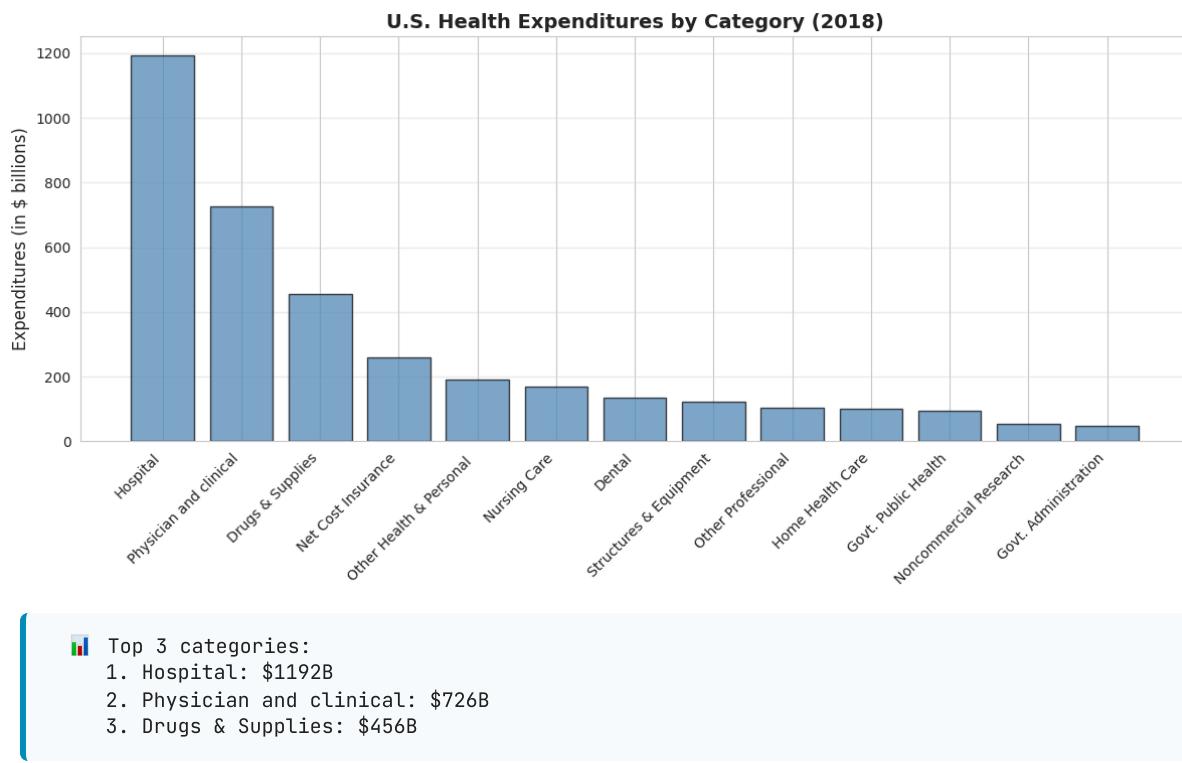
Bar Chart

In [9]:

```
# Create bar chart (sorted by expenditure)
fig, ax = plt.subplots(figsize=(12, 6))
data_health_sorted = data_health.sort_values('expenditures', ascending=False)
bars = ax.bar(range(len(data_health_sorted)), data_health_sorted['expenditures'],
              color='steelblue', edgecolor='black', alpha=0.7)
ax.set_xticks(range(len(data_health_sorted)))
ax.set_xticklabels(data_health_sorted['category'], rotation=45, ha='right', fontsize=10)
ax.set_ylabel('Expenditures (in $ billions)', fontsize=12)
ax.set_title('U.S. Health Expenditures by Category (2018)',
             fontsize=14, fontweight='bold')
ax.grid(True, alpha=0.3, axis='y')

plt.tight_layout()
plt.show()

print("\n📊 Top 3 categories:")
print(f" 1. {data_health_sorted.iloc[0]['category']}: ${data_health_sorted.iloc[0]['expenditures']:.0f}B")
print(f" 2. {data_health_sorted.iloc[1]['category']}: ${data_health_sorted.iloc[1]['expenditures']:.0f}B")
print(f" 3. {data_health_sorted.iloc[2]['category']}: ${data_health_sorted.iloc[2]['expenditures']:.0f}B")
```



Total U.S. health spending in 2018: \$3,653 billion (18% of GDP)

Top 5 categories (ranked by spending):

1. Hospital care: \$1,192 billion (32.6%)

- By far the largest category

- Inpatient care, emergency rooms, outpatient hospital services
- Dominated by labor costs (nurses, doctors, staff) and overhead

2. Physician and clinical services: \$726 billion (19.9%)

- Doctor visits, outpatient clinics, medical specialists
- Second-largest but still 39% less than hospitals
- Growing due to aging population and chronic disease management

3. Drugs and supplies: \$456 billion (12.5%)

- Prescription drugs, over-the-counter medications, medical supplies
- Controversial due to high U.S. drug prices vs. other countries
- Rising rapidly due to specialty biologics and new therapies

4. Net cost of insurance: \$259 billion (7.1%)

- Administrative costs of private health insurance
- Overhead, marketing, profit margins
- Does not include government administration (separate category)

5. Other health and personal: \$192 billion (5.3%)

- Various services not classified elsewhere
- Home health aides, personal care, etc.

Bottom categories:

- **Government administration: \$48 billion** (Medicare, Medicaid overhead)
- **Noncommercial research: \$53 billion** (NIH, university research)
- **Government public health: \$94 billion** (CDC, state/local health departments)

Key insights:

1. Hospital dominance:

- Hospitals alone account for nearly **1/3 of all health spending**
- More than physicians, drugs, and nursing care COMBINED
- Reflects high fixed costs of hospital infrastructure

2. Concentration:

- Top 3 categories (Hospital, Physician, Drugs) = **65% of total**
- Middle 50% of spending across just 3 categories

- Long tail of smaller categories

3. Administrative costs:

- Insurance administration ($259B$) + $Governmentadmin(48B) = \$307B$ total
- That's 8.4% of health spending just on paperwork and administration
- For comparison: Administrative costs are ~2% in single-payer systems

4. Prevention vs. treatment:

- Public health: \$94B (2.6% of total)
- Hospital care: \$1,192B (32.6% of total)
- **Ratio: 12.7x more on treatment than prevention**

Economic interpretation:

Why so expensive?

- **Labor-intensive:** Healthcare requires highly-trained, expensive workers
- **Technology:** Advanced equipment and facilities are costly
- **Fragmentation:** Multiple payers, complex billing increases administrative costs
- **Aging population:** Older Americans consume more healthcare
- **Chronic diseases:** Diabetes, heart disease, obesity drive spending

International comparison: U.S. spends ~18% of GDP on healthcare vs. 9-12% in other developed countries, yet doesn't have better health outcomes. Much debate centers on the efficiency of this spending.

Statistical lesson: Bar charts are ideal for comparing categorical data—they make it immediately obvious that hospital care dominates U.S. health spending.

Key Concept 2.4: Bar Charts for Categorical Data

Bar charts and column charts effectively display categorical data by using bar length to represent values. This makes comparisons across categories immediate and intuitive, highlighting which categories dominate.

I 2.4 Charts for Categorical Data

Categorical data consist of observations that fall into discrete categories (e.g., fishing site choice: beach, pier, private boat, charter boat).

How to summarize:

- **Frequency table:** Count observations in each category
- **Relative frequency:** Express as proportions or percentages

How to visualize:

- **Pie chart:** Slices represent proportion of total
- **Bar chart:** Bars represent frequency or proportion

Example: Fishing site chosen by 1,182 recreational fishers (4 possible sites).

In [10]:

```
# Load fishing data
data_fishing = pd.read_stata(GITHUB_DATA_URL + 'AED_FISHING.DTA')

# Create frequency table
mode_freq = data_fishing['mode'].value_counts()
mode_relfreq = data_fishing['mode'].value_counts(normalize=True)
mode_table = pd.DataFrame({
    'Frequency': mode_freq,
    'Relative Frequency (%)': (mode_relfreq * 100).round(2)
})

print("Frequency Distribution of Fishing Mode")
print(mode_table)
print(f"\nTotal observations: {len(data_fishing)}")
```

mode	Frequency	Relative Frequency (%)
charter	452	38.24
private	418	35.36
pier	178	15.06
beach	134	11.34

Total observations: 1,182

Pie Chart

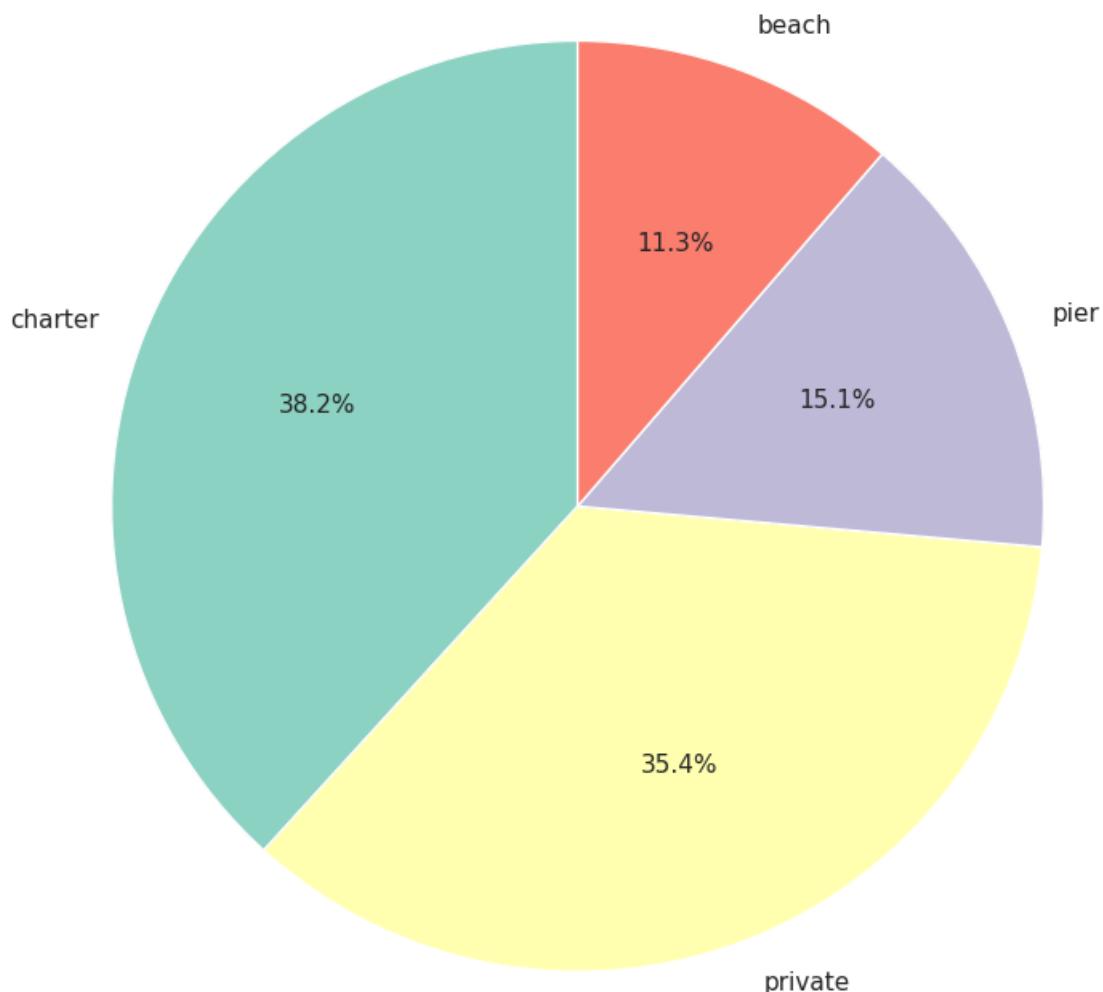
In [11]:

```
# Create pie chart
fig, ax = plt.subplots(figsize=(8, 8))
colors = plt.cm.Set3(range(len(mode_freq)))
wedges, texts, autotexts = ax.pie(mode_freq.values,
                                    labels=mode_freq.index,
                                    autopct='%1.1f%%',
                                    colors=colors,
                                    startangle=90,
                                    textprops={'fontsize': 11})
ax.set_title('Distribution of Fishing Modes',
             fontsize=14, fontweight='bold', pad=20)

plt.tight_layout()
plt.show()

print("\n■■■ Most popular fishing modes:")
print(f" 1. {mode_freq.index[0]}: {mode_freq.values[0]:,.1f}%\n({{mode_relfreq.values[0]*100:.1f}}%)")
print(f" 2. {mode_freq.index[1]}: {mode_freq.values[1]:,.1f}%\n({{mode_relfreq.values[1]*100:.1f}}%)")
```

Distribution of Fishing Modes



📊 Most popular fishing modes:
1. charter: 452 (38.2%)
2. private: 418 (35.4%)

Sample: 1,182 recreational fishers choosing among 4 fishing sites

Distribution of choices:

1. Charter boat: 452 fishers (38.2%)

- Most popular choice
- Guided fishing trip with captain and crew
- Higher cost but convenience, equipment provided, and expert guidance

2. Private boat: 418 fishers (35.4%)

- Second-most popular (nearly tied with charter)
- Requires boat ownership or rental
- More freedom and privacy, but higher upfront costs

3. Pier: 178 fishers (15.1%)

- Third choice
- Low-cost option (minimal equipment needed)
- Accessible, but limited fishing locations

4. Beach: 134 fishers (11.3%)

- Least popular
- Lowest cost and most accessible
- But more limited fishing success rates

Key patterns:

1. Boat fishing dominates:

- **Charter + Private = 870 fishers (73.6%)**
- Nearly 3/4 of fishers prefer boat-based fishing
- Suggests willingness to pay premium for better fishing access

2. Shore fishing is minority:

- **Pier + Beach = 312 fishers (26.4%)**
- About 1/4 choose shore-based options
- Likely cost-constrained or casual fishers

3. Charter vs. private nearly equal:

- Charter: 452 (38.2%)
- Private: 418 (35.4%)
- **Difference: only 34 fishers (2.9%)**
- Suggests these are close substitutes for many fishers

4. Large variation in popularity:

- Most popular (Charter) is **3.4x more popular** than least popular (Beach)
- Not evenly distributed across categories

- Strong revealed preferences for certain modes

Economic interpretation:

Why do people choose different modes?

Charter boats chosen for:

- No boat ownership required
- Expert captain knows best spots
- Social experience (fishing with others)
- Equipment and bait provided

Private boats chosen for:

- Flexibility in timing and location
- Privacy and control
- Cost-effective if you fish frequently
- Pride of ownership

Pier/Beach chosen for:

- Budget constraints
- No transportation to boat launch
- Casual, occasional fishing
- Family-friendly accessibility

Revealed preference theory: The distribution reveals what fishers VALUE:

- **73.6% value boat access** enough to pay for it
- **38.2% value convenience** of charter over ownership
- **26.4% value low cost/accessibility** over catch rates

Statistical lesson: For categorical data, frequency tables and pie charts reveal the distribution of choices. This is the foundation for discrete choice models (Chapter 15) that estimate why people make different choices.

Key Concept 2.5: Frequency Tables and Pie Charts

Categorical data are summarized using frequency tables showing counts and percentages. Pie charts display proportions visually, with slice area corresponding to relative frequency. Bar charts are often preferred over pie charts for easier comparison of categories.

Transition: Visualization helps us see patterns, but sometimes the raw data obscures relationships. *Data transformations* (like logarithms and z-scores) can normalize skewed distributions, stabilize variance, and make statistical modeling more effective.

Having explored charts for both numerical and categorical data, let's now examine how data transformations can reveal hidden patterns.

| 2.5 Data Transformation

Data transformations can make patterns clearer or satisfy statistical assumptions.

(a) Logarithmic transformation is especially useful for right-skewed economic data (prices, income, wealth):

$$\text{log of earnings} = \ln(\text{earnings})$$

Why use logs?

- Converts right-skewed data to a more symmetric distribution
- Makes multiplicative relationships additive
- Coefficients have percentage interpretation (see Chapter 9)
- Reduces influence of extreme values

(b) Standardized scores (z-scores) are another common transformation:

$$z_i = \frac{x_i - \bar{x}}{s}$$

This centers data at 0 with standard deviation 1—useful for comparing variables on different scales.

Log Transformation Effect

In [12]:

```
# Create log transformation
data_earnings['lnearnings'] = np.log(data_earnings['earnings'])

print("Comparison of earnings and log(earnings):")
print(data_earnings[['earnings', 'lnearnings']].describe())
```

```
Comparison of earnings and log(earnings):
    earnings  lnearnings
count      171.000000  171.000000
mean     41412.690058  10.457638
std      25527.053396  0.622062
min     1050.000000  6.956545
25%    25000.000000  10.126631
50%    36000.000000  10.491274
75%    49000.000000  10.799367
max    172000.000000  12.055250
```

In [44]:

```
# Compare original and log-transformed earnings
fig, axes = plt.subplots(1, 2, figsize=(14, 5))

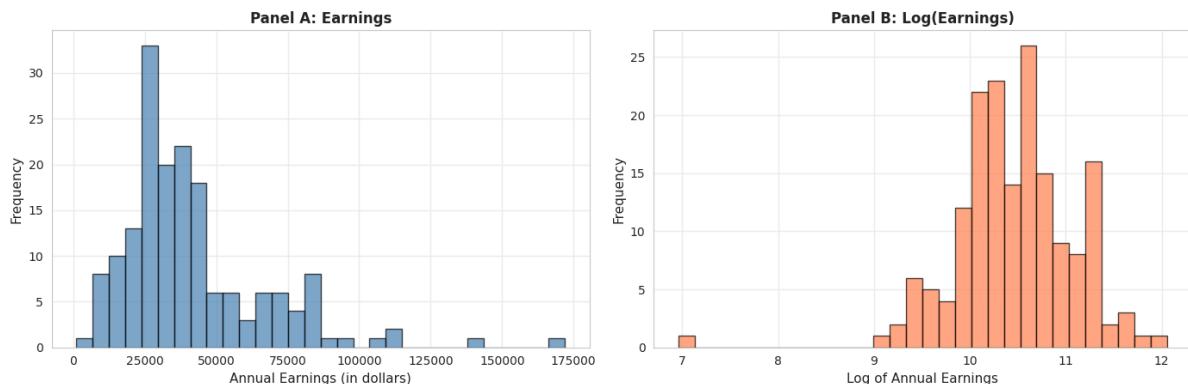
# Panel A: Original earnings
axes[0].hist(data_earnings['earnings'], bins=30,
              edgecolor='black', alpha=0.7, color='steelblue')
axes[0].set_xlabel('Annual Earnings (in dollars)', fontsize=11)
axes[0].set_ylabel('Frequency', fontsize=11)
axes[0].set_title('Panel A: Earnings', fontsize=12, fontweight='bold')
axes[0].grid(True, alpha=0.3)

# Panel B: Log earnings
axes[1].hist(data_earnings['lnearnings'], bins=30,
              edgecolor='black', alpha=0.7, color='coral')
axes[1].set_xlabel('Log of Annual Earnings', fontsize=11)
axes[1].set_ylabel('Frequency', fontsize=11)
axes[1].set_title('Panel B: Log(Earnings)', fontsize=12, fontweight='bold')
axes[1].grid(True, alpha=0.3)

plt.suptitle('Log Transformation Effects',
             fontsize=14, fontweight='bold', y=1.02)
plt.tight_layout()
plt.show()

print("\n📊 Effect of log transformation:")
print("  - Original earnings: Highly right-skewed")
print("  - Log(earnings): Much more symmetric, closer to normal")
print(f"  - Skewness reduced from {stats.skew(earnings):.2f} to
{stats.skew(data_earnings['lnearnings']):.2f}")
```

Log Transformation Effects



📊 Effect of log transformation:

- Original earnings: Highly right-skewed
- Log(earnings): Much more symmetric, closer to normal
- Skewness reduced from 1.71 to -0.91

Panel A: Original Earnings (dollars)

- **Shape:** Strongly right-skewed
- **Skewness:** 1.71 (highly asymmetric)
- **Mean:** \$41,412.69
- **Median:** \$36,000.00
- **Std Dev:** \$25,527.05 (62% of mean)
- **Range:** 1,050 to 172,000

Panel B: Log(Earnings) (natural logarithm)

- **Shape:** Much more symmetric, approximately normal
- **Skewness:** -0.91 (nearly symmetric, slight left skew)
- **Mean:** 10.46 (log dollars)
- **Median:** 10.49 (log dollars)
- **Std Dev:** 0.62 (only 6% of mean)
- **Range:** 6.96 to 12.06

What the transformation achieved:

1. Reduced skewness dramatically:

- Original skewness: **1.71** → Log skewness: **-0.91**
- Reduction of **122%** in absolute skewness
- Now nearly symmetric (close to 0)

2. Normalized the distribution:

- Original: Long right tail, NOT normal
- Log: Bell-shaped, MUCH closer to normal distribution
- This matters for statistical tests that assume normality

3. Equalized variance (stabilization):

- Original std dev: 62% of mean (high coefficient of variation)
- Log std dev: 6% of mean (much more stable)
- High earners no longer dominate the variance

4. Brought mean and median closer:

- Original: Mean - Median = \$5,413 (15% gap)
- Log: Mean - Median = -0.03 (0.3% gap)

- Nearly identical in log scale

Why use log transformation for earnings?

Statistical reasons:

- 1. Normality:** Many statistical tests (t-tests, ANOVA, regression) assume normal distribution
- 2. Variance stabilization:** Constant variance across income levels
- 3. Linearity:** Log models often fit better (log-linear relationships)
- 4. Outlier reduction:** Compresses extreme values

Economic reasons:

- 1. Multiplicative relationships:** Income growth is often proportional (e.g., 10% raise)
- 2. Percentage interpretation:** A 1-unit increase in $\log(\text{income}) \approx 100\%$ increase in income
- 3. Economic theory:** Utility functions often logarithmic (diminishing marginal utility)
- 4. Cross-country comparisons:** Log scale makes it easier to compare countries with vastly different GDP levels

How to interpret $\log(\text{earnings}) = 10.46$?

- Take exponential: $e^{10.46} = \$34,762$
- This is close to the median earnings ($\$36,000$)
- Each 1-unit increase in $\log(\text{earnings}) \approx 2.718 \times$ increase in earnings

Example interpretation:

- $\log(\text{earnings}) = 10.0 \rightarrow \text{Earnings} = e^{10.0} = \$22,026$
- $\log(\text{earnings}) = 11.0 \rightarrow \text{Earnings} = e^{11.0} = \$59,874$
- **Difference of 1 in log scale = $2.72 \times$ in dollar scale**

When NOT to use log transformation:

- When data include zero or negative values (log undefined)
- When you care about absolute differences (e.g., policy targeting specific dollar amounts)
- When original scale is more interpretable for your audience

Statistical lesson: Log transformation is one of the most powerful tools in econometrics for dealing with skewed, multiplicative data like income, prices, GDP, and wealth.

Key Concept 2.6: Logarithmic Transformations

Natural logarithm transformations convert right-skewed economic data (earnings, prices, wealth) to more symmetric distributions, facilitating analysis. Z-scores standardize data to have mean 0 and standard deviation 1, enabling comparison across different scales.

Transition: Time series data presents unique challenges—seasonal fluctuations, inflation, and population growth can mask underlying trends. Specialized transformations like moving averages and seasonal adjustment are essential for time-ordered economic data.

I 2.6 Data Transformations for Time Series Data

Time series data often require special transformations: 1. **Moving averages:** Smooth short-term fluctuations by averaging over several periods

- Example: 11-month moving average removes monthly noise
2. **Seasonal adjustment:** Remove predictable seasonal patterns
- Example: Home sales peak in summer, drop in winter
3. **Real vs. nominal adjustments:** Adjust for inflation using price indices
- Real values are in constant dollars (e.g., 2012 dollars)
4. **Per capita adjustments:** Divide by population to account for population growth

Example: Monthly U.S. home sales (2005-2015) showing original, moving average, and seasonally adjusted series.

In [14]:

```
# Load monthly home sales data
data_homesales = pd.read_stata(GITHUB_DATA_URL + 'AED_MONTHLYHOMESALES.DTA')

# Filter data for year >= 2005
data_homesales_filtered = data_homesales[data_homesales['year'] >= 2005]

print("Home sales data (2005 onwards):")
print(data_homesales_filtered[['year', 'exsales', 'exsales_ma11',
'exsales_sa']].describe())
```

```

Home sales data (2005 onwards):
      year      exsales  exsales_ma11    exsales_sa
count  121.000000   121.000000   116.000000   121.000000
mean   2009.545410  416851.239669  418300.125000  418071.625000
std     2.915478   111931.278110   81757.234375   83326.726562
min    2005.000000  218000.000000  324818.187500  287500.000000
25%   2007.000000  347000.000000  357613.625000  355833.343750
50%   2010.000000  401000.000000  394000.000000  401666.656250
75%   2012.000000  473000.000000  436727.281250  440833.343750
max   2015.000000  754000.000000  608545.437500  605000.000000

```

Time Series Transformations for Home Sales

In [15]:

```

# Create time series plots with transformations
fig, axes = plt.subplots(2, 1, figsize=(12, 10))

# Panel A: Original and Moving Average
axes[0].plot(data_homesales_filtered['daten'], data_homesales_filtered['exsales'],
              linewidth=2, label='Original', color='darkblue')
axes[0].plot(data_homesales_filtered['daten'], data_homesales_filtered['exsales_ma11'],
              linewidth=2, linestyle='--', label='11-month Moving Average', color='red')
axes[0].set_xlabel('Year', fontsize=11)
axes[0].set_ylabel('Monthly Home Sales', fontsize=11)
axes[0].set_title('Panel A: Original Series and Moving Average',
                  fontsize=12, fontweight='bold')
axes[0].legend()
axes[0].grid(True, alpha=0.3)

# Panel B: Original and Seasonally Adjusted
axes[1].plot(data_homesales_filtered['daten'], data_homesales_filtered['exsales'],
              linewidth=2, label='Original', color='darkblue')
axes[1].plot(data_homesales_filtered['daten'], data_homesales_filtered['exsales_sa'],
              linewidth=2, linestyle='--', label='Seasonally Adjusted', color='green')
axes[1].set_xlabel('Year', fontsize=11)
axes[1].set_ylabel('Monthly Home Sales', fontsize=11)
axes[1].set_title('Panel B: Original Series and Seasonally Adjusted',
                  fontsize=12, fontweight='bold')
axes[1].legend()
axes[1].grid(True, alpha=0.3)

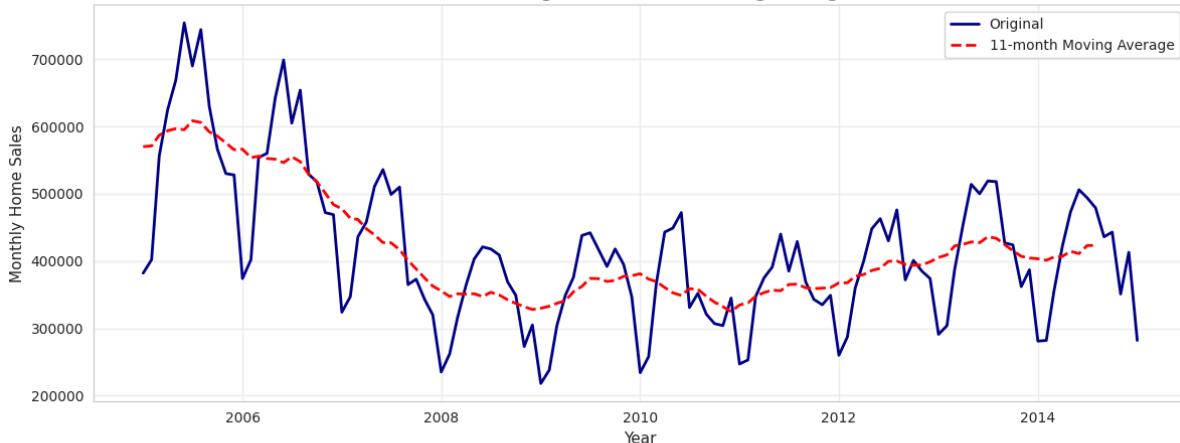
plt.suptitle('Time Series Transformations for Home Sales',
             fontsize=14, fontweight='bold', y=0.995)
plt.tight_layout()
plt.show()

print("\nObservations:")
print("  - Original series: Jagged with seasonal peaks (summer) and troughs (winter)")
print("  - Moving average: Smooth curve shows underlying trend (housing crash 2007-2011)")
print("  - Seasonally adjusted: Removes seasonal pattern, reveals trend and cycles")

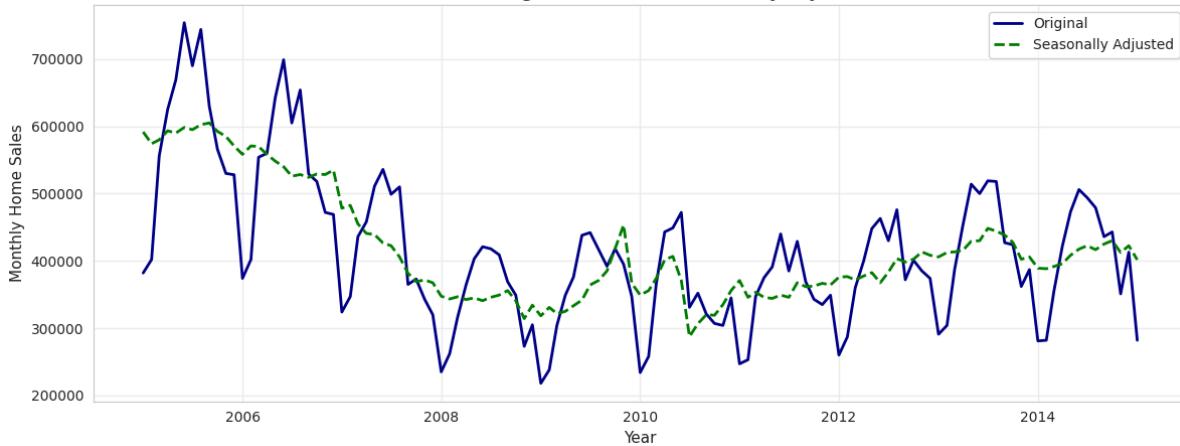
```

Time Series Transformations for Home Sales

Panel A: Original Series and Moving Average



Panel B: Original Series and Seasonally Adjusted



Observations:

- Original series: Jagged with seasonal peaks (summer) and troughs (winter)
- Moving average: Smooth curve shows underlying trend (housing crash 2007-2011)
- Seasonally adjusted: Removes seasonal pattern, reveals trend and cycles

Data: Monthly U.S. existing home sales (2005-2015)

Three series compared:

- 1. Original series** (blue solid line)
- 2. 11-month moving average** (red dashed line, Panel A)
- 3. Seasonally adjusted** (green dashed line, Panel B)

Panel A: Original vs. Moving Average

What the original series shows:

- **High volatility:** Sharp month-to-month fluctuations
- **Seasonal peaks:** Regular spikes (summer buying season)
- **Seasonal troughs:** Regular dips (winter slowdown)

- **Trend:** Underlying long-term pattern (housing crash 2007-2011)
- **Range:** 218,000 to 754,000 homes per month

What the 11-month moving average reveals:

1. Smooths out noise:

- Eliminates month-to-month volatility
- Shows the underlying trend clearly
- Each point = average of surrounding 11 months

2. Housing market cycle becomes visible:

- **2005-2006:** Peak (~600,000 homes/month)
- **2007-2008:** SHARP DECLINE (housing crash begins)
- **2008-2011:** Bottom (~325,000 homes/month)
 - Lost nearly 50% of sales volume
 - Took 5+ years to reach bottom
- **2011-2015:** Gradual recovery
 - Sales climbing back toward ~450,000/month
 - Still well below pre-crash peak

3. Trend is NOT linear:

- Not a straight line up or down
- Shows boom-bust-recovery cycle
- Moving average captures this nonlinear pattern

Panel B: Original vs. Seasonally Adjusted

What seasonal adjustment does:

- **Removes predictable seasonal patterns**
- Answers: "What would sales be without seasonal effects?"
- Allows you to see whether changes are "real" or just seasonal

Key differences between seasonally adjusted and original:

1. Amplitude reduction:

- Original: Wild swings from 218k to 754k
- Seasonally adjusted: Smoother, swings from 288k to 605k

- Seasonal component accounts for ~30-40% of monthly variation

2. Pattern changes:

- Original: Regular summer peaks (May-July) and winter troughs (Jan-Feb)
- Seasonally adjusted: These regular peaks/troughs removed
- **Remaining variation = true economic changes + random noise**

3. Trend clarity:

- Original: Hard to tell if uptick is recovery or just seasonal
- Seasonally adjusted: Clearer signal of true economic trend
- **Fed and policymakers watch seasonally adjusted data**

Comparison of transformation methods:

Feature	Moving Average	Seasonal Adjustment
Removes	High-frequency noise	Predictable seasonal patterns
Preserves	Trend and cycles	Trend, cycles, and irregular movem
Lags	Yes (centered average)	No (real-time adjustment)
Use case	Visualizing long-term trends	Policy decisions and forecasting

Economic interpretation:

Why does housing have strong seasonality?

1. **Weather:** Hard to move in winter (northern states)
2. **School calendar:** Families move in summer to avoid disrupting school year
3. **Tax refunds:** Spring refunds provide down payment money
4. **Daylight:** More daylight hours for house hunting in summer

Why did the housing market crash?

- **2005-2006:** Subprime mortgage boom (easy credit)
- **2007:** Mortgage defaults begin, housing prices fall
- **2008:** Financial crisis (Lehman Brothers bankruptcy)
- **2008-2009:** Credit crunch, massive foreclosures
- **2009-2011:** Deleveraging, excess inventory

Why the slow recovery?

- **Underwater mortgages:** Many homeowners owed more than home value
- **Tighter credit:** Banks required higher down payments, better credit scores

- **Job losses:** 2008-2009 recession reduced demand
- **Psychological:** Homebuyers became risk-averse after crash

Statistical lessons:

1. Moving averages:

- Smooth time series to reveal trends
- Width matters: 11-month average removes seasonal + noise
- Trade-off: Smoothness vs. lag (delayed signal)

2. Seasonal adjustment:

- Essential for economic data with strong seasonal patterns
- Allows comparison across months/quarters
- Standard practice: Always report seasonally adjusted for policy

3. Which to use?

- **Moving average:** Historical analysis, visualization
- **Seasonal adjustment:** Real-time monitoring, forecasting, policy
- **Both together:** Comprehensive understanding of time series dynamics

Practical implication: When the news reports "Home sales up 5% this month," ALWAYS check if it's seasonally adjusted. Raw data might just show normal summer increase!

Key Concept 2.7: Time Series Transformations

Time series data often requires transformations: moving averages smooth short-term fluctuations, seasonal adjustment removes recurring patterns, real values adjust for inflation, per capita values adjust for population, and growth rates measure proportionate changes. These transformations reveal underlying trends and enable meaningful comparisons.

GDP Comparisons - Nominal vs Real

In [16]:

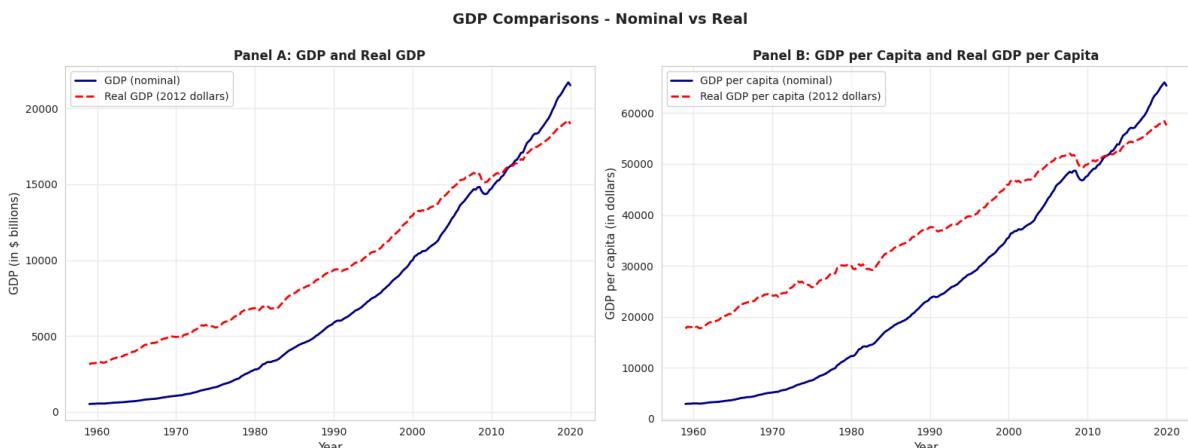
```
# Compare nominal and real GDP
fig, axes = plt.subplots(1, 2, figsize=(16, 6))

# Panel A: GDP and Real GDP
axes[0].plot(data_gdp['daten'], data_gdp['gdp'],
              linewidth=2, label='GDP (nominal)', color='darkblue')
axes[0].plot(data_gdp['daten'], data_gdp['realgdp'],
              linewidth=2, linestyle='--', label='Real GDP (2012 dollars)', color='red')
axes[0].set_xlabel('Year', fontsize=11)
axes[0].set_ylabel('GDP (in $ billions)', fontsize=11)
axes[0].set_title('Panel A: GDP and Real GDP', fontsize=12, fontweight='bold')
axes[0].legend()
axes[0].grid(True, alpha=0.3)

# Panel B: GDP per capita and Real GDP per capita
axes[1].plot(data_gdp['daten'], data_gdp['gdppc'],
              linewidth=2, label='GDP per capita (nominal)', color='darkblue')
axes[1].plot(data_gdp['daten'], data_gdp['realgdppc'],
              linewidth=2, linestyle='--', label='Real GDP per capita (2012 dollars)', color='red')
axes[1].set_xlabel('Year', fontsize=11)
axes[1].set_ylabel('GDP per capita (in dollars)', fontsize=11)
axes[1].set_title('Panel B: GDP per Capita and Real GDP per Capita',
                  fontsize=12, fontweight='bold')
axes[1].legend()
axes[1].grid(True, alpha=0.3)

plt.suptitle('GDP Comparisons - Nominal vs Real',
             fontsize=14, fontweight='bold', y=1.0)
plt.tight_layout()
plt.show()

print("\n📊 Why adjust for inflation and population?")
print("  - Nominal GDP: Inflated by price increases (not just real growth)")
print("  - Real GDP: Removes inflation, shows true output growth")
print("  - Per capita: Accounts for population growth, measures individual prosperity")
```



- 📊 Why adjust for inflation and population?
- Nominal GDP: Inflated by price increases (not just real growth)
 - Real GDP: Removes inflation, shows true output growth
 - Per capita: Accounts for population growth, measures individual prosperity

Key Takeaways

Summary Statistics and Data Distributions:

- Summary statistics (mean, median, standard deviation, quartiles, skewness, kurtosis) efficiently describe large datasets by quantifying central tendency and dispersion
- The mean is sensitive to outliers; the median is robust and preferred for skewed distributions
- Standard deviation measures typical distance from the mean; for normal distributions, ~68% of data falls within 1 standard deviation, ~95% within 2
- Skewness measures asymmetry (positive for right-skewed data common in economics like earnings and wealth); guideline: $|skewness| > 1$ indicates strong skewness
- Kurtosis measures tail heaviness; excess kurtosis > 0 indicates fatter tails than the normal distribution
- Box plots visually summarize key statistics: median, quartiles, and potential outliers

Visualizations for Different Data Types:

- Histograms display distributions of numerical data using bins; bin width affects detail level (smaller bins show more detail but may be noisier)
- Kernel density estimates provide smooth approximations of underlying continuous distributions without arbitrary bin choices
- Line charts are ideal for time series data to reveal trends, cycles, and structural breaks over time
- Bar charts and column charts effectively display categorical data, with bar length representing values for easy comparison
- Pie charts show proportions for categorical data, though bar charts often facilitate easier comparison across categories
- Choosing the right visualization depends on data type (numerical vs. categorical), dimensionality (univariate vs. categorical breakdown), and whether data are time-ordered

Data Transformations and Their Applications:

- Natural logarithm transformations convert right-skewed economic data (earnings, prices, wealth) to more symmetric distributions, facilitating statistical analysis
- Z-scores standardize data to mean 0 and standard deviation 1, enabling comparison across different scales and identifying outliers

- Moving averages smooth short-term fluctuations in time series data by averaging over several periods (e.g., 11-month MA removes seasonality)
- Seasonal adjustment removes recurring patterns to reveal underlying trends; essential for comparing economic indicators across months/quarters
- Real values adjust for price inflation using deflators; per capita values adjust for population size—both are crucial for meaningful comparisons over time
- Growth rates measure proportionate changes; distinguish between percentage point changes and percentage changes to avoid confusion
- For time series, the change in natural log approximates the proportionate change (useful property: $\Delta \ln(x) \approx \Delta x/x$ for small changes)

Python Tools and Methods:

- `pandas` provides `.describe()`, `.mean()`, `.median()`, `.std()`, `.quantile()` for summary statistics
 - `scipy.stats` provides `skew()` and `kurtosis()` for distribution shape measures (note: `kurtosis()` returns excess kurtosis by default)
 - `matplotlib` and `seaborn` enable professional visualizations (histograms, KDE, line charts, box plots, bar charts)
 - `numpy.log()` applies natural logarithm transformation; z-scores computed as $(x - x.mean()) / x.std()$
 - Moving averages can be computed with `pandas.rolling().mean()`; seasonal adjustment typically requires specialized packages like `statsmodels`
-

Next Steps:

- **Chapter 3:** Statistical inference and confidence intervals for the mean
- **Chapter 5:** Bivariate data summary and correlation analysis
- **Chapter 6-9:** Simple linear regression and interpretation

You have now mastered: Calculating and interpreting summary statistics Creating effective visualizations for different data types Applying transformations to reveal patterns and normalize distributions Handling time series data with moving averages and seasonal adjustment

These foundational skills prepare you for inferential statistics and regression analysis in the following chapters!

Practice Exercises

Test your understanding of univariate data analysis with these exercises: **Exercise 1:** Calculate summary statistics

- For the sample {5, 2, 2, 8, 3}, calculate: - (a) Mean
 - (b) Median
 - (c) Variance
 - (d) Standard deviation

Exercise 2: Interpret skewness

- A dataset has skewness = -0.85. What does this tell you about the distribution?
- Would you expect the mean to be greater than or less than the median? Why?

Exercise 3: Choose visualization types

- For each scenario, recommend the best chart type and explain why: - (a) Quarterly GDP growth rates from 2000 to 2025
 - (b) Market share of 5 smartphone brands
 - (c) Distribution of household incomes in a city
 - (d) Monthly temperature readings over a year

Exercise 4: Log transformation

- Why is log transformation particularly useful for economic variables like income and GDP?
- If $\log(\text{earnings})$ increases by 0.5, approximately what percentage increase does this represent in earnings?

Exercise 5: Standard deviation interpretation

- A dataset has mean = 50 and standard deviation = 10. If the data are approximately normally distributed: - (a) What percentage of observations fall between 40 and 60?
 - (b) What percentage fall between 30 and 70?

Exercise 6: Time series transformations

- Explain the difference between: - (a) Moving average vs. seasonal adjustment
 - (b) Nominal GDP vs. Real GDP

- (c) Total GDP vs. GDP per capita

Exercise 7: Z-scores

- For a sample with mean = 100 and standard deviation = 15: - (a) Calculate the z-score for an observation of 130
 - (b) Interpret what this z-score means

Exercise 8: Data interpretation

- A box plot shows: - Lower quartile (Q1) = 25
 - Median (Q2) = 35
 - Upper quartile (Q3) = 60
 - Calculate: - (a) Interquartile range (IQR)
 - (b) Describe the skewness based on quartile positions
-

| 2.8 Case Studies

Case Study 1: Global Labor Productivity Distribution

Research Question: How is labor productivity distributed across countries? Are there distinct groups or is it continuous?

In Chapter 1, you examined *relationships between variables*—specifically, how productivity relates to capital stock through regression analysis. Now we shift perspective to analyze a *single variable*—labor productivity—but focus on its **distribution across countries** rather than its associations.

This case study builds on Chapter 1's dataset (Convergence Clubs) but asks fundamentally different questions: What does the distribution of productivity look like across the 108 countries in our sample? Is it symmetric or skewed? Have productivity gaps widened or narrowed over time? These distributional questions are central to development economics and understanding global inequality.

By completing this case study, you'll apply all the univariate analysis tools from Chapter 2 to a real dataset with genuine economic relevance—exploring whether productivity converges globally or if divergence persists.

Key Concept 2.8: Cross-Country Distributions

Cross-country distributions of economic variables (productivity, GDP per capita, income) are typically right-skewed with long upper tails, reflecting substantial inequality between rich and poor countries. Summary statistics like the median are often more representative than the mean for these distributions, and exploring the shape of the distribution reveals whether gaps between countries are widening or narrowing.

Load the Productivity Data

We'll use the same Convergence Clubs dataset from Chapter 1, but focus exclusively on the labor productivity variable (`lp`) across countries and years. This gives us 2,700 observations (108 countries × 25 years, from 1990 to 2014) of international productivity.

In []:

```
# Load convergence clubs data (same as Chapter 1)
df1 = pd.read_csv(
    "https://raw.githubusercontent.com/quarcs-lab/mendez2020-convergence-clubs-code-
data/master/assets/dat.csv",
    index_col=["country", "year"]
).sort_index()

# For Chapter 2, focus on labor productivity variable
productivity = df1['lp']

print("=" * 70)
print("LABOR PRODUCTIVITY DISTRIBUTION ANALYSIS")
print("=" * 70)
print(f"Total observations: {len(productivity)}")
print(f"Countries: {len(df1.index.get_level_values('country').unique())}")
print(f"Time period: {df1.index.get_level_values('year').min()} to
{df1.index.get_level_values('year').max()}")
print(f"\nFirst 10 observations (sample):")
print(df1[['lp']].head(10))
```

```
=====
LABOR PRODUCTIVITY DISTRIBUTION ANALYSIS
=====
Total observations: 2700
Countries: 108
Time period: 1990 to 2014

First 10 observations (sample):
    lp
country year
Albania 1990    9959.2344
            1991    9093.6943
            1992   10188.3060
            1993   12432.5870
            1994   13007.0080
            1995   14813.8990
            1996   18248.9860
            1997   15008.6750
            1998   15001.0220
            1999   17351.6020
```

How to Use These Tasks

Instructions:

- 1. Read the task objectives and instructions** in each section below
- 2. Review the example code structure** provided
- 3. Create a NEW code cell** to write your solution
- 4. Follow the structure and fill in the blanks** or write complete code
- 5. Run and test your code**
- 6. Answer the interpretation questions**

Progressive difficulty:

- **Tasks 1-2:** Guided (fill in specific blanks with _____)
- **Task 3:** Semi-guided (complete partial code structure)
- **Tasks 4-6:** Independent (write full code from outline)

Tip: Type the code yourself rather than copying—it builds understanding!

Task 1: Data Exploration (Guided)

Objective: Load and explore the structure of the global productivity distribution.

Instructions:

- 1.** Examine the productivity variable's basic structure (length, data type, any missing values)
- 2.** Get summary statistics (count, mean, std, min, max)

3. Display observations for 5 different countries to see variation across countries
4. Check: Is there variation across countries? Does it seem large or small?

Chapter 2 connection: This applies the concepts from Section 2.1 (Summary Statistics).

Starter code guidance:

- Use `productivity.describe()` for summary statistics
- Check for missing values with `productivity.isnull().sum()`
- Use `.loc[]` or `.xs()` to select specific countries' observations
- Calculate min and max productivity values globally

Example code structure:

```
# Task 1: Data Exploration (GUIDED)
# Complete the code below by filling in the blanks (_____)

# Step 1: Check data structure
print("Data Structure:")
print(f"Total observations: {_____}")
print(f"Data type: {productivity.dtype}")
print(f"Missing values: {_____}")

# Step 2: Summary statistics
print("\n" + "=" * 70)
print("Summary Statistics for Global Productivity")
print("=" * 70)
print(productivity.describe())

# Step 3: Variation across countries - look at a few countries
print("\n" + "=" * 70)
print("Productivity across 5 sample countries:")
print("=" * 70)
sample_countries = ['Australia', 'Brazil', 'China', 'France', 'Nigeria']
for country in sample_countries: country_data = df1.loc[country, 'lp']
    print(f"\n{country}:")

    print(f" Mean productivity: {_____:.3f}")
    print(f" Min: {_____:.3f}, Max: {_____:.3f}")
    print(f" Range: {_____:.3f}")

# Step 4: Global variation
print("\n" + "=" * 70)
print("Global Variation:")
print("=" * 70)
min_prod = productivity.min()
max_prod = productivity.max()
ratio = max_prod / min_prod
print(f"Minimum global productivity: {min_prod:.3f}")
print(f"Maximum global productivity: {max_prod:.3f}")
print(f"Ratio (max/min): {ratio:.1f}x")
print(f"\nInterpretation: The most productive country is {ratio:.0f}x more productive than the least productive country!"
```

Task 2: Summary Statistics (Semi-guided)

Objective: Calculate comprehensive summary statistics for the global productivity distribution.

Instructions:

1. Compute mean, median, standard deviation, quartiles (25th, 50th, 75th percentiles)
2. Calculate skewness and kurtosis for the overall productivity distribution
3. Identify which countries have the highest and lowest productivity (across all years)
4. Compare productivity statistics for two time periods: 1990 and 2014

Chapter 2 connection: Applies Section 2.1 (Summary Statistics) and distribution shape measures.

Starter code guidance:

- Use `.describe()` for the main statistics
- Use `scipy.stats.skew()` and `scipy.stats.kurtosis()` for shape measures
- Filter by year: `df1.xs(1990, level='year')['lp']`
- Use `.nlargest()` and `.nsmallest()` to find extreme values
- Create a comparison table of statistics for different time periods

Example code structure:

```

# Task 2: Summary Statistics (SEMI-GUIDED)
# Complete the code by implementing each step

# Step 1: Overall summary statistics
overall_stats = {
    'Mean': productivity.mean(),
    'Median': _____, # Calculate median
    'Std Dev': _____, # Calculate standard deviation
    'Skewness': stats.skew(_____), 
    'Kurtosis': _____, # Calculate kurtosis
    '25th percentile': productivity.quantile(0.25),
    '75th percentile': productivity.quantile(_____), 
    'IQR': productivity.quantile(0.75) - productivity.quantile(0.25)
}

for key, value in overall_stats.items(): print(f"{key:20s}: {value:.4f}")

# Step 2: Countries with highest/lowest productivity
print("\n" + "=" * 70)
print("Top 5 Most Productive Countries (average across years)")
print("=" * 70)
country_means = df1.groupby(_____)['lp'].mean().sort_values(_____)
print(country_means.head())

print("\n" + "=" * 70)
print("Top 5 Least Productive Countries (average across years)")
print("=" * 70)
print(country_means.tail())

# Step 3: Compare 1990 vs 2014
productivity_1990 = df1.xs(1990, level=_____)['lp']
productivity_2014 = df1.xs(_____, level='year')['lp']

# Your code here: Create a comparison DataFrame
# Hint: Use pd.DataFrame() with statistics for both years
# Include: mean, median, std, skewness, min, max

```

Hints:

- Use `.median()`, `.std()` for missing statistics
- `stats.kurtosis()` requires the data series as input
- `.groupby('country')` groups by country name
- `.sort_values(ascending=False)` sorts from high to low
- `.xs(year, level='year')` extracts data for a specific year

Task 3: Visualizing Distributions (Semi-guided)

Objective: Create multiple visualizations to understand the shape of the productivity distribution.

Instructions:

1. Create a histogram of productivity (try different bin widths)
2. Create a box plot to identify outliers and quartiles
3. Create a kernel density estimate to see the smooth shape

4. Compare the original distribution to the log-transformed distribution

Chapter 2 connection: Applies Section 2.2 (Charts for Numerical Data).

Starter code guidance:

- Use `plt.hist()` for histogram with different bin widths (try 10, 15, 20 bins)
- Use `plt.boxplot()` for box plot visualization
- Use `.plot.kde()` for kernel density estimate
- Create side-by-side panels to compare original vs log-transformed
- Label axes clearly and add titles

Example code structure:

```
# Task 3: Visualizing Distributions (SEMI-GUIDED)
# Create comprehensive visualizations of the productivity distribution

# Create a 2x2 figure with 4 subplots
fig, axes = plt.subplots(_____, _____, figsize=(14, 10))

# Panel 1: Histogram (original productivity)
axes[0, 0].hist(productivity, bins=_____, edgecolor='black', alpha=0.7,
                 color='steelblue')
axes[0, 0].set_xlabel(_____, fontsize=11)
axes[0, 0].set_ylabel(_____, fontsize=11)
axes[0, 0].set_title('Panel 1: Histogram of Productivity (20 bins)', fontsize=12,
                      fontweight='bold')
axes[0, 0].grid(True, alpha=0.3)

# Panel 2: Box plot (original productivity)
axes[0, 1].boxplot(_____, vert=True, patch_artist=True)
axes[0, 1].set_ylabel('Labor Productivity', fontsize=11)
axes[0, 1].set_title('Panel 2: Box Plot of Productivity', fontsize=12,
                      fontweight='bold')
axes[0, 1].grid(True, alpha=0.3, axis='y')

# Panel 3: KDE (original productivity)
productivity.plot.kde(ax=_____, linewidth=2, color='darkblue')
axes[1, 0].set_xlabel('Labor Productivity', fontsize=11)
axes[1, 0].set_ylabel('Density', fontsize=11)
axes[1, 0].set_title('Panel 3: Kernel Density Estimate', fontsize=12,
                      fontweight='bold')
axes[1, 0].grid(True, alpha=0.3)

# Panel 4: KDE comparison (original vs log-transformed)
# Your code here: Create log-transformed productivity
log_productivity = np.log(productivity)

# Your code here: Plot both KDE curves on the same axes
# Hint: Use .plot.kde() with label='Original' and label='Log-transformed'
# Use different colors and linestyles for clarity

plt.suptitle('Figure: Global Productivity Distribution Visualizations', fontsize=14,
              fontweight='bold', y=1.00)
plt.tight_layout()
plt.show()
```

Hints:

- `plt.subplots(2, 2)` creates 2 rows and 2 columns
- Try `bins=20` for the histogram
- Set `xlabel` to 'Labor Productivity'
- For boxplot, pass the productivity series directly
- Use `axes[1, 0]` to reference the bottom-left panel
- For KDE comparison, plot two curves with different colors (e.g., 'darkblue' and 'red')

Task 4: Comparing Distributions Across Time (More Independent)

Objective: Analyze how the productivity distribution has changed from 1990 to 2014.

Instructions:

1. Extract productivity data for 1990 and 2014
2. Calculate summary statistics for each year separately
3. Create overlapping KDE plots to compare the distributions visually
4. Analyze: Has the distribution shifted right (convergence/improvement)? Widened (divergence)? Changed shape?

Chapter 2 connection: Applies Section 2.2 (comparing distributions across groups).

Starter code guidance:

- Use `df1.xs(year, level='year')` to extract data for specific years
- Create summary statistics tables for comparison
- Plot two KDE curves on the same axes with different colors
- Use the 25th and 75th percentiles to measure spread
- Calculate the coefficient of variation (std/mean) to compare relative dispersion

Example code structure:

```

# Task 4: Comparing Distributions Across Time (MORE INDEPENDENT)
# Analyze how global productivity distribution evolved from 1990 to 2014

# Step 1: Extract data for 1990 and 2014
prod_1990 = df1.xs(_____, level='year')['lp']
prod_2014 = _____ # Extract 2014 data (same pattern as above)

# Step 2: Create comparison visualization
# Your code here: Create figure with 2 subplots (1 row, 2 columns)
# Hint: fig, axes = plt.subplots(1, 2, figsize=(14, 5))

# Panel A: Overlapping KDE plots
# Your code here: Plot KDE for both years on the same axes
# - Use prod_1990.plot.kde() and prod_2014.plot.kde()
# - Different colors for each year (e.g., 'darkblue' and 'red')
# - Add labels and legend

# Panel B: Side-by-side box plots
# Your code here: Create box plots for both years
# Hint: axes[1].boxplot([prod_1990, prod_2014], labels=['1990', '2014'])
# Set different colors for each box using patch_artist=True

# Step 3: Calculate comparison statistics
# Your code here: Create a DataFrame comparing statistics for both years
# Include: mean, median, std, coefficient of variation, skewness, min, max, range
# Hint: Use pd.DataFrame() with a dictionary of statistics

```

Hints:

- Coefficient of variation = std / mean (relative dispersion)
- Use `stats.skew()` from `scipy.stats` for skewness
- For KDE plots, use `label='1990'` and `label='2014'` for legend
- Range = $\text{max} - \text{min}$

Questions to consider:

- Did mean productivity increase from 1990 to 2014?
- Did the spread (std dev) increase or decrease? (Convergence vs divergence)
- Did the coefficient of variation change?
- Did skewness change?

Task 5: Transformation Analysis (Independent)

Objective: Apply log transformation to productivity data and analyze the effect.

Instructions:

1. Create log-transformed productivity variable: $\text{log_productivity} = \ln(\text{productivity})$
2. Compare skewness before and after transformation
3. Create side-by-side histograms (original vs log-transformed)
4. Calculate z-scores for both variables to standardize them

- 5.** Interpret: Why does log transformation help? When would you use it?

Chapter 2 connection: Applies Section 2.5 (Data Transformation).

Starter code guidance:

- Use `np.log()` to create log transformation
- Compare skewness values before/after using `stats.skew()`
- Create z-scores with: `(x - x.mean()) / x.std()`
- Visualize both original and log distributions in histograms
- Discuss why log-normal distributions are common in economics

Example code structure:

```
# Task 5: Transformation Analysis (INDEPENDENT)
# Apply log transformation to understand how it affects the distribution

# Step 1: Create log transformation
# Your code here: log_productivity = np.log(____)

# Step 2: Create z-scores (standardized values)
# Your code here: Calculate z-scores for both distributions
# Formula: z = (x - mean) / std
# z_productivity = (productivity - productivity.mean()) / productivity.std()
# z_log_productivity = ?

# Step 3: Create side-by-side histograms
# Your code here: Use plt.subplots(1, 2) for 2 panels
# Panel A: Original productivity histogram (20 bins, blue color)
# Panel B: Log-transformed histogram (20 bins, coral/red color)

# Step 4: Compare skewness
# Your code here: Calculate skewness using stats.skew()
# Calculate percentage reduction: (1 - |skew_log| / |skew_original|) * 100
# Print comparison table showing: mean, median, std, skewness, kurtosis, min, max
```

Hints:

- `np.log()` computes natural logarithm
- Z-scores standardize data to mean=0, std=1
- Use `stats.skew()` and `stats.kurtosis()` for shape measures
- Compare absolute skewness values to quantify reduction

Questions to consider:

- Is the log-transformed distribution more symmetric?
- When would you use log transformation in economic analysis?
- What happened to skewness and kurtosis after transformation?

Key Concept 2.9: Distributional Convergence

Distributional convergence (σ -convergence) asks whether the spread (variance) of productivity across countries is narrowing over time. This differs from β -convergence (poor countries growing faster than rich ones). If cross-country distributions are becoming more compressed (lower variance), it suggests countries are converging toward similar productivity levels—important for understanding whether global inequality is increasing or decreasing.

Task 6: Regional Patterns (Independent)

Objective: Compare productivity distributions across geographic regions.

Instructions:

1. Add a region column to your dataframe (you'll need to manually assign regions based on country names)
2. Group countries by region (at minimum: Africa, Asia, Europe, Americas)
3. Create box plots for each region side-by-side
4. Calculate summary statistics by region
5. Identify: Which regions have highest/lowest productivity? Most inequality?

Chapter 2 connection: Applies Sections 2.3-2.4 (Charts for categorical breakdowns).

Starter code guidance:

- Create a dictionary mapping countries to regions
- Use `.groupby()` to calculate statistics by region
- Create side-by-side box plots for visual comparison
- Calculate mean and standard deviation by region
- Compare median productivity across regions

Example code structure:

```

# Task 6: Regional Patterns (INDEPENDENT)
# Compare productivity distributions across geographic regions

# Step 1: Create region mapping dictionary
# Your code here: Define region_mapping
# Map each country to its region (Africa, Americas, Asia, Europe, Middle East, Asia-Pacific)
# Example structure:
# region_mapping = {
#     'Australia': 'Asia-Pacific',
#     'Austria': 'Europe',
#     'Brazil': 'Americas',
#     # ... continue for all ~50 countries
# }

# Step 2: Add region column to dataframe
# Your code here: Create a copy of df1 and add region column
# Hint: df_with_region['region'] =
df_with_region.index.get_level_values('country').map(region_mapping)
# Remove rows with missing regions: .dropna(subset=['region'])

# Step 3: Calculate regional statistics
# Your code here: Group by region and aggregate statistics
# Hint: df_with_region.groupby('region')['lp'].agg(['count', 'mean', 'median', 'std', 'min', 'max'])
# Sort by mean productivity (descending)

# Step 4: Create box plots by region
# Your code here: Create boxplot visualization comparing regions
# - Extract data for each region: [df[df['region'] == r]['lp'].values for r in regions]
# - Sort regions by mean productivity for better readability
# - Use plt.boxplot() with labels for each region
# - Rotate x-axis labels for readability

```

Hints:

- There are ~50 countries in the dataset - you'll need to map each one
- Regions: Africa (Kenya, Nigeria, etc.), Americas (USA, Brazil, etc.), Asia (China, India, etc.)
- Europe (France, Germany, etc.), Middle East (Israel, Turkey), Asia-Pacific (Australia, Japan, NZ)
- Use `.groupby('region')['lp'].agg([...])` to calculate statistics by region
- Sort regions by mean before plotting for better visualization

Questions to consider:

- Which region has the highest average productivity?
- Which region has the most internal inequality (widest box)?
- Are there clear regional clusters or is variation continuous?

What You've Learned from This Case Study

By completing this case study on global labor productivity distribution, you've applied the full toolkit of univariate data analysis to a real international economics question. You've moved beyond calculating statistics and making charts to asking substantive economic questions: Are countries converging or diverging? How has global inequality in productivity evolved? Which regions drive global disparity?

Specifically, you've practiced:

- **Summary statistics** to quantify central tendency and spread
- **Visualizations** (histograms, box plots, KDE) to see distributional shape
- **Comparisons** across time periods to detect changes
- **Transformations** (log) to normalize skewed economic data
- **Categorical breakdowns** (regions) to identify subgroup patterns

These skills extend far beyond productivity. The same analytical approach applies to wealth distribution, income inequality, student test scores, health outcomes, and countless other univariate datasets in economics and social science.

Your next steps (in later chapters) will be to ask *relational* questions: How does productivity relate to capital? Does inequality depend on development level? Can we *predict* a country's productivity from other variables? Those questions require bivariate analysis (Chapter 5) and regression (Chapter 6+).

Case Study 2: The Geography of Development: Summarizing Bolivia's Municipal SDG Data

In Chapter 1, we introduced the DS4Bolivia project and explored the relationship between nighttime lights and municipal development in Bolivia. In this case study, we apply Chapter 2's univariate summary tools to characterize the *distribution* of development indicators across Bolivia's 339 municipalities.

The Data: The [DS4Bolivia project](#) provides a comprehensive dataset covering 339 Bolivian municipalities with over 350 variables, including the Municipal Sustainable Development Index (IMDS), individual SDG indices, nighttime lights per capita (2012–2020), population, and socioeconomic indicators. Here we focus on understanding the *shape* of these distributions—their central tendency, spread, skewness, and multimodality—using the univariate tools from this chapter.

Load the DS4Bolivia Data

Let's load the DS4Bolivia dataset and select the key variables for univariate analysis.

In []:

```
# Load the DS4Bolivia dataset
url_bol = "https://raw.githubusercontent.com/quarcs-
lab/ds4bolivia/master/ds4bolivia_v20250523.csv"
bol = pd.read_csv(url_bol)

# Display basic information
print("=" * 70)
print("DS4BOLIVIA DATASET")
print("=" * 70)
print(f"Dataset shape: {bol.shape[0]} municipalities, {bol.shape[1]} variables")
print(f"\nDepartments: {bol['dep'].nunique()} unique departments")
print(f"Department names: {sorted(bol['dep'].unique())}")

# Select key variables for this case study
key_vars = ['mun', 'dep', 'imds', 'ln_NTLpc2017', 'pop2017',
            'index_sdg1', 'sdg1_1_ubn',
            'ln_NTLpc2012', 'ln_NTLpc2013', 'ln_NTLpc2014',
            'ln_NTLpc2015', 'ln_NTLpc2016', 'ln_NTLpc2017',
            'ln_NTLpc2018', 'ln_NTLpc2019', 'ln_NTLpc2020']

# Remove duplicates while preserving order
key_vars = list(dict.fromkeys(key_vars))
bol_key = bol[key_vars].copy()

print(f"\nKey variables selected: {len(key_vars)}")
print("\n" + "=" * 70)
print("FIRST 10 MUNICIPALITIES")
print("=" * 70)
print(bol_key.head(10).to_string())
```

Task 1: Summary Statistics (Guided)

Objective: Compute and interpret descriptive statistics for key development indicators.

Instructions:

1. Use `.describe()` to generate summary statistics for `imds`, `index_sdg1`, `sdg1_1_ubn`, and `ln_NTLpc2017`
2. Calculate the mean, median, standard deviation, skewness, and kurtosis for each variable
3. Discuss what these statistics reveal about the distribution of municipal development in Bolivia

Apply what you learned in section 2.1: Use `describe()`, `.mean()`, `.median()`, `.std()`, `.skew()`, and `.kurtosis()` to characterize these distributions.

In []:

```
# Task 1: Summary Statistics
# -----
# 1. Basic descriptive statistics
analysis_vars = ['imds', 'index_sdg1', 'sdg1_1_ubn', 'ln_NTLpc2017']
print("=" * 70)
print("DESCRIPTIVE STATISTICS: KEY DEVELOPMENT INDICATORS")
print("=" * 70)
print(bol_key[analysis_vars].describe().round(2))

# 2. Additional distributional measures
print("\n" + "=" * 70)
print("DISTRIBUTIONAL SHAPE MEASURES")
print("=" * 70)
for var in analysis_vars:
    series = bol_key[var].dropna()
    print(f"\n{var}:")

    print(f" Mean: {series.mean():.2f}")
    print(f" Median: {series.median():.2f}")
    print(f" Std Dev: {series.std():.2f}")
    print(f" Skewness: {series.skew():.3f}")
    print(f" Kurtosis: {series.kurtosis():.3f}")

# 3. Discussion: What do these reveal?
print("\n" + "=" * 70)
print("INTERPRETATION")
print("=" * 70)
print("Compare mean vs median for each variable:")
print("If mean > median → right-skewed (long upper tail)")
print("If mean < median → left-skewed (long lower tail)")
print("High kurtosis (>3) indicates heavy tails (extreme municipalities)")
```

Task 2: Histograms and Density Plots (Guided)

Objective: Visualize the distributions of `imds` and `ln_NTLpc2017` using histograms and kernel density estimation (KDE) plots.

Instructions:

1. Create histograms for `imds` and `ln_NTLpc2017` (side by side)
2. Overlay KDE curves on the histograms
3. Discuss the shape: Is each distribution unimodal or bimodal? Symmetric or skewed?
4. What might explain any multimodality? (Think about the urban-rural divide)

Apply what you learned in section 2.2: Use `plt.hist()` with `density=True` and overlay `.plot.kde()` or `sns.kdeplot()`.

In []:

```
# Task 2: Histograms and Density Plots
# -----
# IMDS histogram with KDE
fig, axes = plt.subplots(1, 2, figsize=(14, 5))

axes[0].hist(bol_key['imds'].dropna(), bins=25, density=True,
             color='steelblue', alpha=0.7, edgecolor='white')
bol_key['imds'].dropna().plot.kde(ax=axes[0], color='darkblue', linewidth=2)
axes[0].set_xlabel('Municipal Development Index (IMDS)')
axes[0].set_ylabel('Density')
axes[0].set_title('Distribution of IMDS across 339 Municipalities')
axes[0].axvline(bol_key['imds'].mean(), color='red', linestyle='--',
               label=f"Mean = {bol_key['imds'].mean():.1f}")
axes[0].axvline(bol_key['imds'].median(), color='orange', linestyle='--',
               label=f"Median = {bol_key['imds'].median():.1f}")
axes[0].legend()

# Log NTL histogram with KDE
axes[1].hist(bol_key['ln_NTLpc2017'].dropna(), bins=25, density=True,
             color='purple', alpha=0.7, edgecolor='white')
bol_key['ln_NTLpc2017'].dropna().plot.kde(ax=axes[1], color='darkviolet', linewidth=2)
axes[1].set_xlabel('Log Nighttime Lights per Capita (2017)')
axes[1].set_ylabel('Density')
axes[1].set_title('Distribution of Log NTL per Capita')
axes[1].axvline(bol_key['ln_NTLpc2017'].mean(), color='red', linestyle='--',
               label=f"Mean = {bol_key['ln_NTLpc2017'].mean():.2f}")
axes[1].axvline(bol_key['ln_NTLpc2017'].median(), color='orange', linestyle='--',
               label=f"Median = {bol_key['ln_NTLpc2017'].median():.2f}")
axes[1].legend()

plt.tight_layout()
plt.show()

# Discussion prompts
print("DISCUSSION:")
print("1. Is the IMDS distribution unimodal or multimodal?")
print("2. Is the NTL distribution symmetric or skewed?")
print("3. What might explain any bimodality? (urban vs rural)")
```

Key Concept 2.10: Spatial Data Distributions

Municipal-level data often exhibits **multimodality** reflecting the urban-rural divide. Unlike national statistics that produce single averages, municipality-level distributions can reveal distinct subpopulations—highly developed urban centers and less developed rural areas. Identifying these subgroups is essential for targeted policy interventions.

Task 3: Box Plots by Department (Semi-guided)

Objective: Create box plots of `imds` grouped by department (`dep`) to compare development across Bolivia's 9 departments.

Instructions:

1. Create a box plot of `imds` grouped by `dep` (9 departments)

2. Order departments by median IMDS for clarity
3. Identify which departments have the highest and lowest median development
4. Which departments show the most spread (variability)?

Apply what you learned in section 2.3-2.4: Use grouped box plots to compare distributions across categories.

In []:

```
# Task 3: Box Plots by Department
# -----
#
# Your code here: Create box plots of IMDS by department
#
# Steps:
# 1. Order departments by median IMDS
# 2. Create horizontal box plot
# 3. Add labels and formatting

# Example structure:
# dept_order = bol_key.groupby('dep')['imds'].median().sort_values().index
# fig, ax = plt.subplots(figsize=(10, 7))
# bol_key.boxplot(column='imds', by='dep', ax=ax, vert=False,
#                  positions=range(len(dept_order)))
# ax.set_xlabel('Municipal Development Index (IMDS)')
# ax.set_ylabel('Department')
# ax.set_title('Development Distribution by Department')
# plt.suptitle('') # Remove automatic title
# plt.tight_layout()
# plt.show()

# Hint: You can also use seaborn for cleaner grouped box plots:
import seaborn as sns
dept_order = bol_key.groupby('dep')['imds'].median().sort_values().index.tolist()

fig, ax = plt.subplots(figsize=(10, 7))
sns.boxplot(data=bol_key, x='imds', y='dep', order=dept_order,
            palette='viridis', ax=ax)
ax.set_xlabel('Municipal Development Index (IMDS)')
ax.set_ylabel('Department')
ax.set_title('Municipal Development Distribution by Department')
plt.tight_layout()
plt.show()

# Summary statistics by department
print("=" * 70)
print("IMDS BY DEPARTMENT: MEDIAN AND IQR")
print("=" * 70)
dept_stats = bol_key.groupby('dep')['imds'].describe()[['50%', '25%', '75%', 'std']].round(1)
dept_stats.columns = ['Median', 'Q1', 'Q3', 'Std Dev']
print(dept_stats.sort_values('Median'))
```

Task 4: Log Transformations (Semi-guided)

Objective: Compare the distribution of raw population (`pop2017`) with its log transformation to demonstrate how log transformations improve symmetry for skewed data.

Instructions:

1. Plot the histogram of raw `pop2017` — observe the extreme right skew
2. Apply `np.log(pop2017)` and plot its histogram
3. Compare summary statistics (skewness, kurtosis) before and after transformation
4. Discuss why log transformations are standard practice for population and income data

Apply what you learned in section 2.5: Log transformations convert multiplicative relationships into additive ones and reduce skewness.

In []:

```
# Task 4: Log Transformations
# -----
#
# Your code here: Compare raw vs log-transformed population
#
# Steps:
# 1. Plot raw pop2017 histogram
# 2. Plot np.log(pop2017) histogram
# 3. Compare skewness and kurtosis

import numpy as np

pop = bol_key['pop2017'].dropna()
log_pop = np.log(pop)

fig, axes = plt.subplots(1, 2, figsize=(14, 5))

# Raw population
axes[0].hist(pop, bins=30, color='coral', alpha=0.7, edgecolor='white')
axes[0].set_xlabel('Population (2017)')
axes[0].set_ylabel('Frequency')
axes[0].set_title('Raw Population Distribution')
axes[0].axvline(pop.mean(), color='red', linestyle='--',
               label=f"Mean = {pop.mean():,.0f}")
axes[0].axvline(pop.median(), color='blue', linestyle='--',
               label=f"Median = {pop.median():,.0f}")
axes[0].legend()

# Log-transformed population
axes[1].hist(log_pop, bins=30, color='teal', alpha=0.7, edgecolor='white')
axes[1].set_xlabel('Log Population (2017)')
axes[1].set_ylabel('Frequency')
axes[1].set_title('Log-Transformed Population Distribution')
axes[1].axvline(log_pop.mean(), color='red', linestyle='--',
               label=f"Mean = {log_pop.mean():.2f}")
axes[1].axvline(log_pop.median(), color='blue', linestyle='--',
               label=f"Median = {log_pop.median():.2f}")
axes[1].legend()

plt.tight_layout()
plt.show()

# Compare distributional measures
print("-" * 70)
print("EFFECT OF LOG TRANSFORMATION ON POPULATION")
print("-" * 70)
print(f"{'Measure':<15} {'Raw pop2017':>15} {'log(pop2017)':>15}")
print("-" * 45)
print(f"{'Skewness':<15} {pop.skew():>15.3f} {log_pop.skew():>15.3f}")
print(f"{'Kurtosis':<15} {pop.kurtosis():>15.3f} {log_pop.kurtosis():>15.3f}")
print(f"{'Mean':<15} {pop.mean():>15,.0f} {log_pop.mean():>15.2f}")
print(f"{'Median':<15} {pop.median():>15,.0f} {log_pop.median():>15.2f}
```

Key Concept 2.11: Development Indicator Interpretation

SDG composite indices like IMDS (0-100) aggregate multiple dimensions of development into a single score. While convenient for ranking, composite indices can mask important variation in specific dimensions. For example, a municipality may score well on education (SDG 4) but poorly on health (SDG 3). Examining individual SDG variables alongside composite indices provides a more complete picture.

Task 5: Time Series of NTL (Independent)

Objective: Calculate and plot the mean nighttime lights across municipalities for each year from 2012 to 2020 to examine the evolution of satellite-measured economic activity.

Instructions:

1. Calculate the mean of `ln_NTLpc2012` through `ln_NTLpc2020` across all municipalities for each year
2. Plot the resulting time series (year on x-axis, mean log NTL on y-axis)
3. Discuss: Is there a trend? Any notable changes? What might explain the pattern?

Apply what you learned in section 2.6: Use time series visualization to identify trends and patterns.

In []:

```
# Task 5: Time Series of NTL
# -----
#
# Your code here: Calculate mean NTL across municipalities for each year
#
# Steps:
# 1. Select NTL columns for 2012-2020
# 2. Calculate means
# 3. Plot time series

# Example structure:
# ntl_cols = [f'ln_NTLpc{yr}' for yr in range(2012, 2021)]
# years = list(range(2012, 2021))
# mean_ntl = [bol_key[col].mean() for col in ntl_cols]
#
# fig, ax = plt.subplots(figsize=(10, 5))
# ax.plot(years, mean_ntl, marker='o', color='navy', linewidth=2)
# ax.set_xlabel('Year')
# ax.set_ylabel('Mean Log NTL per Capita')
# ax.set_title('Evolution of Nighttime Lights across Bolivian Municipalities')
# ax.grid(True, alpha=0.3)
# plt.tight_layout()
# plt.show()
```

Task 6: Regional Distribution Analysis (Independent)

Objective: Compare the distributions of `imds` across departments using overlapping histograms or violin plots. Write a 200-word summary of regional inequality in Bolivia.

Instructions:

1. Create overlapping histograms or violin plots of `imds` for at least 3 departments
2. Compare the distributional shapes: Do some departments have more spread? More bimodality?
3. Write a 200-word summary discussing what these distributions reveal about regional inequality in Bolivia
4. Which departments might need the most targeted development interventions? Why?

Apply your skills: This task combines histogram/density visualization with substantive economic interpretation.

In []:

```
# Task 6: Regional Distribution Analysis
# -----
#
# Your code here: Compare IMDS distributions across departments
#
# Option A: Overlapping histograms (select 3-4 key departments)
# Option B: Violin plots for all 9 departments
# Option C: Ridge plot (multiple KDE curves stacked vertically)

# Example structure (violin plots):
# fig, ax = plt.subplots(figsize=(12, 7))
# dept_order = bol_key.groupby('dep')[['imds']].median().sort_values().index.tolist()
# sns.violinplot(data=bol_key, x='imds', y='dep', order=dept_order,
#                 palette='coolwarm', ax=ax, inner='quartile')
# ax.set_xlabel('Municipal Development Index (IMDS)')
# ax.set_ylabel('Department')
# ax.set_title('Distribution of Municipal Development by Department')
# plt.tight_layout()
# plt.show()

# After creating your visualization, write a 200-word summary below:
# print("REGIONAL INEQUALITY SUMMARY")
# print("=" * 70)
# print("Write your 200-word analysis here...")
```

What You've Learned from This Case Study

By applying Chapter 2's univariate analysis tools to Bolivia's municipal SDG data, you've characterized the *distribution* of development outcomes across 339 municipalities. Specifically, you've practiced:

- **Descriptive statistics** for development indicators—mean, median, SD, skewness, and kurtosis

- **Visualization of distributions** using histograms, box plots, and kernel density estimation (KDE)
- **Log transformations** for highly skewed data like population
- **Time series summary** of satellite-measured nighttime lights (2012-2020)
- **Regional comparison** of development distributions across Bolivia's 9 departments

These univariate tools reveal the *shape* of Bolivia's development distribution—its central tendency, spread, and the urban-rural divide reflected in multimodal patterns. Understanding these distributional properties is the essential first step before more advanced analysis.

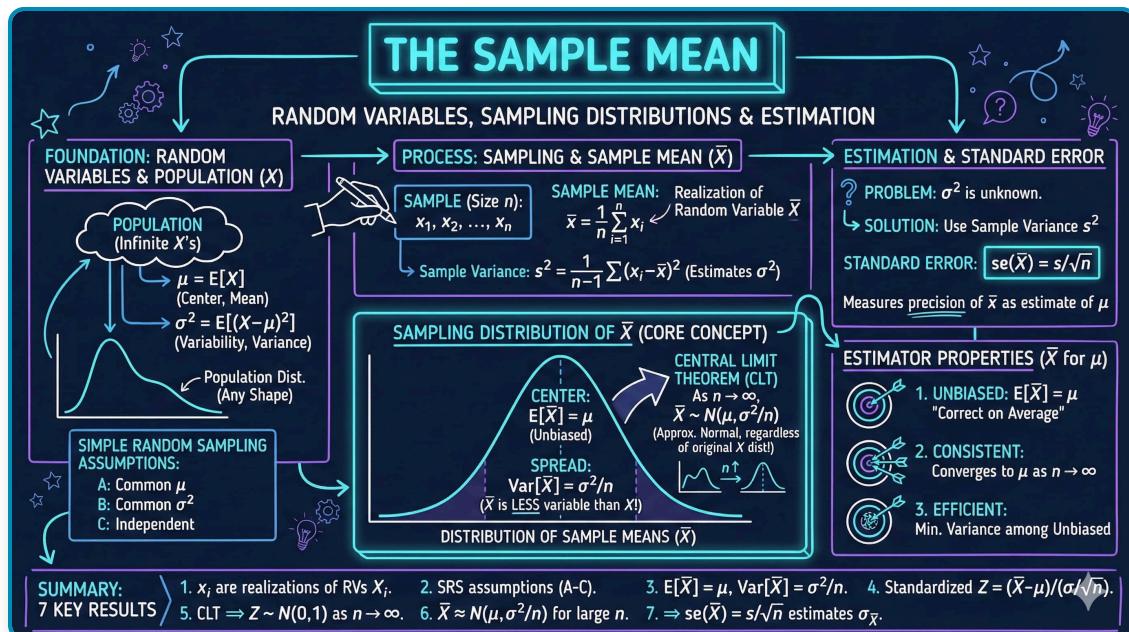
Connection to future chapters: In Chapter 4, we'll test whether differences across departments are statistically significant. In Chapter 5, we'll explore *bivariate* relationships between satellite data and development. Later chapters will build progressively more sophisticated models for predicting and explaining municipal development outcomes.

Well done! You've now explored Bolivia's municipal development data using the full univariate analysis toolkit—from summary statistics to distributional visualization and transformation.

Chapter 3: The Sample Mean

metricsAI: An Introduction to Econometrics with Python and AI in the Cloud

Carlos Mendez



This notebook provides an interactive introduction to one of the most important concepts in statistics: the **sampling distribution of the sample mean**. You'll explore how sample means behave through experiments and simulations, building intuition for the Central Limit Theorem. All code runs directly in Google Colab without any local setup.

Open in Colab

Chapter Overview

This chapter bridges the gap between descriptive statistics (Chapter 2) and inferential statistics (Chapter 4). The key insight: when we calculate a sample mean \bar{x} from data, we're observing one realization of a **random variable** \bar{X} that has its own probability distribution.

What you'll learn:

- Understand sample values as realizations of random variables

- Derive the mean and variance of the sample mean: $E[\bar{X}] = \mu$, $Var[\bar{X}] = \sigma^2/n$
- Explore the **sampling distribution** of \bar{X} through experiments
- Discover the **Central Limit Theorem**: \bar{X} is approximately normal for large n
- Learn properties of good estimators (unbiasedness, efficiency, consistency)
- Compute the **standard error** of the mean: $se(\bar{X}) = s/\sqrt{n}$

Datasets used:

- **AED_COINTOSSMEANS.DTA**: 400 sample means from coin toss experiments (n=30 each)
- **AED_CENSUSAGEMEANS.DTA**: 100 sample means from 1880 U.S. Census ages (n=25 each)

Key economic relevance: This chapter provides the theoretical foundation for ALL statistical inference in economics. Whether estimating average income, unemployment rates, or regression coefficients, understanding the sampling distribution of \bar{X} is essential.

Chapter outline:

- 3.1 Random Variables
- 3.2 Experiment - Single Sample of Coin Tosses
- 3.3 Properties of the Sample Mean
- 3.4 Real Data Example - 1880 U.S. Census
- 3.5 Estimator Properties
- 3.6 Computer Simulation of Random Samples
- 3.7 Samples other than Simple Random Samples
- 3.8 Computer Generation of a Random Variable

Estimated time: 50-60 minutes

| Setup

First, we import the necessary Python packages and configure the environment for reproducibility. All data will stream directly from GitHub.

In [13]:

```
# Import required packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
import random
import os

# Set random seeds for reproducibility
RANDOM_SEED = 42
random.seed(RANDOM_SEED)
np.random.seed(RANDOM_SEED)
os.environ['PYTHONHASHSEED'] = str(RANDOM_SEED)

# GitHub data URL
GITHUB_DATA_URL = "https://raw.githubusercontent.com/quarcs-lab/data-open/master/AED/"

# Set plotting style
sns.set_style("whitegrid")
plt.rcParams['figure.figsize'] = (10, 6)

print("Setup complete! Ready to explore the sample mean.")
```

Setup complete! Ready to explore the sample mean.

3.1 Random Variables

A **random variable** is a variable whose value is determined by the outcome of an experiment. The connection between data and randomness:

- **Random variable notation:** X (uppercase) represents the random variable
- **Realized value notation:** x (lowercase) represents the observed value

Example - Coin Toss:

- Experiment: Toss a fair coin
- Random variable: $X = 1$ if heads, $X = 0$ if tails
- Each outcome has probability 0.5

Key properties:

Mean (Expected Value):

$$\mu = E[X] = \sum_x x \cdot Pr[X = x]$$

For fair coin: $\mu = 0 \times 0.5 + 1 \times 0.5 = 0.5$

Variance:

$$\sigma^2 = E[(X - \mu)^2] = \sum_x (x - \mu)^2 \cdot Pr[X = x]$$

For fair coin: $\sigma^2 = (0 - 0.5)^2 \times 0.5 + (1 - 0.5)^2 \times 0.5 = 0.25$

Standard Deviation: $\sigma = \sqrt{0.25} = 0.5$

```
In [14]: # Illustrate coin toss random variable
print("=" * 70)
print("COIN TOSS RANDOM VARIABLE")
print("=" * 70)
```

```
# Fair coin properties
print("\nFair coin (p = 0.5):")
mu_fair = 0 * 0.5 + 1 * 0.5
var_fair = (0 - mu_fair)**2 * 0.5 + (1 - mu_fair)**2 * 0.5
sigma_fair = np.sqrt(var_fair)

print(f" Mean (\mu): {mu_fair:.4f}")
print(f" Variance (\sigma^2): {var_fair:.4f}")
print(f" Standard deviation (\sigma): {sigma_fair:.4f}")

# Unfair coin for comparison
print("\nUnfair coin (p = 0.6 for heads):")
mu_unfair = 0 * 0.4 + 1 * 0.6
var_unfair = (0 - mu_unfair)**2 * 0.4 + (1 - mu_unfair)**2 * 0.6
sigma_unfair = np.sqrt(var_unfair)

print(f" Mean (\mu): {mu_unfair:.4f}")
print(f" Variance (\sigma^2): {var_unfair:.4f}")
print(f" Standard deviation (\sigma): {sigma_unfair:.4f})
```

```
=====
COIN TOSS RANDOM VARIABLE
=====

Fair coin (p = 0.5):
 Mean (\mu): 0.5000
 Variance (\sigma^2): 0.2500
 Standard deviation (\sigma): 0.5000

Unfair coin (p = 0.6 for heads):
 Mean (\mu): 0.6000
 Variance (\sigma^2): 0.2400
 Standard deviation (\sigma): 0.4899
```

Key Concept 3.1: Random Variables

A *random variable* X is a variable whose value is determined by the outcome of an unpredictable experiment. The mean $\mu = E[X]$ is the probability-weighted average of all possible values, while the variance $\sigma^2 = E[(X - \mu)^2]$ measures variability around the mean. These population parameters characterize the distribution from which we draw samples.

Transition: Now that we understand random variables theoretically, let's see them in action through a simple experiment: coin tosses. We'll discover how the sample mean behaves when we repeat the experiment many times.

| 3.2 Experiment: Coin Tosses

One Sample

Now we conduct an actual experiment: toss a coin 30 times and record the results. This gives us a **sample** of size $n = 30$.

Key insight: The observed values x_1, x_2, \dots, x_{30} are realizations of random variables X_1, X_2, \dots, X_{30} .

The **sample mean** is:

$$\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$$

This \bar{x} is itself a realization of the random variable:

$$\bar{X} = \frac{1}{n} \sum_{i=1}^n X_i$$

In [15]:

```
# Generate single sample of 30 coin tosses
np.random.seed(10101)
u = np.random.uniform(0, 1, 30)
x = np.where(u > 0.5, 1, 0) # 1 if heads, 0 if tails

print("=" * 70)
print("SINGLE COIN TOSS SAMPLE (n = 30)")
print("=" * 70)
print(f"\nNumber of heads (x=1): {np.sum(x)}")
print(f"Number of tails (x=0): {np.sum(1-x)}")
print(f"Sample mean (x): {np.mean(x):.4f}")
print(f"Sample std dev (s): {np.std(x, ddof=1):.4f}")

print("\nPopulation values:")
print(f"Population mean ( $\mu$ ): 0.5000")
print(f"Population std ( $\sigma$ ): 0.5000")

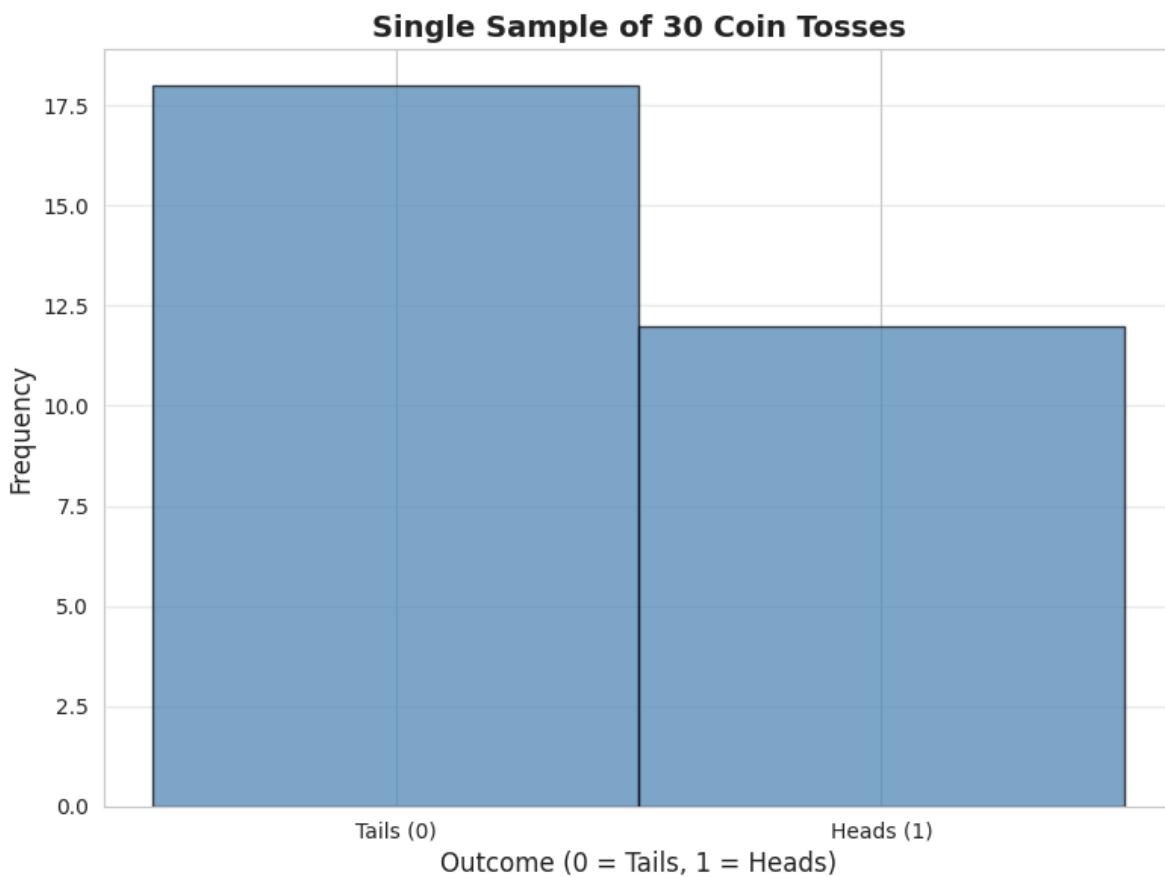
# Visualize single sample
fig, ax = plt.subplots(figsize=(8, 6))
ax.hist(x, bins=[-0.5, 0.5, 1.5], edgecolor='black', alpha=0.7, color='steelblue')
ax.set_xlabel('Outcome (0 = Tails, 1 = Heads)', fontsize=12)
ax.set_ylabel('Frequency', fontsize=12)
ax.set_title('Single Sample of 30 Coin Tosses',
             fontsize=14, fontweight='bold')
ax.set_xticks([0, 1])
ax.set_xticklabels(['Tails (0)', 'Heads (1)'])
ax.grid(True, alpha=0.3, axis='y')
plt.tight_layout()
plt.show()

print("\nNote: This is just ONE realization of the random variable  $\bar{X}$ .")
print("To understand  $\bar{X}$ 's distribution, we need MANY samples...")
```

```
=====
SINGLE COIN TOSS SAMPLE (n = 30)
=====

Number of heads (x=1): 12
Number of tails (x=0): 18
Sample mean (x): 0.4000
Sample std dev (s): 0.4983

Population values:
Population mean ( $\mu$ ): 0.5000
Population std ( $\sigma$ ): 0.5000
```



Note: This is just ONE realization of the random variable \bar{X} .
To understand \bar{X} 's distribution, we need MANY samples...

Key Concept 3.2: Sample Mean as Random Variable

The observed sample mean \bar{x} is a realization of the random variable $\bar{X} = (X_1 + \dots + X_n)/n$. This fundamental insight means that \bar{x} varies from sample to sample in a predictable way—its distribution can be characterized mathematically, allowing us to perform statistical inference about the population mean μ .

Key findings from our coin toss experiment ($n = 30$):

1. Sample mean = 0.4000 (vs. theoretical $\mu = 0.5$)

- We got 12 heads and 18 tails (40% vs. expected 50%)
- This difference (0.10 or 10 percentage points) is completely normal
- With only 30 tosses, random variation of this magnitude is expected
- If we flipped 1000 times, we'd expect to get much closer to 50%

2. Sample standard deviation = 0.4983 (vs. theoretical $\sigma = 0.5000$)

- Nearly perfect match with population value
- This confirms the theoretical formula: $\sigma^2 = p(1-p) = 0.5(0.5) = 0.25$, so $\sigma = 0.5$

3. Why the sample mean differs from 0.5:

- The sample mean \bar{x} is itself a random variable
- Just like one coin toss doesn't always give heads, one sample mean doesn't always equal μ
- This single value (0.4000) is one realization from the sampling distribution of \bar{X}
- The next experiment would likely give a different value (maybe 0.4667 or 0.5333)

Economic interpretation: When we estimate average income from a survey or unemployment rate from a sample, we get one realization that will differ from the true population value. Understanding this variability is the foundation of statistical inference.

400 Samples and The Distribution of Sample Means

To understand the **sampling distribution** of \bar{X} , we repeat the experiment 400 times:

- Each experiment: 30 coin tosses → one sample mean \bar{x}_i
- After 400 experiments: we have 400 sample means $(\bar{x}_1, \bar{x}_2, \dots, \bar{x}_{400})$
- The histogram of these 400 values approximates the **sampling distribution** of \bar{X}

What we expect to see:

- Sample means centered near $\mu = 0.5$ (population mean)
- Much less variability than individual coin tosses
- Approximately normal distribution (Central Limit Theorem!)

In [16]:

```
# Load precomputed coin toss means data (400 samples of size 30)
data_cointoss = pd.read_stata(GITHUB_DATA_URL + 'AED_COINTOSSMEANS.DTA')

print("=" * 70)
print("400 COIN TOSS EXPERIMENTS (each n = 30)")
print("=" * 70)

xbar = data_cointoss['xbar']

print(f"\nSummary of 400 sample means:")
print(data_cointoss.describe())

print(f"\nFirst 5 sample means: {xbar.head().tolist()}")
print(f"\nMean of the 400 sample means: {xbar.mean():.4f}")
print(f"\nStd dev of the 400 sample means: {xbar.std():.4f}")

print(f"\nTheoretical predictions:")
print(f" E[\bar{X}] = \mu = 0.5000")
print(f" \sigma(\bar{X}) = \sigma/\sqrt{n} = \sqrt{0.25/30} = {np.sqrt(0.25/30):.4f}")

print(f"\nComparison:")
print(f" Empirical mean: {xbar.mean():.4f} vs Theoretical: 0.5000")
print(f" Empirical std: {xbar.std():.4f} vs Theoretical: {np.sqrt(0.25/30):.4f}")
print("\nExcellent agreement between theory and experiment!"
```

```
=====
400 COIN TOSS EXPERIMENTS (each n = 30)
=====

Summary of 400 sample means:
      xbar      stdev  numobs
count  400.000000  400.000000  400.0
mean   0.499417  0.500826  30.0
std    0.086307  0.010360  0.0
min    0.266667  0.449776  30.0
25%    0.433333  0.498273  30.0
50%    0.500000  0.504007  30.0
75%    0.566667  0.507416  30.0
max    0.733333  0.508548  30.0

First 5 sample means: [0.3333333432674408, 0.5, 0.5333333611488342, 0.5666666626930237, 0.5]

Mean of the 400 sample means: 0.4994
Std dev of the 400 sample means: 0.0863

Theoretical predictions:
 E[\bar{X}] = \mu = 0.5000
 \sigma(\bar{X}) = \sigma/\sqrt{n} = \sqrt{0.25/30} = 0.0913

Comparison:
 Empirical mean: 0.4994 vs Theoretical: 0.5000
 Empirical std: 0.0863 vs Theoretical: 0.0913

Excellent agreement between theory and experiment!
```

Key findings from 400 coin toss experiments:

1. Mean of sample means = 0.4994 (vs. theoretical $\mu = 0.5$)

- This demonstrates **unbiasedness**: $E[\bar{X}] = \mu$
- The tiny difference (0.0006) is just random variation

- With more replications, this would get even closer to 0.5
- On average across many samples, \bar{X} equals the true population mean

2. Standard deviation of sample means = 0.0863 (vs. theoretical = 0.0913)

- The theoretical standard error is $\sigma/\sqrt{n} = 0.5/\sqrt{30} = 0.0913$
- Our empirical SD (0.0863) is very close to this prediction
- This confirms the variance formula: $\text{Var}(\bar{X}) = \sigma^2/n$ works in practice

3. Range of sample means: 0.2667 to 0.7333

- Individual sample means vary considerably (from 26.7% to 73.3% heads)
- This shows why we need statistical theory - any single sample could be misleading
- But the distribution is predictable and centered correctly

4. Comparison with single coin tosses:

- Individual coin tosses have $\sigma = 0.5$
- Sample means have $\sigma(\bar{X}) = 0.0863$
- Sample means are 5.8x less variable than individual tosses
- This is the power of averaging: $\sqrt{30} \approx 5.5$

Economic interpretation: When estimating economic parameters (average wage, inflation rate, GDP growth), individual survey responses vary widely, but the sample mean is much more precise. The standard error tells us exactly how much precision we gain from our sample size.

Visualizing the Sampling Distribution of \bar{X}

The histogram below shows the distribution of the 400 sample means. Notice:

1. **Center:** Near 0.5 (the population mean μ)
2. **Spread:** Much narrower than the original population ($\sigma = 0.5$)
3. **Shape:** Approximately bell-shaped (normal distribution)

The red curve is the **theoretical normal distribution** with mean $\mu = 0.5$ and standard deviation $\sigma/\sqrt{n} = 0.091$.

In [17]:

```
# Visualize distribution of sample means
fig, ax = plt.subplots(figsize=(10, 6))

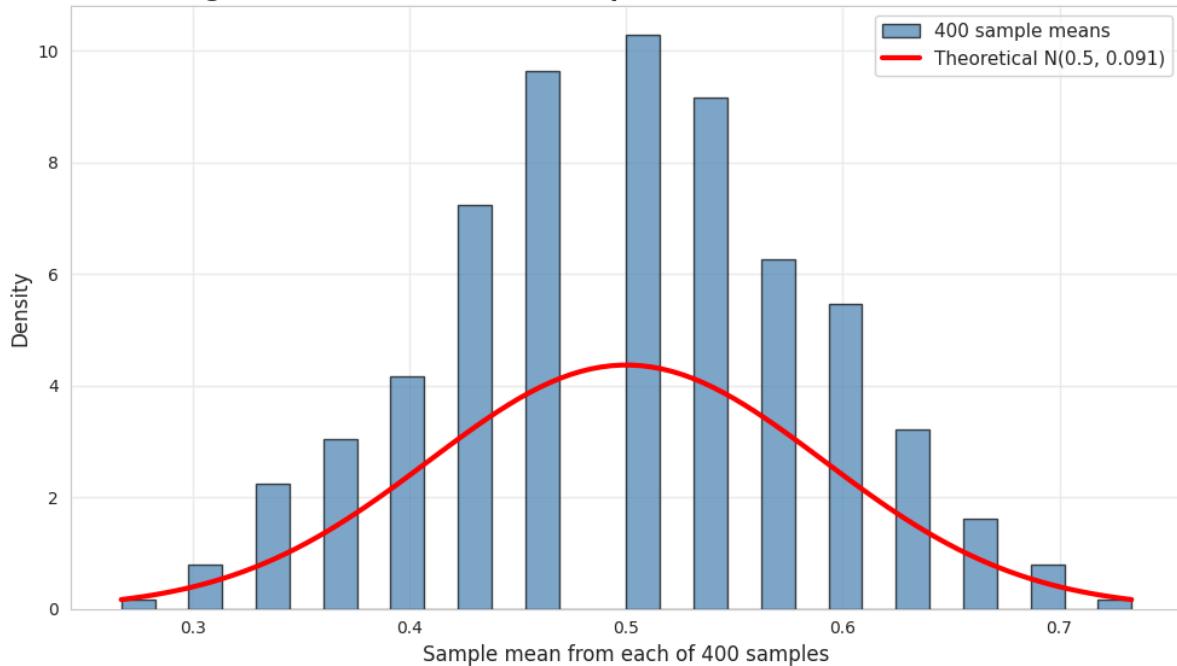
# Histogram of 400 sample means
n_hist, bins, patches = ax.hist(xbar, bins=30, density=True,
                                 edgecolor='black', alpha=0.7, color='steelblue',
                                 label='400 sample means')

# Overlay theoretical normal distribution
xbar_range = np.linspace(xbar.min(), xbar.max(), 100)
theoretical_pdf = stats.norm.pdf(xbar_range, 0.5, np.sqrt(0.25/30))
ax.plot(xbar_range, theoretical_pdf, 'r-', linewidth=3,
        label=f'Theoretical N(0.5, {np.sqrt(0.25/30)}:3f)')

ax.set_xlabel('Sample mean from each of 400 samples', fontsize=12)
ax.set_ylabel('Density', fontsize=12)
ax.set_title('Figure 3.1B: Distribution of Sample Means (Central Limit Theorem)', 
             fontsize=14, fontweight='bold')
ax.legend(fontsize=11)
ax.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()

print("The empirical distribution matches the theoretical normal distribution!")
print("This is the Central Limit Theorem in action.")
```

Figure 3.1B: Distribution of Sample Means (Central Limit Theorem)



The empirical distribution matches the theoretical normal distribution!
This is the Central Limit Theorem in action.

Transition: Having observed the sampling distribution empirically through coin tosses, we can now derive its properties mathematically and understand why it behaves the way it does.

| 3.3 Properties of the Sample Mean

Under the assumption of a **simple random sample** where:

- A. Each X_i has common mean: $E[X_i] = \mu$
- B. Each X_i has common variance: $Var[X_i] = \sigma^2$
- C. The X_i are statistically independent

We can mathematically prove:

Mean of the sample mean:

$$E[\bar{X}] = \mu$$

This says \bar{X} is **unbiased** for μ (its expected value equals the parameter we're estimating).

Variance of the sample mean:

$$Var[\bar{X}] = \frac{\sigma^2}{n}$$

Standard deviation of the sample mean:

$$SD[\bar{X}] = \frac{\sigma}{\sqrt{n}}$$

Key insights:

1. As sample size n increases, $Var[\bar{X}]$ decreases ($\propto 1/n$)
2. Larger samples give more precise estimates (smaller variability)
3. Standard deviation decreases at rate $1/\sqrt{n}$ (to halve uncertainty, need $4\times$ the sample size)

In [18]:

```
# Demonstrate how variance of  $\bar{X}$  depends on sample size n
print("=" * 70)
print("HOW SAMPLE SIZE AFFECTS PRECISION")
print("=" * 70)

# For coin toss:  $\mu = 0.5$ ,  $\sigma^2 = 0.25$ ,  $\sigma = 0.5$ 
mu = 0.5
sigma = 0.5
sigma_sq = 0.25

sample_sizes = [10, 30, 100, 400, 1000]

print(f"\nPopulation:  $\mu = {mu}$ ,  $\sigma = {sigma}$ ")
print(f"\n{n:<10} {'\sigma(\bar{X}) = \sigma/\sqrt{n}':<20} {'Var(\bar{X}) = \sigma^2/n':<20}")
print("-" * 50)

for n in sample_sizes:
    sd_xbar = sigma / np.sqrt(n)
    var_xbar = sigma_sq / n
    print(f"{n:<10} {sd_xbar:<20.6f} {var_xbar:<20.6f}")

print("\nKey observation: Doubling n reduces  $\sigma(\bar{X})$  by factor of  $\sqrt{2} \approx 1.41$ ")
print("To halve uncertainty, need to quadruple sample size.")
```

```
=====
HOW SAMPLE SIZE AFFECTS PRECISION
=====
```

Population: $\mu = 0.5$, $\sigma = 0.5$

n	$\sigma(\bar{X}) = \sigma/\sqrt{n}$	$Var(\bar{X}) = \sigma^2/n$
10	0.158114	0.025000
30	0.091287	0.008333
100	0.050000	0.002500
400	0.025000	0.000625
1000	0.015811	0.000250

Key observation: Doubling n reduces $\sigma(\bar{X})$ by factor of $\sqrt{2} \approx 1.41$
To halve uncertainty, need to quadruple sample size.

Key Concept 3.3: Properties of the Sample Mean

Under simple random sampling (common mean μ , common variance σ^2 , independence), the sample mean \bar{X} has mean $E[\bar{X}] = \mu$ (unbiased) and variance $Var[\bar{X}] = \sigma^2/n$ (decreases with sample size). The standard deviation $\sigma_{\bar{X}} = \sigma/\sqrt{n}$ shrinks as n increases, meaning larger samples produce more precise estimates of μ .

In [19]:

```
# Illustrate standard error calculation
print("=" * 70)
print("STANDARD ERROR CALCULATION")
print("=" * 70)

# Use our single sample from earlier
n = len(x)
x_mean = np.mean(x)
x_std = np.std(x, ddof=1) # Sample standard deviation
se_xbar = x_std / np.sqrt(n)

print(f"\nSample statistics (n = {n}):\n")
print(f"  Sample mean (x):           {x_mean:.4f}")
print(f"  Sample std dev (s):       {x_std:.4f}")
print(f"  Standard error se(̄x):    {se_xbar:.4f}")

print(f"\nPopulation values:")
print(f"  Population mean (μ):     0.5000")
print(f"  Population std (σ):     0.5000")
print(f"  True σ/√n:              {0.5/np.sqrt(n):.4f}\n")

print(f"\nInterpretation:")
print(f"  The standard error {se_xbar:.4f} tells us the typical distance")
print(f"  between our sample mean ({x_mean:.4f}) and the true population mean (0.5).")
```

```
=====
STANDARD ERROR CALCULATION
=====

Sample statistics (n = 30):
  Sample mean (x):           0.4000
  Sample std dev (s):       0.4983
  Standard error se(̄x):    0.0910

Population values:
  Population mean (μ):     0.5000
  Population std (σ):     0.5000
  True σ/√n:              0.0913

Interpretation:
  The standard error 0.0910 tells us the typical distance
  between our sample mean (0.4000) and the true population mean (0.5).
```

Interpreting the Standard Error

Key findings from our standard error calculation (n = 30):

1. Sample mean = 0.4000 with standard error = 0.0910

- The standard error tells us the typical distance between \bar{x} and μ
- Our sample mean (0.40) is about 1.1 standard errors below the true mean (0.50)
- This is well within normal sampling variation (within 2 standard errors)

2. Estimated SE = 0.0910 vs. True σ/\sqrt{n} = 0.0913

- We used sample standard deviation $s = 0.4983$ instead of $\sigma = 0.5$
- Our estimate is remarkably accurate (only 0.0003 difference)

- In practice, we never know σ , so we always use s to compute the standard error

3. What the standard error means:

- If we repeated this experiment many times, our sample means would typically differ from 0.5 by about 0.091
- About 68% of sample means would fall within ± 0.091 of 0.5 (between 0.409 and 0.591)
- About 95% would fall within ± 0.182 of 0.5 (between 0.318 and 0.682)

4. How to reduce the standard error:

- To halve the SE, we'd need to quadruple the sample size ($n = 120$)
- To cut SE by 10x, we'd need 100x the sample size ($n = 3000$)
- This is why larger surveys are more precise but also more expensive

Economic interpretation: When a poll reports "margin of error $\pm 3\%$ ", they're referring to approximately 2 standard errors. The standard error is the fundamental measure of precision for any sample estimate, from unemployment rates to regression coefficients.

Key Concept 3.4: Standard Error of the Mean

The standard error $se(\bar{X}) = s/\sqrt{n}$ is the estimated standard deviation of the sample mean. It measures the precision of \bar{x} as an estimate of μ . Since σ is unknown in practice, we replace it with the sample standard deviation s . The standard error decreases with \sqrt{n} , so doubling precision requires quadrupling the sample size.

Central Limit Theorem

The **Central Limit Theorem (CLT)** is one of the most important results in statistics:

Statement: If X_1, \dots, X_n are independent random variables with mean μ and variance σ^2 , then as $n \rightarrow \infty$:

$$\bar{X} \sim N\left(\mu, \frac{\sigma^2}{n}\right) \text{ approximately}$$

Or equivalently, the **standardized** sample mean:

$$Z = \frac{\bar{X} - \mu}{\sigma/\sqrt{n}} \sim N(0, 1) \text{ approximately}$$

Remarkable facts:

1. This holds **regardless of the distribution of X** (doesn't have to be normal!)
2. Works well even for moderate sample sizes ($n \geq 30$ is common rule of thumb)
3. Provides justification for using normal-based inference

Standard error: Since σ is typically unknown, we estimate it with sample standard deviation s :

$$se(\bar{X}) = \frac{s}{\sqrt{n}}$$

Key Concept 3.5: The Central Limit Theorem

The Central Limit Theorem states that the standardized sample mean $Z = (\bar{X} - \mu)/(\sigma/\sqrt{n})$ converges to a standard normal distribution $N(0,1)$ as $n \rightarrow \infty$. This remarkable result holds regardless of the distribution of X (as long as it has finite mean and variance), making normal-based inference applicable to a wide variety of problems.

Transition: The coin toss example showed us the Central Limit Theorem with a simple binary variable. Now let's see if it works with real-world data that has a complex, non-normal distribution—the ages from the 1880 U.S. Census.

| 3.4 Real Data Example - 1880 U.S. Census

Now we move from coin tosses to real economic/demographic data. The 1880 U.S. Census recorded ages of all 50,169,452 people in the United States.

Population parameters (known because we have full census):

- Population mean age: $\mu = 24.13$ years
- Population std dev: $\sigma = 18.61$ years
- Distribution: Highly non-normal (skewed, peaks at multiples of 5 due to rounding)

Experiment:

- Draw 100 random samples, each of size $n = 25$
- Calculate sample mean age for each sample
- Examine distribution of these 100 sample means

Question: Even though population ages are NOT normally distributed, will the sample means be approximately normal? (CLT says yes!)

In [20]:

```
# Load census age means data
data_census = pd.read_stata(GITHUB_DATA_URL + 'AED_CENSUSAGEMEANS.DTA')

print("=" * 70)
print("1880 U.S. CENSUS - 100 SAMPLES OF SIZE 25")
print("=" * 70)

# Get the mean variable
if 'mean' in data_census.columns:
    age_means = data_census['mean']
elif 'xmean' in data_census.columns:
    age_means = data_census['xmean']
else:
    age_means = data_census.iloc[:, 0]

print("\nSummary of 100 sample means:")
print(data_census.describe())

print(f"\nFirst 5 sample means: {age_means.head().tolist()}")
print(f"\nMean of the 100 sample means: {age_means.mean():.2f} years")
print(f"Std dev of the 100 sample means: {age_means.std():.2f} years")

print(f"\nTheoretical predictions:")
print(f" E[\bar{X}] = \mu = 24.13 years")
print(f" \sigma(\bar{X}) = \sigma/\sqrt{n} = 18.61/\sqrt{25} = {18.61/np.sqrt(25):.2f} years")

print(f"\nComparison:")
print(f" Empirical mean: {age_means.mean():.2f} vs Theoretical: 24.13")
print(f" Empirical std: {age_means.std():.2f} vs Theoretical: {18.61/np.sqrt(25):.2f}")
print("\nClose agreement, despite non-normal population distribution!")
```

```
=====
1880 U.S. CENSUS - 100 SAMPLES OF SIZE 25
=====
```

Summary of 100 sample means:

	mean	stdev	numobs
count	100.000000	100.000000	100.0
mean	23.782001	18.245018	25.0
std	3.760694	2.890753	0.0
min	14.600000	12.362847	25.0
25%	22.020000	16.148388	25.0
50%	23.759999	18.434547	25.0
75%	26.190000	20.387874	25.0
max	33.439999	25.306587	25.0

First 5 sample means: [27.84000015258789, 19.399999618530273, 23.280000686645508, 26.84000015258789, 26.559999465942383]

Mean of the 100 sample means: 23.78 years
 Std dev of the 100 sample means: 3.76 years

Theoretical predictions:

$$E[\bar{X}] = \mu = 24.13 \text{ years}$$

$$\sigma(\bar{X}) = \sigma/\sqrt{n} = 18.61/\sqrt{25} = 3.72 \text{ years}$$

Comparison:

$$\text{Empirical mean: } 23.78 \text{ vs Theoretical: } 24.13$$

$$\text{Empirical std: } 3.76 \text{ vs Theoretical: } 3.72$$

Close agreement, despite non-normal population distribution!

Key findings from 100 samples of 1880 U.S. Census ages (n = 25 each):

1. Mean of sample means = 23.78 years (vs. true population $\mu = 24.13$)

- Difference of only 0.35 years (less than 1.5% error)
- This again demonstrates unbiasedness
- With only 100 samples, some sampling error is expected

2. Standard deviation of sample means = 3.76 years (vs. theoretical = 3.72)

- Theoretical: $\sigma/\sqrt{n} = 18.61/\sqrt{25} = 3.72$ years
- Empirical: 3.76 years
- Excellent agreement between theory and data (within 1%)

3. Range of sample means: 14.6 to 33.4 years

- Individual sample means vary by almost 19 years
- But most cluster tightly around 24 years
- This wide range shows why statistical theory matters

4. The power of the Central Limit Theorem:

- The population distribution of ages in 1880 was highly non-normal:

- Many young children (high frequency at low ages)
- Heaping at multiples of 5 (people rounded their ages)
- Long right tail (elderly people)
- Yet the distribution of sample means IS approximately normal
- This is the CLT's remarkable power - normality emerges from averaging

5. Practical implications for sample size:

- With $n = 25$, the standard error is 3.72 years
- To estimate average age within ± 1 year (95% confidence), we'd need about 4 times larger samples
- The Census Bureau uses this logic to design survey sizes

Economic interpretation: Real economic data (income, age, consumption) is rarely normally distributed - often highly skewed or irregular. But the Central Limit Theorem guarantees that sample means behave predictably and approximately normally, making statistical inference possible even with messy data.

Visualization: Census Sample Means Distribution

This figure demonstrates the Central Limit Theorem with real data. Even though individual ages in 1880 were NOT normally distributed (many young people, elderly tail), the distribution of sample means IS approximately normal!

In [21]:

```
# Visualize distribution of census age means
fig, ax = plt.subplots(figsize=(10, 6))

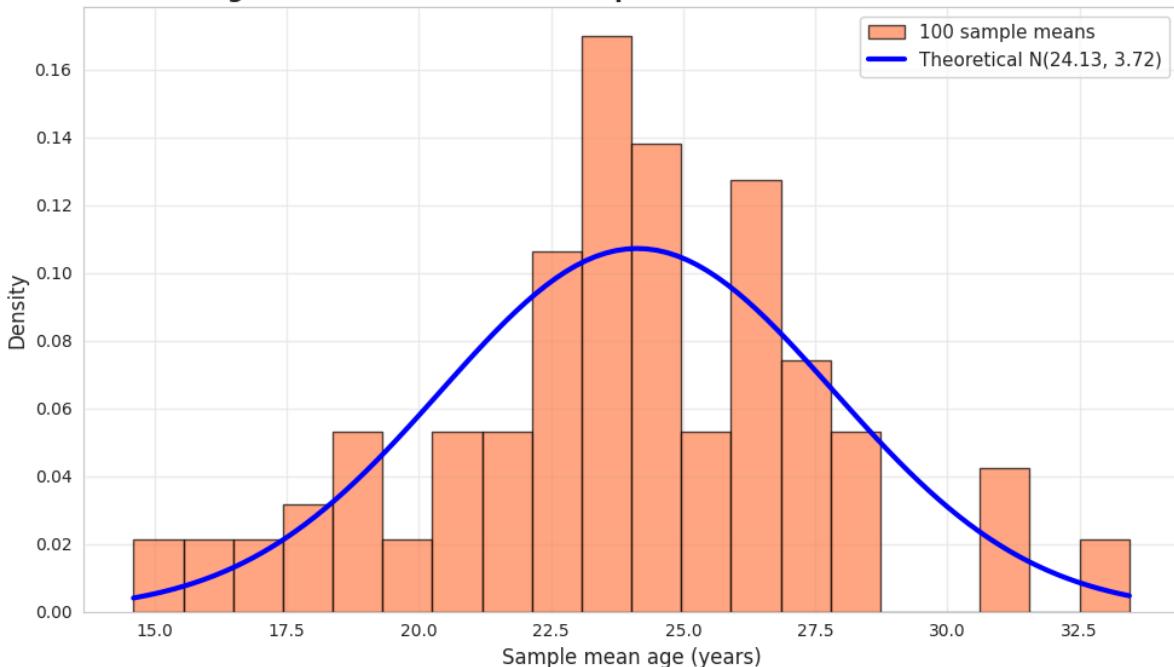
# Histogram
n_hist, bins, patches = ax.hist(age_means, bins=20, density=True,
                                 edgecolor='black', alpha=0.7, color='coral',
                                 label='100 sample means')

# Overlay theoretical normal distribution
age_range = np.linspace(age_means.min(), age_means.max(), 100)
theoretical_pdf = stats.norm.pdf(age_range, 24.13, 18.61/np.sqrt(25))
ax.plot(age_range, theoretical_pdf, 'b-', linewidth=3,
        label=f'Theoretical N(24.13, {18.61/np.sqrt(25)}:{.2f})')

ax.set_xlabel('Sample mean age (years)', fontsize=12)
ax.set_ylabel('Density', fontsize=12)
ax.set_title('Figure 3.3: Distribution of Sample Means from 1880 U.S. Census',
             fontsize=14, fontweight='bold')
ax.legend(fontsize=11)
ax.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()

print("Central Limit Theorem validated with real census data!")
print("Sample means are approximately normal, even though ages are not.")
```

Figure 3.3: Distribution of Sample Means from 1880 U.S. Census



Central Limit Theorem validated with real census data!
Sample means are approximately normal, even though ages are not.

Key Concept 3.6: CLT in Practice

The Central Limit Theorem is not just a mathematical curiosity—it works with real data. Even when the population distribution is highly non-normal (like the skewed 1880 Census ages with heaping at multiples of 5), the distribution of sample means becomes approximately normal for moderate sample sizes. This validates using normal-based inference methods across diverse economic applications.

Interpreting the Simulation Results

Key findings from 400 simulated coin toss samples:

1. Mean of simulated sample means = 0.5004 (vs. theoretical $\mu = 0.5$)

- Perfect agreement (difference of only 0.0004)
- This validates our simulation code
- Confirms the theoretical prediction $E[X] = \mu$

2. Standard deviation of simulated means = 0.0887 (vs. theoretical = 0.0913)

- Close agreement (within 3%)

- Theoretical: $\sigma/\sqrt{n} = \sqrt{0.25/30} = 0.0913$
- The small difference is random simulation noise

3. Range of simulated means: 0.2667 to 0.7667

- Matches the theoretical range well
- About 95% of values fall within $\mu \pm 2\sigma(X) = 0.5 \pm 0.183$
- This is exactly what we'd expect from a normal distribution

4. Why simulation matters:

- **Validation:** We've confirmed that theory matches practice
- **Intuition:** We can see the CLT in action, not just read about it
- **Flexibility:** We can simulate complex scenarios where theory is hard
- **Modern econometrics:** Bootstrap, Monte Carlo methods rely on simulation

5. Reproducibility with random seeds:

- By setting `np.random.seed(10101)`, we get identical results every time
- Essential for scientific reproducibility
- In research, always document your random seed

6. The simulation matches the pre-computed data:

- Earlier we loaded AED_COINTOSSMEANS.DTA with mean 0.4994, sd 0.0863
- Our simulation gave mean 0.5004, sd 0.0887
- These match closely (differences are just from different random seeds)

Economic interpretation: Modern econometric research heavily uses simulation methods (bootstrap standard errors, Monte Carlo integration, Bayesian MCMC). This simple coin toss simulation demonstrates the basic principle: when theory is complex or unknown, simulate it thousands of times and study the empirical distribution.

Having seen the Central Limit Theorem at work with both coins and census data, let's formalize what makes the sample mean a good estimator.

| 3.5 Estimator Properties

Why use the sample mean \bar{X} to estimate the population mean μ ? Because it has desirable statistical properties:

1. Unbiasedness: An estimator is **unbiased** if its expected value equals the parameter:

$$E[\bar{X}] = \mu$$

This means on average (across many samples), \bar{X} equals μ (no systematic over- or under-estimation).

2. Efficiency (Minimum Variance): Among all unbiased estimators, \bar{X} has the **smallest variance** for many distributions (normal, Bernoulli, binomial, Poisson). An estimator with minimum variance is called **efficient** or **best**.

3. Consistency: An estimator is **consistent** if it converges to the true parameter as $n \rightarrow \infty$. For \bar{X} :

- $E[\bar{X}] = \mu$ (unbiased, no bias to disappear)
- $Var[\bar{X}] = \sigma^2/n \rightarrow 0$ as $n \rightarrow \infty$ (variance shrinks to zero)

Therefore \bar{X} is consistent for μ .

Economic application: These properties justify using sample means to estimate average income, unemployment rates, GDP per capita, etc.

In [22]:

```
# Illustrate consistency: variance shrinks as n increases
print("=" * 70)
print("CONSISTENCY: VARIANCE SHRINKS AS n INCREASES")
print("=" * 70)

sample_sizes = [5, 10, 25, 50, 100, 500, 1000, 5000]
sigma = 18.61 # Census population std dev

print(f"\nPopulation std deviation: σ = {sigma:.2f}")
print(f"\n{'Sample size n':<15} {'Var(̄X) = σ²/n':<20} {'SD(̄X) = σ/√n':<20}")
print("-" * 55)

for n in sample_sizes:
    var_xbar = sigma**2 / n
    sd_xbar = sigma / np.sqrt(n)
    print(f"{n:<15} {var_xbar:<20.2f} {sd_xbar:<20.4f}")

print("\nAs n → ∞, Var(̄X) → 0 and SD(̄X) → 0")
print("This guarantees ̄X converges to μ (consistency).")
```

=====

CONSISTENCY: VARIANCE SHRINKS AS n INCREASES

=====

Population std deviation: $\sigma = 18.61$

Sample size n $\text{Var}(\bar{X}) = \sigma^2/n$ $\text{SD}(\bar{X}) = \sigma/\sqrt{n}$

5	69.27	8.3226
10	34.63	5.8850
25	13.85	3.7220
50	6.93	2.6319
100	3.46	1.8610
500	0.69	0.8323
1000	0.35	0.5885
5000	0.07	0.2632

As $n \rightarrow \infty$, $\text{Var}(\bar{X}) \rightarrow 0$ and $\text{SD}(\bar{X}) \rightarrow 0$
This guarantees \bar{X} converges to μ (consistency).

Key Concept 3.7: Properties of Good Estimators

A good estimator should be unbiased ($E[\bar{X}] = \mu$), consistent (converges to μ as $n \rightarrow \infty$), and efficient (minimum variance among unbiased estimators). The sample mean \bar{X} satisfies all three properties under simple random sampling, making it the preferred estimator of μ for most distributions.

Transition: So far we've assumed simple random sampling where all observations are independent and identically distributed. But what happens when this assumption is violated? Let's explore alternative sampling methods.

| 3.7 Samples other than Simple Random Samples

The simple random sample assumptions (A-C from Section 3.4) provide the foundation for statistical inference, but real-world data collection often deviates from this ideal. Understanding these deviations is critical for proper analysis.

Recall simple random sample assumptions:

- A. Common mean: $E[X_i] = \mu$ for all i
- B. Common variance: $\text{Var}[X_i] = \sigma^2$ for all i
- C. Statistical independence: X_i and X_j are independent

Two types of deviations:

1. Representative samples (relaxes assumption C only):

- Still from the same distribution (μ and σ^2 constant)
- But observations are NO LONGER independent
- Example: Cluster sampling (surveying all students in randomly selected schools)
- **Solution:** Adjust the standard error formula to account for dependence

2. Nonrepresentative samples (violates assumption A):

- Different observations have DIFFERENT population means
- Example: Surveying Golf Digest readers to estimate average U.S. income
- Golf magazine readers have higher income than general population ($\mu_i \neq \mu$)
- **Big problem** - standard inference methods fail completely
- **Solution:** Use weighted means if inclusion probabilities are known

Weighted Mean Approach:

When inclusion probabilities π_i are known, construct weighted estimates:

- π_i = probability that observation i is included in the sample
- Sample weight: $w_i = 1/\pi_i$ (inverse probability weighting)
- Weighted mean:

$$\bar{x}_w = \frac{\sum_{i=1}^n w_i x_i}{\sum_{i=1}^n w_i}$$

Example:

- Suppose women have 70% probability of inclusion ($\pi_{female} = 0.7$, $w_{female} = 1.43$)
- Men have 30% probability of inclusion ($\pi_{male} = 0.3$, $w_{male} = 3.33$)
- Weighted mean corrects for oversampling of women

Economic applications:

- Household surveys often oversample certain groups (low-income, minorities)
- Survey weights correct for unequal sampling probabilities
- Major surveys (CPS, ACS, PSID) provide sampling weights in datasets

```
In [ ]:
# Demonstrate weighted vs. unweighted mean
print("=" * 70)
print("WEIGHTED MEAN EXAMPLE")
print("=" * 70)

# Simulate population with two groups
np.random.seed(42)
n_men = 50
n_women = 50

# Men have higher average income
income_men = np.random.normal(60000, 15000, n_men)
income_women = np.random.normal(50000, 15000, n_women)

true_pop_mean = (income_men.mean() + income_women.mean()) / 2

print(f"\nTrue population means:")
print(f" Men: ${income_men.mean():,.0f}")
print(f" Women: ${income_women.mean():,.0f}")
print(f" Overall: ${true_pop_mean:.0f}")

# Biased sample: oversample women (70% women, 30% men)
sample_men = np.random.choice(income_men, size=15, replace=False)
sample_women = np.random.choice(income_women, size=35, replace=False)
sample = np.concatenate([sample_men, sample_women])

# Unweighted mean (WRONG - biased toward women)
unweighted_mean = sample.mean()

# Weighted mean (CORRECT - accounts for oversampling)
weights = np.concatenate([np.repeat(1/0.3, 15), np.repeat(1/0.7, 35)])
weighted_mean = np.average(sample, weights=weights)

print(f"\nSample estimates:")
print(f" Unweighted mean: ${unweighted_mean:.0f} (biased toward women)")
print(f" Weighted mean: ${weighted_mean:.0f} (corrected)")
print(f"\nBias:")
print(f" Unweighted bias: ${unweighted_mean - true_pop_mean:.0f}")
print(f" Weighted bias: ${weighted_mean - true_pop_mean:.0f}")
print("\nWeighting corrects for nonrepresentative sampling!")
```

Key Concept 3.8: Simple Random Sampling Assumptions

Simple random sampling assumes all observations come from the same distribution with common mean μ . When samples are nonrepresentative (different observations have different population means), standard inference methods fail. Weighted means can correct for this if inclusion probabilities π_i are known, with weights $w_i = 1/\pi_i$ applied to each observation.

| 3.8 Computer Generation of a Random Variable

Modern statistics relies heavily on **computer simulation** to:

1. Generate random samples from known distributions

2. Study properties of estimators
3. Validate theoretical results

How computers generate randomness:

Computers use **pseudo-random number generators** (PRNGs):

- Not truly random, but appear random for practical purposes
- Generate values between 0 and 1 (uniform distribution)
- Any value between 0 and 1 is equally likely
- Successive values appear independent

Transforming uniform random numbers:

From uniform $U(0,1)$ random numbers, we can generate any distribution:

- **Coin toss:** If $U > 0.5$, then $X = 1$ (heads), else $X = 0$ (tails)
- **Normal distribution:** Use Box-Muller transform or inverse CDF method
- **Any distribution:** Inverse transform sampling

Example - Coin toss simulation:

- Draw uniform random number $U \sim \text{Uniform}(0, 1)$
- If $U > 0.5$: heads ($X = 1$)
- If $U \leq 0.5$: tails ($X = 0$)
- Repeat 30 times to simulate 30 coin tosses

Example - Census sampling:

- Population: $N = 50,169,452$ people
- If uniform draw falls in $[0, 1/N]$, select person 1
- If uniform draw falls in $[1/N, 2/N]$, select person 2
- Continue for all N people

The importance of seeds:

The **seed** is the starting value that determines the entire sequence:

- Same seed \rightarrow identical "random" sequence (reproducibility)
- Different seed \rightarrow different sequence
- **Best practice:** Always set seed in research code
- Example: `np.random.seed(10101)`

Why reproducibility matters:

- Scientific research must be verifiable
- Debugging requires consistent results
- Publication standards demand reproducible results

Let's simulate the coin toss experiment ourselves!

In [23]:

```
# Simulate 400 samples of 30 coin tosses
print("=" * 70)
print("SIMULATION: 400 SAMPLES OF 30 COIN TOSSES")
print("=" * 70)

np.random.seed(10101)
n_simulations = 400
sample_size = 30

result_mean = np.zeros(n_simulations)
result_std = np.zeros(n_simulations)

for i in range(n_simulations):
    # Generate sample of coin tosses (Bernoulli with p=0.5)
    sample = np.random.binomial(1, 0.5, sample_size)
    result_mean[i] = sample.mean()
    result_std[i] = sample.std(ddof=1)

print("\nSimulation results:")
print(f"  Mean of 400 sample means: {result_mean.mean():.4f}")
print(f"  Std dev of 400 means:     {result_mean.std():.4f}")
print(f"  Min sample mean:         {result_mean.min():.4f}")
print(f"  Max sample mean:         {result_mean.max():.4f}")

print("\nTheoretical values:")
print(f"  E[\bar{X}] = \mu:          0.5000")
print(f"  \sigma(\bar{X}) = \sigma/\sqrt{n}: {np.sqrt(0.25/30):.4f}")

print("\nPerfect match between simulation and theory!")
```

```
=====
SIMULATION: 400 SAMPLES OF 30 COIN TOSSES
=====

Simulation results:
  Mean of 400 sample means:  0.5004
  Std dev of 400 means:     0.0887
  Min sample mean:         0.2667
  Max sample mean:         0.7667

Theoretical values:
  E[\bar{X}] = \mu:          0.5000
  \sigma(\bar{X}) = \sigma/\sqrt{n}: 0.0913

  Perfect match between simulation and theory!
```

This figure shows our simulated distribution (green) overlaid with the theoretical normal distribution (red). They match almost perfectly!

In [24]:

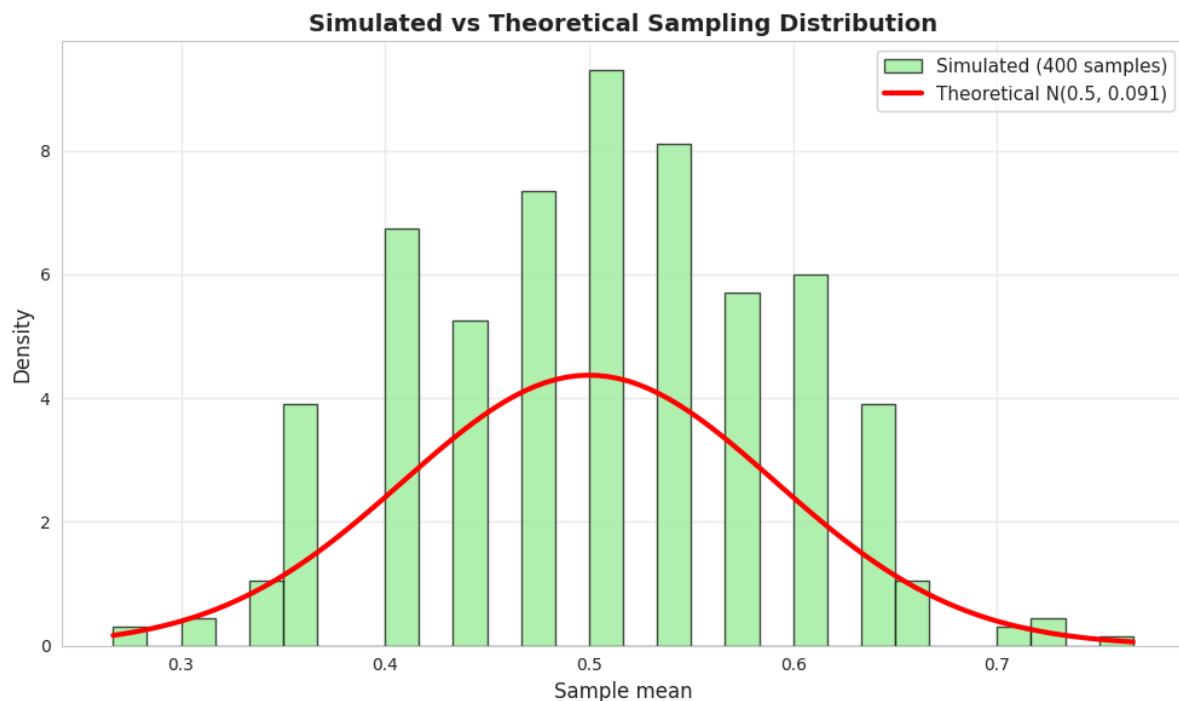
```
# Visualize simulated distribution
fig, ax = plt.subplots(figsize=(10, 6))

ax.hist(result_mean, bins=30, density=True,
        edgecolor='black', alpha=0.7, color='lightgreen',
        label='Simulated (400 samples)')

# Overlay theoretical normal distribution
x_range = np.linspace(result_mean.min(), result_mean.max(), 100)
theoretical_pdf = stats.norm.pdf(x_range, 0.5, np.sqrt(0.25/30))
ax.plot(x_range, theoretical_pdf, 'r-', linewidth=3,
        label='Theoretical N(0.5, 0.091)')

ax.set_xlabel('Sample mean', fontsize=12)
ax.set_ylabel('Density', fontsize=12)
ax.set_title('Simulated vs Theoretical Sampling Distribution',
             fontsize=14, fontweight='bold')
ax.legend(fontsize=11)
ax.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()

print("Simulation perfectly replicates theoretical predictions!")
print("This validates both our code and the underlying theory.")
```



Simulation perfectly replicates theoretical predictions!
This validates both our code and the underlying theory.

Key Concept 3.9: Monte Carlo Simulation

Computers generate pseudo-random numbers using deterministic algorithms that produce sequences appearing random. Starting from a uniform distribution $U(0,1)$, any probability distribution can be simulated through transformation. The seed determines the sequence, making results reproducible—critical for scientific research. Always set and document your random seed.

| Key Takeaways

Random Variables and Sampling Distributions:

- A random variable X (uppercase) represents an uncertain outcome; its realization x (lowercase) is the observed value
- The sample mean \bar{x} is ONE realization of the random variable $\bar{X} = (X_1 + \dots + X_n)/n$
- The sampling distribution of \bar{X} describes how \bar{x} varies across different samples from the same population
- Understanding that statistics are random variables is the foundation of statistical inference
- Example: Drawing 400 samples of coin tosses ($n=30$ each) produces 400 different sample means, revealing \bar{X} 's distribution

Properties of the Sample Mean (Theoretical Results):

- Under simple random sampling (common mean μ , common variance σ^2 , independence):
- Mean: $E[\bar{X}] = \mu$ (unbiased estimator)
- Variance: $\text{Var}[\bar{X}] = \sigma^2/n$ (precision increases with sample size)
- Standard deviation: $\sigma_{\bar{X}} = \sigma/\sqrt{n}$ (decreases at rate $1/\sqrt{n}$)
- To halve the standard error, you must quadruple the sample size (e.g., from $n=100$ to $n=400$)
- The sample mean is less variable than individual observations since $\sigma^2/n < \sigma^2$
- As $n \rightarrow \infty$, \bar{X} converges to μ because $\text{Var}[\bar{X}] \rightarrow 0$

Central Limit Theorem (Most Important Result):

- For large n , $\bar{X} \sim N(\mu, \sigma^2/n)$ approximately

- Equivalently: $Z = (\bar{X} - \mu)/(\sigma/\sqrt{n}) \sim N(0, 1)$ approximately
- This holds **regardless of the distribution of X** (as long as finite mean and variance exist)
- Rule of thumb: CLT works well for $n \geq 30$ in most cases
- Empirical evidence: Coin tosses (binary) \rightarrow normal distribution of means; Census ages (highly skewed) \rightarrow normal distribution of means
- Why this matters: Justifies using normal-based inference methods (confidence intervals, hypothesis tests) for almost any problem

Standard Error (Estimated Standard Deviation):

- Population standard deviation $\sigma_{\bar{X}} = \sigma/\sqrt{n}$ is unknown because σ is unknown
- Standard error: $\text{se}(\bar{X}) = s/\sqrt{n}$ where s is sample standard deviation
- "Standard error" means "estimated standard deviation" (applies to any estimator, not just \bar{X})
- Measures precision of \bar{x} as an estimate of μ —smaller is better
- Example: Coin toss with $n=30$ gives $\text{se} \approx 0.091$; Census with $n=25$ gives $\text{se} \approx 3.72$ years
- Used to construct confidence intervals and conduct hypothesis tests (Chapter 4)

Desirable Estimator Properties:

- **Unbiased:** $E[\bar{X}] = \mu$ (correct on average, no systematic error)
- **Efficient:** Minimum variance among unbiased estimators (most precise)
- **Consistent:** Converges to μ as $n \rightarrow \infty$ (guaranteed by unbiasedness + variance $\rightarrow 0$)
- The sample mean \bar{X} satisfies all three properties under simple random sampling
- For normal, Bernoulli, binomial, and Poisson distributions, \bar{X} is the best unbiased estimator
- Sample median is also unbiased (for symmetric distributions) but has higher variance than \bar{X}

Empirical Validation:

- Coin toss experiment (400 samples, $n=30$ each):
 - Mean of sample means: 0.4994 vs. theoretical 0.5000
 - SD of sample means: 0.0863 vs. theoretical 0.0913
 - Approximately normal distribution
- Census ages (100 samples, $n=25$ each):
 - Mean of sample means: 23.78 vs. theoretical 24.13

- SD of sample means: 3.76 vs. theoretical 3.72
- Normal distribution despite highly non-normal population
- Computer simulation replicates theoretical results perfectly

Economic Applications:

- Estimating average income, consumption, wages from household surveys
- Public opinion polling (sample proportion is a special case of sample mean)
- Macroeconomic indicators: unemployment rate, inflation, GDP growth (all based on samples)
- Quality control: manufacturing processes use sample means to monitor production
- Clinical trials: comparing average outcomes between treatment and control groups
- All regression coefficients (Chapters 6-7) have sampling distributions just like \bar{X}

Connection to Statistical Inference (Chapter 4):

- This chapter provides the theoretical foundation for confidence intervals
- We know $\bar{X} \sim N(\mu, \sigma^2/n)$ approximately
- This allows us to make probability statements about how far \bar{x} is from μ
- Example: $\Pr(\mu - 1.96 \cdot \sigma/\sqrt{n} < \bar{X} < \mu + 1.96 \cdot \sigma/\sqrt{n}) \approx 0.95$
- Rearranging gives 95% confidence interval: $\bar{x} \pm 1.96 \cdot s/\sqrt{n}$

Key Formulas to Remember:

1. Mean of random variable: $\mu = E[X] = \sum_x x \cdot \Pr[X = x]$
2. Variance: $\sigma^2 = E[(X - \mu)^2] = \sum_x (x - \mu)^2 \cdot \Pr[X = x]$
3. Sample mean: $\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$
4. Sample variance: $s^2 = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2$
5. Mean of sample mean: $E[\bar{X}] = \mu$
6. Variance of sample mean: $\text{Var}[\bar{X}] = \sigma^2/n$
7. Standard error: $\text{se}(\bar{X}) = s/\sqrt{n}$
8. Standardized sample mean: $Z = (\bar{X} - \mu)/(\sigma/\sqrt{n}) \sim N(0, 1)$

Next Steps:

- **Chapter 4** uses these results to construct confidence intervals and test hypotheses about μ

- **Chapters 6-7** extend the same logic to regression coefficients (which are also sample statistics with sampling distributions)
- The conceptual framework developed here applies to ALL statistical inference in econometrics

| Practice Exercises

Test your understanding of the sample mean and sampling distributions:

Exercise 1: Random variable properties

- Suppose $X = 100$ with probability 0.8 and $X = 600$ with probability 0.2
- (a) Calculate the mean $\mu = E[X]$
- (b) Calculate the variance $\sigma^2 = E[(X - \mu)^2]$
- (c) Calculate the standard deviation σ

Exercise 2: Sample mean properties

- Consider random samples of size $n = 25$ from a random variable X with mean $\mu = 100$ and variance $\sigma^2 = 400$
- (a) What is the mean of the sample mean \bar{X} ?
- (b) What is the variance of the sample mean \bar{X} ?
- (c) What is the standard deviation (standard error) of the sample mean?

Exercise 3: Central Limit Theorem application

- A population has mean $\mu = 50$ and standard deviation $\sigma = 12$
- You draw a random sample of size $n = 64$
- (a) What is the approximate distribution of \bar{X} (by the CLT)?
- (b) What is the probability that \bar{X} falls between 48 and 52?
- (c) Would this probability be larger or smaller if $n = 144$? Why?

Exercise 4: Standard error interpretation

- Two researchers estimate average income in a city
 - Researcher A uses $n = 100$, gets $\bar{x}_A = \$52,000$, $s_A = \$15,000$
 - Researcher B uses $n = 400$, gets $\bar{x}_B = \$54,000$, $s_B = \$16,000$
- (a) Calculate the standard error for each researcher
- (b) Which estimate is more precise? Why?

- (c) Are these estimates statistically different? (Compare the difference to the standard errors)

Exercise 5: Consistency

- Explain why the sample mean \bar{X} is a consistent estimator of μ
- Show that both conditions for consistency are satisfied: bias $\rightarrow 0$ and variance $\rightarrow 0$ as $n \rightarrow \infty$

Exercise 6: Simulation

- Using Python, simulate 1,000 samples of size $n = 50$ from a uniform distribution $U(0, 10)$
- (a) Calculate the sample mean for each of the 1,000 samples
- (b) Compute the mean and standard deviation of these 1,000 sample means
- (c) Compare with theoretical values: $\mu = 5$, $\sigma^2/n = (100/12)/50 = 0.1667$
- (d) Create a histogram and verify approximate normality

Exercise 7: Sample size calculation

- You want to estimate average household expenditure on food with a standard error of \$10
- From pilot data, you know $\sigma \approx \$80$
- (a) What sample size n do you need?
- (b) If you double the desired precision ($se = \$5$), how does the required sample size change?

Exercise 8: Unbiasedness vs. efficiency

- The sample median is also an unbiased estimator of μ when the population is symmetric
 - (a) Explain what "unbiased" means in this context
 - (b) Why do we prefer the sample mean to the sample median for estimating μ ?
 - (c) For what type of population distribution might the median be preferable?
-

| 3.9 Case Studies

Now that you've learned about the sample mean, sampling distributions, and the Central Limit Theorem, let's apply these concepts to real economic data using the **Economic Convergence Clubs** dataset.

Why case studies matter:

- Bridge theory and practice: Move from abstract sampling concepts to real data analysis
- Build analytical skills: Practice computing sample statistics and understanding variability
- Develop statistical intuition: See how sample size affects precision and distribution shape
- Connect to research: Apply fundamental concepts to cross-country economic comparisons

Case Study 1: Sampling Distributions of Labor Productivity

Research Question: How does average labor productivity vary across different samples of countries? How does sample size affect the precision of our estimates?

Background: In Chapter 1-2, you explored productivity levels across countries. Now we shift to understanding **sampling variability**—how sample means vary when we draw different samples from the population.

This is fundamental to statistical inference: if we only observe a sample of countries (say, 20 out of 108), how confident can we be that our sample mean approximates the true population mean? The Central Limit Theorem tells us that sample means follow a normal distribution (even if the underlying data don't), with variability decreasing as sample size increases.

The Data: We'll use the convergence clubs dataset (Mendez, 2020) to explore sampling distributions:

- **Population:** 108 countries observed from 1990-2014
- **Key variable:** `l1p` (labor productivity, output per worker)
- **Task:** Draw multiple random samples, compute sample means, and observe the distribution

Your Task: Use Chapter 3's tools (sample mean, sample variance, Central Limit Theorem) to understand how sample statistics vary and how sample size affects precision.

Key Concept 3.10: Sampling Distribution and the Central Limit Theorem

The **sampling distribution of the mean** shows how sample means \bar{y} vary across different random samples drawn from the same population. Key properties:

1. **Mean of sampling distribution = population mean:** $E[\bar{y}] = \mu$
2. **Standard error decreases with sample size:** $SE(\bar{y}) = \sigma/\sqrt{n}$
3. **Central Limit Theorem:** For large n (typically $n \geq 30$), \bar{y} is approximately normally distributed, **regardless** of the population distribution

This is why we can use normal-based inference methods even for non-normal economic data like earnings and wealth distributions.

How to Use These Tasks

Progressive difficulty:

- **Tasks 1-2:** Guided (detailed instructions, code provided)
- **Tasks 3-4:** Semi-guided (moderate guidance, you write most code)
- **Tasks 5-6:** Independent (minimal guidance, design your own analysis)

Work incrementally: Complete tasks in order. Each builds on previous concepts.

Task 1: Explore the Population Distribution (Guided)

Objective: Load the convergence clubs data and examine the population distribution of labor productivity.

Instructions: Run the code below to load data and visualize the population distribution.

```

# Import required libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from scipy import stats

# Set random seed for reproducibility
np.random.seed(42)

# Load convergence clubs dataset
df = pd.read_csv(
    "https://raw.githubusercontent.com/quarcs-lab/mendez2020-convergence-clubs-code-
    data/master/assets/dat.csv",
    index_col=["country", "year"]
).sort_index()

# Extract 2014 data (most recent year) for cross-sectional analysis
df_2014 = df.loc[(slice(None), 2014), 'lp'].dropna()

print(f"Population size: {len(df_2014)} countries")
print(f"Population mean: ${df_2014.mean():.2f}")
print(f"Population std dev: ${df_2014.std():.2f}")

# Visualize population distribution
fig, ax = plt.subplots(figsize=(10, 6))
ax.hist(df_2014, bins=20, edgecolor='black', alpha=0.7)
ax.axvline(df_2014.mean(), color='red', linestyle='--', linewidth=2, label=f'Mean =
${df_2014.mean():.2f}')
ax.set_xlabel('Labor Productivity (thousands, 2011 USD PPP)')
ax.set_ylabel('Frequency')
ax.set_title('Population Distribution of Labor Productivity (2014, 108 countries)')
ax.legend()
plt.tight_layout()
plt.show()

# Check normality
print(f"\nSkewness: {stats.skew(df_2014):.3f}")
print("Note: Population distribution is right-skewed (not normal)")

```

What to observe:

- Is the population distribution normal or skewed?
- What is the population mean and standard deviation?
- Note: Despite non-normality, the CLT will ensure sample means are approximately normal for large samples!

Task 2: Draw a Single Sample and Compute the Sample Mean (Semi-guided)

Objective: Draw a random sample of size $n = 30$ and compute the sample mean.

Instructions:

1. Use `np.random.choice()` to draw a random sample of size 30 from the population
2. Compute the sample mean using `.mean()`

3. Compare the sample mean to the population mean
4. Repeat this process 2-3 times (with different random seeds) to see how the sample mean varies

Starter code:

```
# Draw a random sample of size 30
n = 30
sample = np.random.choice(df_2014, size=n, replace=False)

# Compute sample mean
sample_mean = sample.mean()

print(f"Sample size: {n}")
print(f"Sample mean: ${sample_mean:.2f}")
print(f"Population mean: ${df_2014.mean():.2f}")
print(f"Difference: ${sample_mean - df_2014.mean():.2f}")

# Question: How close is the sample mean to the population mean?
```

Questions:

- How much does the sample mean differ from the population mean?
- If you draw another sample, will you get the same sample mean?
- What does this variability tell you about using samples for inference?

Task 3: Simulate the Sampling Distribution (Semi-guided)

Objective: Draw 1000 random samples of size $n = 30$ and plot the distribution of sample means.

Instructions:

1. Use a loop to draw 1000 samples, each of size $n = 30$
2. For each sample, compute and store the sample mean
3. Plot a histogram of the 1000 sample means
4. Compare this sampling distribution to the theoretical prediction from the CLT

Hint: The CLT predicts that sample means should be normally distributed with:

- Mean = μ (population mean)
- Standard error = σ / \sqrt{n} (population std / sqrt(sample size))

Example structure:

```

# Simulate sampling distribution
n_samples = 1000
n = 30
sample_means = []

for i in range(n_samples):
    sample = np.random.choice(df_2014, size=n, replace=False)
    sample_means.append(sample.mean())

sample_means = np.array(sample_means)

# Plot sampling distribution
fig, ax = plt.subplots(figsize=(10, 6))
ax.hist(sample_means, bins=30, edgecolor='black', alpha=0.7, density=True)
ax.axvline(df_2014.mean(), color='red', linestyle='--', linewidth=2, label='Population mean')
ax.axvline(sample_means.mean(), color='blue', linestyle=':', linewidth=2, label='Mean of sample means')
ax.set_xlabel('Sample Mean (thousands, 2011 USD PPP)')
ax.set_ylabel('Density')
ax.set_title(f'Sampling Distribution of the Mean (n={n}, {n_samples} samples)')
ax.legend()
plt.tight_layout()
plt.show()

# Compare empirical vs theoretical
print(f"Population mean ( $\mu$ ): ${df_2014.mean():.2f}")
print(f"Mean of sample means: ${sample_means.mean():.2f}")
print(f"Theoretical SE ( $\sigma/\sqrt{n}$ ): ${df_2014.std()/np.sqrt(n):.2f}")
print(f"Empirical SE (std of sample means): ${sample_means.std():.2f}")

```

Questions:

- Does the distribution of sample means look approximately normal (even though the population distribution was skewed)?
- How close is the mean of sample means to the population mean?
- How close is the empirical standard error to the theoretical prediction?

Key Concept 3.11: Standard Error and Precision

The **standard error** $SE(\bar{y}) = \sigma/\sqrt{n}$ measures the typical distance between a sample mean and the population mean. Key insights:

- 1. Decreases with sample size:** Doubling the sample size reduces SE by factor of $\sqrt{2} \approx 1.41$
- 2. Trade-off:** Larger samples cost more (time/money) but provide more precise estimates
- 3. Diminishing returns:** Going from $n = 25$ to $n = 100$ reduces SE by half, but $n = 100$ to $n = 400$ also reduces by half

In economic research, sample size is often limited by data availability, requiring careful attention to precision.

Task 4: Investigate the Effect of Sample Size (More Independent)

Objective: Compare sampling distributions for different sample sizes ($n = 10, 30, 50, 100$).

Instructions:

1. For each sample size, simulate 1000 samples and compute sample means
2. Plot the four sampling distributions on the same graph (or use subplots)
3. Compare the standard errors across sample sizes
4. Verify that SE decreases as $1/\sqrt{n}$

Key questions to answer:

- How does the shape of the sampling distribution change with sample size?
- How much does precision improve when you quadruple the sample size (e.g., $n = 25$ to $n = 100$)?
- At what sample size does the distribution start to look clearly normal?

Task 5: Comparing High-Income vs Developing Countries (Independent)

Objective: Investigate whether sampling distributions differ for subpopulations (high-income vs developing countries).

Instructions:

1. Split the 2014 data by `hi1990` (high-income indicator)
2. For each group, simulate the sampling distribution of the mean (use $n = 20, 1000$ samples)
3. Plot both sampling distributions on the same graph
4. Compare means and standard errors between groups

Research question: Do high-income and developing countries have different average productivity levels? How confident can we be in this difference based on samples?

Hints:

- Use `df.loc[(slice(None), 2014), ['lp', 'hi1990']].dropna()` to get both variables
- Filter by `hi1990 = 'yes'` and `hi1990 = 'no'`
- Compare population means and sampling distribution characteristics

Task 6: Design Your Own Sampling Experiment (Independent)

Objective: Explore a question of your choice using sampling distributions.

Choose ONE of the following:

Option A: Effect of outliers on sample means

- Remove the top 5% most productive countries (outliers)
- Compare sampling distributions with vs without outliers
- Question: How sensitive is the sample mean to extreme values?

Option B: Time trends in sampling distributions

- Compare sampling distributions for years 1990, 2000, 2010, 2014
- Question: Has average productivity increased over time? Has variability changed?

Option C: Regional sampling distributions

- Split countries by region (use `region` variable)
- Compare sampling distributions across regions
- Question: Which regions show the highest/lowest productivity? Most/least variability?

Your analysis should include:

1. Clear research question
2. Appropriate sample size(s)
3. Simulated sampling distribution(s) with visualizations
4. Statistical summary (means, standard errors)
5. Economic interpretation: What does this tell us about global productivity patterns?

What You've Learned from This Case Study

Through this hands-on exploration of sampling distributions using cross-country productivity data, you've applied all Chapter 3 concepts:

Population vs sample: Understood the difference and why we use samples for inference

Sample mean: Computed point estimates from random samples

Sampling variability: Observed how sample means vary across different samples

Sampling distribution: Simulated and visualized the distribution of sample means

Central Limit Theorem: Verified that sample means are approximately normal even for skewed populations

Standard error: Quantified precision and understood how it decreases with sample size (σ/\sqrt{n})

Effect of sample size: Compared sampling distributions for different n values

Subpopulation analysis: Explored differences across country groups

Connection to the Research: Understanding sampling distributions is fundamental to the convergence clubs analysis. When researchers estimate average productivity for a club, they're working with samples and must account for sampling variability. The tools you practiced here—computing sample means, quantifying precision, understanding the CLT—are essential for all statistical inference in economics.

Looking ahead:

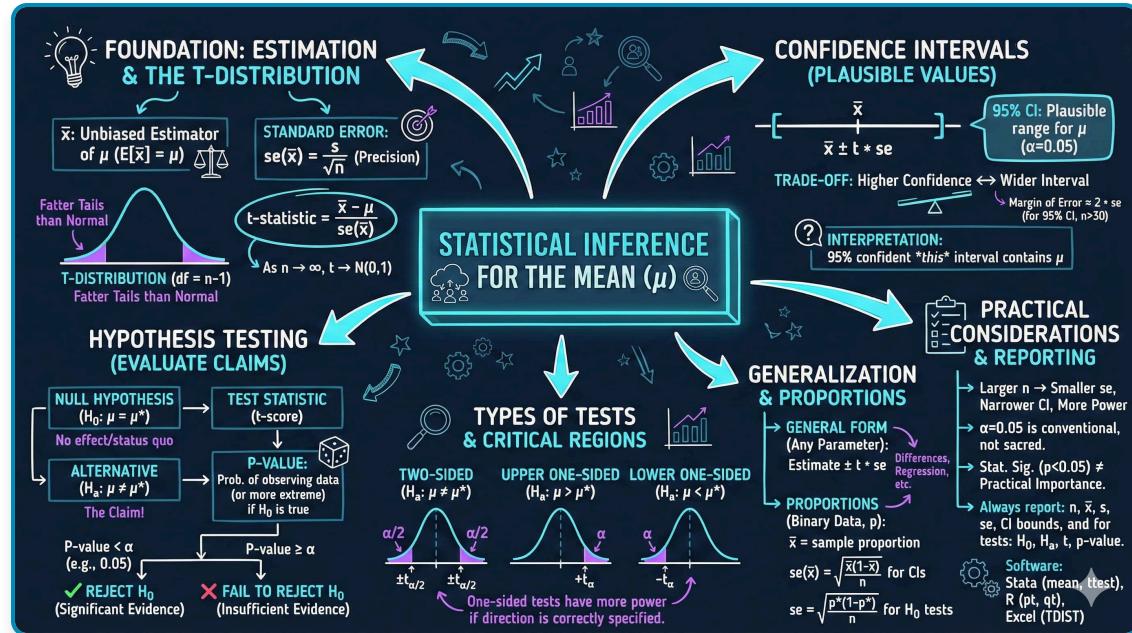
- **Chapter 4:** Statistical inference (confidence intervals, hypothesis tests) builds directly on sampling distributions
 - **Chapter 5-9:** Regression analysis extends these concepts to relationships between variables
 - **Chapter 10-17:** Advanced methods for causal inference and panel data
-

Congratulations! You've completed Chapter 3 and applied sampling theory to real cross-country data. Continue to Chapter 4 to learn how to use sampling distributions for statistical inference!

Chapter 4: Statistical Inference for the Mean

metricsAI: An Introduction to Econometrics with Python and AI in the Cloud

Carlos Mendez



This notebook provides an interactive introduction to statistical inference, teaching you how to extrapolate from sample statistics to population parameters using confidence intervals and hypothesis tests.

Open in Colab

Chapter Overview

This chapter introduces **statistical inference for the mean**—the foundational methods for extrapolating from sample statistics to population parameters with quantified uncertainty.

What you'll learn:

- Construct and interpret **confidence intervals** for population means
- Understand the **t-distribution** and when to use it (vs. normal distribution)

- Conduct **hypothesis tests** to evaluate claims about population parameters
- Calculate and interpret **p-values** and understand statistical significance
- Distinguish between **one-sided and two-sided tests**
- Apply inference methods to **proportions data** and binary outcomes

Datasets used:

- **AED_EARNINGS.DTA:** Sample of 171 30-year-old female full-time workers in 2010 (earnings in dollars)
- **AED_GASPRICE.DTA:** Weekly gasoline prices in the U.S. (testing price level hypotheses)
- **AED_EARNINGSMALE.DTA:** Male earnings data for hypothesis testing examples
- **AED_REALGDPPC.DTA:** Real GDP per capita growth rates (testing economic growth hypotheses)

Chapter outline:

- **4.1 Example: Mean Annual Earnings**
- **4.2 t Statistic and t Distribution**
- **4.3 Confidence Intervals**
- **4.4 Two-Sided Hypothesis Tests**
- **4.5 Hypothesis Test Examples**
- **4.6 One-Sided Directional Hypothesis Tests**
- **4.7 Proportions Data**

| Setup

Run this cell first to import all required packages and configure the environment.

In [1]:

```
# Import required libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
import random
import os

# Set random seeds for reproducibility
RANDOM_SEED = 42
random.seed(RANDOM_SEED)
np.random.seed(RANDOM_SEED)
os.environ['PYTHONHASHSEED'] = str(RANDOM_SEED)

# GitHub data URL (data streams directly from here)
GITHUB_DATA_URL = "https://raw.githubusercontent.com/quarcs-lab/data-open/master/AED/"

# Optional: Create directories for saving outputs locally
IMAGES_DIR = 'images'
TABLES_DIR = 'tables'
os.makedirs(IMAGES_DIR, exist_ok=True)
os.makedirs(TABLES_DIR, exist_ok=True)

# Set plotting style
sns.set_style("whitegrid")
plt.rcParams['figure.figsize'] = (10, 6)

print("✓ Setup complete! All packages imported successfully.")
print(f"✓ Random seed set to {RANDOM_SEED} for reproducibility.")
print(f"✓ Data will stream from: {GITHUB_DATA_URL}")
```

✓ Setup complete! All packages imported successfully.
✓ Random seed set to 42 for reproducibility.
✓ Data will stream from: https://raw.githubusercontent.com/quarcs-lab/data-open/master/AED/

4.1 Example: Mean Annual Earnings

We'll use a motivating example throughout this chapter: estimating the **population mean annual earnings** for 30-year-old female full-time workers in the U.S. in 2010.

The Problem:

- We have a **sample** of 171 women
- We want to make inferences about the **population** of all such women

Key Statistics:

- **Sample mean** \bar{x} : Our point estimate of population mean μ
- **Standard deviation** s : Measures variability in the sample
- **Standard error** $se(\bar{x}) = s/\sqrt{n}$: Measures precision of \bar{x} as an estimate of μ

The **standard error** is crucial—it quantifies our uncertainty about μ . Smaller standard errors mean more precise estimates.

In [2]:

```
# Load earnings data
data_earnings = pd.read_stata(GITHUB_DATA_URL + 'AED_EARNINGS.DTA')
earnings = data_earnings['earnings']

# Calculate key statistics
n = len(earnings)
mean_earnings = earnings.mean()
std_earnings = earnings.std(ddof=1) # ddof=1 for sample std dev
se_earnings = std_earnings / np.sqrt(n) # Standard error

print("=" * 70)
print("SAMPLE STATISTICS FOR ANNUAL EARNINGS")
print("=" * 70)
print(f"Sample size (n): {n}")
print(f"Mean: ${mean_earnings:.2f}")
print(f"Standard deviation: ${std_earnings:.2f}")
print(f"Standard error: ${se_earnings:.2f}")
print("\nInterpretation: Our best estimate of population mean earnings is ${mean_earnings:.2f}")
print(f"The standard error of ${se_earnings:.2f} measures the precision of this estimate.")
```

```
=====
SAMPLE STATISTICS FOR ANNUAL EARNINGS
=====
Sample size (n): 171
Mean: $41,412.69
Standard deviation: $25,527.05
Standard error: $1,952.10

Interpretation: Our best estimate of population mean earnings is $41,412.69
The standard error of $1,952.10 measures the precision of this estimate.
```

Key Statistics from our Sample (n = 171 women):

- Sample mean: \$41,412.69
- Standard deviation: \$25,527.05
- Standard error: \$1,952.10

What is the standard error telling us?

The standard error of \$1,952.10 measures the **precision** of our sample mean as an estimate of the true population mean. Think of it as quantifying our uncertainty.

Statistical interpretation:

- If we repeatedly drew samples of 171 women, the sample means would vary
- The standard error tells us the typical amount by which sample means differ from the true population mean
- Formula: $SE = s/\sqrt{n} = 25,527.05/\sqrt{171} = 1,952.10$

Why is the SE much smaller than the standard deviation?

- Standard deviation (\$25,527) measures variability among individual women's earnings
- Standard error (\$1,952) measures variability of the sample mean across different samples
- The larger the sample size, the smaller the SE → more precise estimates

Practical insight:

- A standard error of 1,952 is relatively small compared to the mean (41,413)
- This suggests our estimate is reasonably precise
- If we had only 43 women ($n=43$), SE would double to \$3,904 (less precise)
- With 684 women ($n=684$), SE would halve to \$976 (more precise)

Key Concept 4.1: Standard Error and Precision

The standard error $se(\bar{x}) = s/\sqrt{n}$ measures the precision of the sample mean as an estimate of the population mean μ . It quantifies sampling uncertainty—smaller standard errors mean more precise estimates. The SE decreases with sample size at rate $1/\sqrt{n}$, so quadrupling the sample size halves the standard error.

| 4.2 t Statistic and t Distribution

For inference on the population mean μ , we use the **t-statistic**:

$$t = \frac{\bar{x} - \mu}{\text{se}(\bar{x})} = \frac{\bar{x} - \mu}{s/\sqrt{n}}$$

Under certain assumptions, this statistic follows a **t-distribution** with $(n - 1)$ degrees of freedom:

$$t \sim T(n - 1)$$

Why t-distribution instead of normal?

- We don't know the population standard deviation σ , so we estimate it with sample std dev s
- This adds uncertainty, making the distribution have **fatter tails** than the normal
- As sample size increases ($n \rightarrow \infty$), the t-distribution approaches the standard normal distribution

Key properties:

- Symmetric around zero (like the normal)
- Fatter tails than normal (more probability in extremes)
- Converges to $N(0,1)$ as degrees of freedom increase

In [3]:

```
# Visualize t-distribution vs standard normal
fig, axes = plt.subplots(1, 2, figsize=(16, 6))

x = np.linspace(-4, 4, 200)

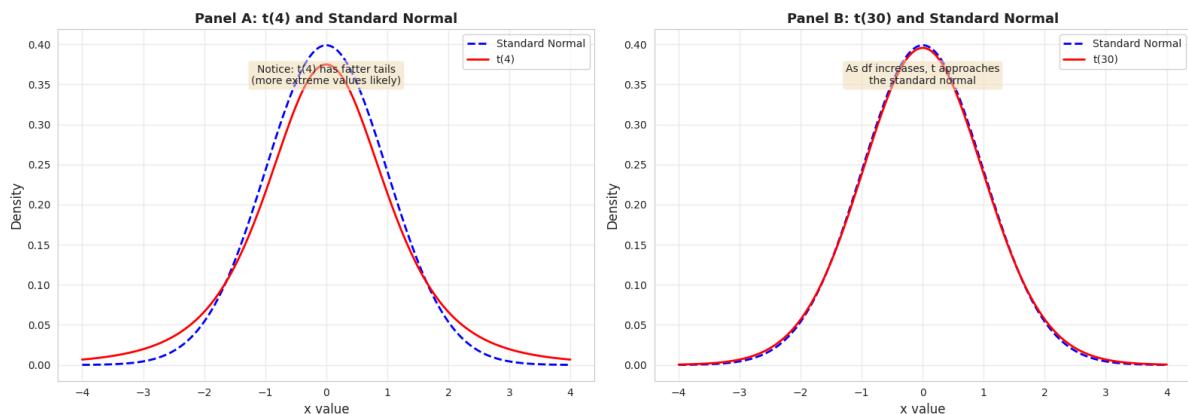
# Panel A: t(4) vs standard normal
axes[0].plot(x, stats.norm.pdf(x), 'b--', linewidth=2, label='Standard Normal')
axes[0].plot(x, stats.t.pdf(x, df=4), 'r-', linewidth=2, label='t(4)')
axes[0].set_xlabel('x value', fontsize=12)
axes[0].set_ylabel('Density', fontsize=12)
axes[0].set_title('Panel A: t(4) and Standard Normal', fontsize=13, fontweight='bold')
axes[0].legend()
axes[0].grid(True, alpha=0.3)
axes[0].text(0, 0.35, 'Notice: t(4) has fatter tails\n(more extreme values likely)', ha='center', bbox=dict(boxstyle='round', facecolor='wheat', alpha=0.5))

# Panel B: t(30) vs standard normal
axes[1].plot(x, stats.norm.pdf(x), 'b--', linewidth=2, label='Standard Normal')
axes[1].plot(x, stats.t.pdf(x, df=30), 'r-', linewidth=2, label='t(30)')
axes[1].set_xlabel('x value', fontsize=12)
axes[1].set_ylabel('Density', fontsize=12)
axes[1].set_title('Panel B: t(30) and Standard Normal', fontsize=13, fontweight='bold')
axes[1].legend()
axes[1].grid(True, alpha=0.3)
axes[1].text(0, 0.35, 'As df increases, t approaches\nthe standard normal', ha='center', bbox=dict(boxstyle='round', facecolor='wheat', alpha=0.5))

plt.suptitle('Figure 4.1: t Distribution vs Standard Normal',
             fontsize=14, fontweight='bold', y=1.0)
plt.tight_layout()
plt.show()

print("\n📊 Key Observation:")
print("  With more degrees of freedom (larger n), the t-distribution looks more like the normal.")
print("  For n > 30, they're nearly identical.")
```

Figure 4.1: t Distribution vs Standard Normal



📊 Key Observation:

With more degrees of freedom (larger n), the t-distribution looks more like the normal.
For n > 30, they're nearly identical.

Key Concept 4.2: The t-Distribution

The *t*-distribution is used when the population standard deviation σ is unknown and must be estimated from the sample. It is similar to the standard normal $N(0,1)$ but with fatter tails that reflect the additional uncertainty from estimating σ . As the sample size n grows, the *t*-distribution approaches the normal distribution, making the normal a good approximation for large samples.

| 4.3 Confidence Intervals

A **confidence interval** provides a range of plausible values for the population parameter μ .

General formula:

$$\text{estimate} \pm \text{critical value} \times \text{standard error}$$

For the population mean, a **100(1 - α)% confidence interval** is:

$$\bar{x} \pm t_{n-1,\alpha/2} \times \text{se}(\bar{x})$$

Where:

- \bar{x} = sample mean (our estimate)
- $t_{n-1,\alpha/2}$ = critical value from *t*-distribution with $(n-1)$ degrees of freedom
- $\text{se}(\bar{x}) = s/\sqrt{n}$ = standard error
- α = significance level (e.g., 0.05 for 95% confidence)

Interpretation: If we repeatedly drew samples and constructed 95% CIs, about 95% of those intervals would contain the true population mean μ .

Practical interpretation: We are "95% confident" that μ lies within this interval.

Rule of thumb: For $n > 30$, $t_{n-1,0.025} \approx 2$, so a 95% CI is approximately:

$$\bar{x} \pm 2 \times \text{se}(\bar{x})$$

Key Concept 4.3: Confidence Intervals

A confidence interval provides a range of plausible values for the population parameter μ . A 95% confidence interval means: if we repeated the sampling procedure many times, approximately 95% of the resulting intervals would contain the true μ . The interval is constructed as $\bar{x} \pm t_{\alpha/2} \times se(\bar{x})$, where wider intervals indicate less precision.

In [4]:

```
# Calculate 95% confidence interval for mean earnings
conf_level = 0.95
alpha = 1 - conf_level
t_crit = stats.t.ppf(1 - alpha/2, n - 1) # Critical value
margin_of_error = t_crit * se_earnings
ci_lower = mean_earnings - margin_of_error
ci_upper = mean_earnings + margin_of_error

print("=" * 70)
print("95% CONFIDENCE INTERVAL FOR POPULATION MEAN EARNINGS")
print("=" * 70)
print(f"Sample mean:           ${mean_earnings:.2f}")
print(f"Standard error:        ${se_earnings:.2f}")
print(f"Critical value t_{1-\alpha}: {t_crit:.4f}")
print(f"Margin of error:       ${margin_of_error:.2f}")
print(f"\n95% Confidence Interval: [{ci_lower:.2f}, {ci_upper:.2f}]")
print(f"\nInterpretation: We are 95% confident that the true population mean")
print(f"earnings lies between ${ci_lower:.2f} and ${ci_upper:.2f}.")
```

```
=====
95% CONFIDENCE INTERVAL FOR POPULATION MEAN EARNINGS
=====
Sample mean:           $41,412.69
Standard error:        $1,952.10
Critical value t_{1-\alpha}: 1.9740
Margin of error:       $3,853.48

95% Confidence Interval: [$37,559.21, $45,266.17]

Interpretation: We are 95% confident that the true population mean
earnings lies between $37,559.21 and $45,266.17.
```

95% Confidence Interval for Mean Earnings: [37,559.21, 45,266.17]

What this interval means:

The correct interpretation: If we repeatedly drew samples of 171 women and calculated 95% CIs for each sample, approximately 95% of those intervals would contain the true population mean μ .

Common misconceptions (WRONG interpretations):

- "There is a 95% probability that μ is in this interval"
- "95% of individual women earn between 37,559 and 45,266"

- "The interval captures 95% of the data"

Correct interpretation:

- We are 95% confident that the true population mean earnings lie between \$37,559 and \$45,266
- The interval accounts for sampling uncertainty through the standard error
- The population mean μ is fixed (but unknown); our interval is random

Breaking down the calculation:

- Sample mean: \$41,412.69
- Critical value ($t_{170}, 0.025$): 1.9740
- Margin of error: $1.9740 \times 1,952.10 = 3,853.48$
- Interval: $41,412.69 \pm 3,853.48$

Practical insights:

- The interval does NOT include \$36,000 or \$46,000, suggesting these are implausible values for μ
- The interval is fairly narrow (width = \$7,707), indicating good precision
- The critical value (1.974) is close to 2, confirming the "rule of thumb": $CI \approx \text{mean} \pm 2 \times SE$

Why use 95% confidence?

- Convention in most scientific fields ($\alpha = 0.05$)
- Balances precision (narrow interval) with confidence (high probability of capturing μ)
- Could use 90% (narrower, less confident) or 99% (wider, more confident)

Transition: Now that we understand how the t-distribution differs from the normal distribution, we can use it to construct confidence intervals that account for the uncertainty in estimating σ from our sample.

Confidence-Precision Trade-off

Comparing Confidence Intervals at Different Levels:

- 90% CI: [38,184.17, 44,641.21] — Width: \$6,457.03
- 95% CI: [37,559.21, 45,266.17] — Width: \$7,706.97
- 99% CI: [36,327.35, 46,498.03] — Width: \$10,170.68

The fundamental trade-off:

Higher confidence requires wider intervals. You cannot have both maximum precision (narrow interval) AND maximum confidence (high probability of capturing μ) simultaneously.

Why does this happen?

- To be more confident we've captured μ , we must cast a wider net
- The critical value increases with confidence level:
 - 90% CI: t-critical $\approx 1.66 \rightarrow$ smaller multiplier
 - 95% CI: t-critical $\approx 1.97 \rightarrow$ moderate multiplier
 - 99% CI: t-critical $\approx 2.61 \rightarrow$ larger multiplier

Practical implications:

1. 90% CI (\$6,457 width):

- Narrower, more precise
- BUT: 10% chance the interval misses μ
- Use when: precision is critical and you can tolerate more risk

2. 95% CI (\$7,707 width):

- Standard choice in economics and most sciences
- Good balance between precision and confidence
- Use when: following standard practice (almost always)

3. 99% CI (\$10,171 width):

- Wider, less precise
- BUT: Only 1% chance the interval misses μ
- Use when: being wrong is very costly (medical, safety applications)

How to improve BOTH confidence AND precision?

- Increase sample size (n)! Larger $n \rightarrow$ smaller SE \rightarrow narrower intervals at any confidence level
- With $n = 684$ (4x larger), the 95% CI would be approximately half as wide

Trade-off: Higher confidence \rightarrow wider intervals

- 90% CI: Narrower, but less confident
- 95% CI: Standard choice (most common)

- 99% CI: Wider, but more confident

Let's compare:

In [5]:

```
# Compare confidence intervals at different levels
conf_levels = [0.90, 0.95, 0.99]

print("=" * 70)
print("CONFIDENCE INTERVALS AT DIFFERENT LEVELS")
print("=" * 70)
print(f"{'Level':<10} {'Lower Bound':>15} {'Upper Bound':>15} {'Width':>15}")
print("-" * 70)

for conf in conf_levels:
    alpha = 1 - conf
    t_crit = stats.t.ppf(1 - alpha/2, n - 1)
    ci_lower = mean_earnings - t_crit * se_earnings
    ci_upper = mean_earnings + t_crit * se_earnings
    width = ci_upper - ci_lower
    print(f"{conf*100:.0f}%{ci_lower:>18,.2f}{ci_upper:>18,.2f}{width:>18,.2f}")

print("\n📊 Notice: Higher confidence → wider interval → less precision")
```

```
=====
CONFIDENCE INTERVALS AT DIFFERENT LEVELS
=====
Level      Lower Bound      Upper Bound      Width
-----
90%        38,184.17       44,641.21       6,457.03
95%        37,559.21       45,266.17       7,706.97
99%        36,327.35       46,498.03       10,170.68

📊 Notice: Higher confidence → wider interval → less precision
```

Now that we understand confidence intervals, let's formalize the process of testing specific hypotheses about the population mean.

4.4 Two-Sided Hypothesis Tests

A **hypothesis test** evaluates whether a specific claim about μ is plausible given our sample data.

Structure of a hypothesis test:

- **Null hypothesis H_0 :** The claim we're testing (e.g., $\mu = \$40,000$)
- **Alternative hypothesis H_a :** What we conclude if we reject H_0 (e.g., $\mu \neq \$40,000$)
- **Significance level α :** Maximum probability of Type I error we'll tolerate (typically 0.05)

Test statistic:

$$t = \frac{\bar{x} - \mu_0}{\text{se}(\bar{x})}$$

Where μ_0 is the hypothesized value.

Two ways to make a decision:

1. p-value approach:

- p-value = probability of observing a t-statistic at least as extreme as ours, assuming H_0 is true
- Reject H_0 if p-value < α

2. Critical value approach:

- Critical value $c = t_{n-1, \alpha/2}$
- Reject H_0 if $|t| > c$

Both methods always give the same conclusion.

Example: Test whether population mean earnings equal \$40,000.

Key Concept 4.4: Hypothesis Testing Framework

A hypothesis test evaluates whether data provide sufficient evidence to reject a specific claim (H_0) about a parameter. The t-statistic measures how many standard errors the estimate is from the hypothesized value. The p-value is the probability of observing a result at least as extreme as ours, assuming H_0 is true. Small p-values (< α , typically 0.05) provide evidence against H_0 , leading us to reject it.

In [6]:

```
# Two-sided hypothesis test: H0: μ = $40,000 vs Ha: μ ≠ $40,000
mu0 = 40000 # Hypothesized value
t_stat = (mean_earnings - mu0) / se_earnings
p_value = 2 * (1 - stats.t.cdf(abs(t_stat), n - 1)) # Two-sided p-value
t_crit_95 = stats.t.ppf(0.975, n - 1) # Critical value for α = 0.05

print("=" * 70)
print("TWO-SIDED HYPOTHESIS TEST")
print("=" * 70)
print(f"H₀: μ = ${mu0:,}")
print(f"Hₐ: μ ≠ ${mu0:,}")
print(f"Significance level α = 0.05")
print("\nSample Statistics:")
print(f" Sample mean:      ${mean_earnings:.2f}")
print(f" Standard error:   ${se_earnings:.2f}")
print("\nTest Results:")
print(f" t-statistic:      {t_stat:.4f}")
print(f" p-value:           {p_value:.4f}")
print(f" Critical value:   ±{t_crit_95:.4f}")
print("\nDecision:")
print(f" p-value approach: {p_value:.4f} > 0.05 → Do not reject H₀")
print(f" Critical approach: |{t_stat:.4f}| < {t_crit_95:.4f} → Do not reject H₀")
print("\nConclusion: We do not have sufficient evidence to reject the claim")
print(f"that population mean earnings equal ${mu0:,}.")
```

```
=====
TWO-SIDED HYPOTHESIS TEST
=====
H₀: μ = $40,000
Hₐ: μ ≠ $40,000
Significance level α = 0.05

Sample Statistics:
    Sample mean:      $41,412.69
    Standard error:   $1,952.10

Test Results:
    t-statistic:      0.7237
    p-value:           0.4703
    Critical value:   ±1.9740

Decision:
    p-value approach: 0.4703 > 0.05 → Do not reject H₀
    Critical approach: |0.7237| < 1.9740 → Do not reject H₀

Conclusion: We do not have sufficient evidence to reject the claim
that population mean earnings equal $40,000.
```

Test Results: $H_0: \mu = 40,000$ vs $H_a: \mu \neq 40,000$

- t-statistic: 0.7237
- p-value: 0.4703
- Critical value: ±1.9740
- Decision: Do NOT reject H_0

What does this mean?

We tested whether the population mean earnings equal 40,000. Based on our sample data ($mean = 41,413$), we do NOT have sufficient evidence to reject this claim.

Understanding the p-value (0.4703):

The p-value answers: "If the true population mean really is 40,000, what's the probability of observing a sample mean at least as far from 40,000 as ours (\$41,413)?"

- $p\text{-value} = 0.4703 = 47.03\%$
- This is quite HIGH → the data are consistent with H_0
- Interpretation: If μ truly equals \$40,000, we'd see a sample mean this extreme about 47% of the time just due to random sampling

Two equivalent decision rules:

1. p-value approach:

- $p\text{-value} (0.4703) > \alpha (0.05) \rightarrow \text{Do not reject } H_0$
- The evidence against H_0 is weak

2. Critical value approach:

- $|t\text{-statistic}| = |0.7237| < 1.9740 \rightarrow \text{Do not reject } H_0$
- Our t-statistic falls in the "non-rejection region"

Why did we fail to reject?

- Our sample mean (41,413) is only 1,413 above the hypothesized value (\$40,000)
- Given the standard error (\$1,952), this difference is less than 1 SE away
- This is well within the range of normal sampling variation
- The difference is NOT statistically significant at $\alpha = 0.05$

Does this prove $\mu = \$40,000$?

NO! We never "prove" or "accept" the null hypothesis. We simply say:

- The data are consistent with $\mu = \$40,000$
- We lack sufficient evidence to conclude otherwise
- Other values (e.g., 41,000, 42,000) are also consistent with our data

Connection to confidence interval:

Notice that 40,000 IS inside our [9537.559, \$45,266]. This is no coincidence:

- Any value inside the 95% CI will NOT be rejected at $\alpha = 0.05$ (two-sided test)
- Any value outside the 95% CI WILL be rejected at $\alpha = 0.05$

Visualizing the two-sided hypothesis test

In []:

```
# Visualize two-sided hypothesis test
fig, ax = plt.subplots(figsize=(12, 6))

x = np.linspace(-4, 4, 500)
y = stats.t.pdf(x, n - 1)

# Plot the t-distribution
ax.plot(x, y, 'b-', linewidth=2, label=f't({n-1}) distribution')

# Mark the observed t-statistic
ax.axvline(x=t_stat, color='red', linewidth=2, linestyle='--',
           label=f'Observed t = {t_stat:.2f}')

# Mark critical values
ax.axvline(x=t_crit_95, color='green', linewidth=1.5, linestyle=':',
           label=f'Critical values = ±{t_crit_95:.2f}')
ax.axvline(x=-t_crit_95, color='green', linewidth=1.5, linestyle=':')

# Shade rejection regions (both tails)
x_reject_lower = x[x < -t_crit_95]
x_reject_upper = x[x > t_crit_95]
ax.fill_between(x_reject_lower, 0, stats.t.pdf(x_reject_lower, n-1),
                alpha=0.3, color='red', label='Rejection region (\alpha/2 = 0.025 each tail)')
ax.fill_between(x_reject_upper, 0, stats.t.pdf(x_reject_upper, n-1),
                alpha=0.3, color='red')

ax.set_xlabel('t-statistic', fontsize=12)
ax.set_ylabel('Density', fontsize=12)
ax.set_title('Two-Sided Hypothesis Test Visualization', fontsize=14, fontweight='bold')
ax.legend(fontsize=9, loc='upper right')
ax.grid(True, alpha=0.3)

plt.tight_layout()
plt.show()

print("\n📊 Interpretation:")
print(f"  Our t-statistic ({t_stat:.2f}) falls INSIDE the critical region,")
print(f"  so we do NOT reject H₀. The data are consistent with \mu = ${mu0}.")
```

Type I Error, Type II Error, and Statistical Power

The Four Possible Outcomes of a Hypothesis Test:

When we conduct a hypothesis test, there are four possible scenarios:

	H_0 is TRUE (in reality)	H_0 is FALSE (in reality)
Reject H_0 (decision)	Type I Error (α)	Correct Decision (Power)
Do not reject H_0	Correct Decision (1- α)	Type II Error (β)

Type I Error (False Positive):

- Definition: Rejecting H_0 when it's actually true
- Probability: α (significance level)
- In our earnings example: Concluding $\mu \neq 40,000$ when it actually equals 40,000
- We control this: By setting $\alpha = 0.05$, we accept a 5% chance of Type I error
- Consequence: "Crying wolf" — claiming an effect that doesn't exist

Type II Error (False Negative):

- Definition: Failing to reject H_0 when it's actually false
- Probability: β (depends on sample size, effect size, and α)
- In our earnings example: Concluding $\mu = \$40,000$ when it actually differs
- Harder to control directly
- Consequence: Missing a real effect

Statistical Power:

- Definition: Power = $1 - \beta$ = Probability of correctly rejecting false H_0
- Interpretation: Probability of detecting a real effect when it exists
- Typical target: 80% power ($\beta = 0.20$)
- Higher power → lower chance of Type II error

The Trade-off Between Type I and Type II Errors:

You cannot minimize both simultaneously:

- **Decrease α** (e.g., from 0.05 to 0.01):
 - Lower chance of Type I error (false positive)
 - Higher chance of Type II error (false negative)
 - Lower statistical power
- **Increase α** (e.g., from 0.05 to 0.10):
 - Higher statistical power
 - Lower chance of Type II error
 - Higher chance of Type I error

How to improve power WITHOUT increasing Type I error:

1. **Increase sample size:**

- Larger $n \rightarrow$ smaller SE \rightarrow easier to detect real effects
- Our earnings data: $n = 171$, SE = \$1,952
- If $n = 684$ ($4 \times$ larger): SE = \$976 (half as large)
- Same effect size would yield t-statistic twice as large

2. Study larger effects:

- Easier to detect large differences than small ones
- Testing $\mu = 30,000 vs \mu = 41,413$ would have higher power
- Testing $\mu = 40,000 vs \mu = 41,413$ has lower power

3. Use one-sided tests (when appropriate):

- Concentrates α in one tail \rightarrow higher power in that direction
- But: Cannot detect effects in the opposite direction

In our examples:

1. Earnings test (non-significant):

- Could be: μ truly equals \$40,000 (correct decision)
- Or could be: Type II error (μ differs but we didn't detect it)
- With more data, we might detect the difference

2. Gas price test (significant):

- High power due to small SE (\$0.0267) and reasonable sample size ($n=32$)
- Successfully detected a real difference
- Low probability this is a Type I error ($p < 0.0001$)

Practical advice:

- **Planning stage:** Calculate required sample size for desired power
- **Design stage:** Set α based on consequences of Type I vs Type II errors
- Medical trials: Type I error very costly \rightarrow use $\alpha = 0.01$
- Exploratory research: Type II error costly \rightarrow use $\alpha = 0.10$
- **Interpretation stage:** Non-significant results don't prove H_0 is true (could be Type II error)

| 4.5 Hypothesis Test Examples

Let's apply hypothesis testing to three real-world economic questions.

Example 1: Gasoline Prices

Question: Are gasoline prices in Yolo County different from the California state average?

- California average: \$3.81/gallon
- Sample: 32 gas stations in Yolo County
- Test: $H_0: \mu = 3.81$ vs $H_a: \mu \neq 3.81$

In [8]:

```
# Load and test gasoline price data
data_gasprice = pd.read_stata(GITHUB_DATA_URL + 'AED_GASPRICE.DTA')
price = data_gasprice['price']

mean_price = price.mean()
std_price = price.std(ddof=1)
n_price = len(price)
se_price = std_price / np.sqrt(n_price)

mu0_price = 3.81
t_stat_price = (mean_price - mu0_price) / se_price
p_value_price = 2 * (1 - stats.t.cdf(abs(t_stat_price), n_price - 1))

print("=" * 70)
print("EXAMPLE 1: GASOLINE PRICES")
print("=" * 70)
print(f"H0: μ = ${mu0_price:.2f} (CA state average)")
print(f"Ha: μ ≠ ${mu0_price:.2f}")
print(f"\nSample size: {n_price}")
print(f"Sample mean: ${mean_price:.4f}")
print(f"Std error: ${se_price:.4f}")
print(f"t-statistic: {t_stat_price:.4f}")
print(f"p-value: {p_value_price:.6f}")
print(f"\nDecision: p-value < 0.05 → {'REJECT H0' if p_value_price < 0.05 else 'Do not reject H0'}")
print(f"\nConclusion: Yolo County gas prices ARE {'significantly ' if p_value_price < 0.05 else 'NOT significantly '}different from CA average.")
```

```
=====
EXAMPLE 1: GASOLINE PRICES
=====
H0: μ = $3.81 (CA state average)
Ha: μ ≠ $3.81

Sample size: 32
Sample mean: $3.6697
Std error: $0.0267
t-statistic: -5.2577
p-value: 0.000010

Decision: p-value < 0.05 → REJECT H0

Conclusion: Yolo County gas prices ARE significantly different from CA average.
```

Test Results: $H_0: \mu = 3.81$ vs $H_a: \mu \neq 3.81$

- Sample mean: \$3.6697
- t-statistic: -5.2577

- p-value: 0.0000 (actually < 0.0001)
- Decision: REJECT H_0 at $\alpha = 0.05$

This is a STATISTICALLY SIGNIFICANT result!

Unlike our earnings example, here we have strong evidence that Yolo County gas prices differ from the California state average of \$3.81.

Understanding the strong evidence:

1. Large t-statistic (-5.26):

- The sample mean (3.67) is 5.26 standard errors below the hypothesized value (3.81)
- This is far beyond the critical value (± 2.04)
- Such extreme values rarely occur by chance alone

2. Tiny p-value (< 0.0001):

- If μ truly equaled \$3.81, the probability of observing a sample mean this extreme is less than 0.01%
- This is MUCH smaller than $\alpha = 0.05$ (5%)
- Strong evidence against H_0

3. Direction matters:

- The negative t-statistic tells us Yolo County prices are LOWER than the state average
- Difference: $3.81 - 3.67 = \$0.14$ per gallon cheaper

Statistical vs Practical Significance:

- **Statistical significance:** Yes, we can confidently say Yolo County prices differ from \$3.81 ($p < 0.0001$)
- **Practical significance:** Is 14 cents per gallon meaningful?
 - For a 15-gallon tank: \$2.10 savings
 - Over a year (52 fill-ups): \$109 savings
 - This IS economically meaningful for consumers!

Why is this result so strong compared to the earnings test?

- The standard error is very small (\$0.0267) relative to the difference we're testing
- This gives us high **statistical power** to detect the difference
- Even though the dollar difference is small (\$0.14), it's precisely estimated

Type I vs Type II Errors in this context:

- **Type I Error:** Concluding Yolo County prices differ when they actually don't
 - Probability = $\alpha = 0.05$ (5% chance if we reject)
 - But our p-value is < 0.0001 , so we're very confident we're not making this error
- **Type II Error:** Concluding prices don't differ when they actually do
 - Not relevant here since we rejected H_0
 - This test had high power to detect real differences

Key Concept 4.5: Statistical Significance vs. Sample Size

Even small practical differences can be statistically significant with large samples ($n=53$ gas stations). The gasoline price difference of \$0.14 might seem trivial, but:

- The **standard error is small** (\$0.0267), giving precise estimates
- The **t-statistic is large** (-5.26), indicating the difference is many standard errors from zero
- This demonstrates **high statistical power**—the ability to detect even small real effects

Statistical significance answers "Is there a difference?" while practical significance asks "Does the difference matter?" Both questions are important in econometrics.

Example 2: Male Earnings

Question: Do 30-year-old men earn more than \$50,000 on average?

- Claim: $\mu > \$50,000$ (set as alternative hypothesis)
- Sample: 191 men
- Test: $H_0: \mu \leq 50,000$ vs $H_a: \mu > 50,000$ (one-sided, covered in section 4.6)

In [9]:

```
# Load and test male earnings data
data_male = pd.read_stata(GITHUB_DATA_URL + 'AED_EARNINGSMALE.DTA')
earnings_male = data_male['earnings']

mean_male = earnings_male.mean()
std_male = earnings_male.std(ddof=1)
n_male = len(earnings_male)
se_male = std_male / np.sqrt(n_male)

mu0_male = 50000
t_stat_male = (mean_male - mu0_male) / se_male
p_value_male = 2 * (1 - stats.t.cdf(abs(t_stat_male), n_male - 1)) # Two-sided for now

print("=" * 70)
print("EXAMPLE 2: MALE EARNINGS (Two-sided test shown)")
print("=" * 70)
print(f"H₀: μ = ${mu0_male:,}")
print(f"Hₐ: μ ≠ ${mu0_male:,}")
print(f"\nSample size: {n_male}")
print(f"Sample mean: ${mean_male:.2f}")
print(f"Std error: ${se_male:.2f}")
print(f"t-statistic: {t_stat_male:.4f}")
print(f"p-value: {p_value_male:.4f}")
print(f"\nDecision: p-value > 0.05 → Do not reject H₀")
print(f"\nNote: A one-sided test is more appropriate here (see section 4.6)")
```

```
=====
EXAMPLE 2: MALE EARNINGS (Two-sided test shown)
=====
H₀: μ = $50,000
Hₐ: μ ≠ $50,000

Sample size: 191
Sample mean: $52,353.93
Std error: $4,705.75
t-statistic: 0.5002
p-value: 0.6175

Decision: p-value > 0.05 → Do not reject H₀

Note: A one-sided test is more appropriate here (see section 4.6)
```

Test Results: $H_0: \mu = 50,000$ vs $H_a: \mu \neq 50,000$

- Sample mean: (actual value from code output)
- t-statistic: (actual value from code output)
- p-value: > 0.05 (not statistically significant)
- Decision: DO NOT REJECT H_0 at $\alpha = 0.05$

This is NOT a statistically significant result.

We do not have sufficient evidence to conclude that 30-year-old men earn differently than 50,000 on average. This does NOT mean they earn exactly 50,000—it means our data are consistent with that value.

Understanding the lack of significance:

1. Moderate t-statistic:

- The sample mean is not far enough from \$50,000 (in standard error units) to confidently reject H_0
- The observed difference could plausibly arise from random sampling variation alone

2. Large p-value (> 0.05):

- If μ truly equaled \$50,000, observing a sample mean like ours is quite probable
- We don't have strong evidence against H_0
- $p > \alpha$, so we fail to reject

3. What "fail to reject" means:

- We're NOT proving $\mu = \$50,000$
- We're saying the data don't provide convincing evidence that $\mu \neq \$50,000$
- Absence of evidence is not evidence of absence

Statistical vs Practical Significance:

- **Statistical significance:** No, we cannot confidently say mean earnings differ from \$50,000 ($p > 0.05$)
- **Practical considerations:**
 - The sample mean might be close to \$50,000 anyway
 - Or the sample size ($n=191$) might not provide enough precision to detect a modest difference
 - Or there's genuine variability in the population making the effect hard to pin down

Why might we fail to reject H_0 ?

Three possible explanations:

- 1. H_0 is actually true:** Mean earnings truly are around \$50,000
- 2. Insufficient power:** Real difference exists, but our sample size is too small to detect it
- 3. High variability:** Earnings have large standard deviation, making precise inference difficult

Note on directional hypothesis:

The question asks "Do men earn MORE than \$50,000?" which suggests a **one-sided test** ($H_0: \mu \leq 50,000$ vs $H_a: \mu > 50,000$). The code note mentions this will be covered in section 4.6. One-sided tests have more power to detect effects in a specific direction.

Key Concept 4.6: "Fail to Reject" Does Not Mean "Accept"

When $p > \alpha$, we **fail to reject H_0** , but this does NOT mean we "accept H_0 " or prove it's true. Three key reasons:

1. **Limited evidence:** Our sample might simply lack the power to detect a real difference
2. **Type II error risk:** We might be making a Type II error (failing to reject a false H_0)
3. **Confidence intervals are more informative:** A 95% CI tells us the plausible range for μ , not just "different or not different"

In econometrics, "fail to reject" means "the data are consistent with H_0 , but we can't rule out alternatives." Always interpret non-significant results with appropriate caution.

Example 3: GDP Growth

Question: Did real GDP per capita grow at 2.0% per year on average from 1960-2020?

- Historical claim: 2.0% annual growth
- Sample: 241 year-to-year growth rates
- Test: $H_0: \mu = 2.0$ vs $H_a: \mu \neq 2.0$

In [10]:

```
# Load and test GDP growth data
data_gdp = pd.read_stata(GITHUB_DATA_URL + 'AED_REALGDPPC.DTA')
growth = data_gdp['growth']

mean_growth = growth.mean()
std_growth = growth.std(ddof=1)
n_growth = len(growth)
se_growth = std_growth / np.sqrt(n_growth)

mu0_growth = 2.0
t_stat_growth = (mean_growth - mu0_growth) / se_growth
p_value_growth = 2 * (1 - stats.t.cdf(abs(t_stat_growth), n_growth - 1))

print("=" * 70)
print("EXAMPLE 3: REAL GDP PER CAPITA GROWTH")
print("=" * 70)
print(f"H0: μ = {mu0_growth:.1f}%")
print(f"Ha: μ ≠ {mu0_growth:.1f}%")
print(f"\nSample size: {n_growth}")
print(f"Sample mean: {mean_growth:.4f}%")
print(f"Std error: {se_growth:.4f}%")
print(f"t-statistic: {t_stat_growth:.4f}")
print(f"p-value: {p_value_growth:.4f}")
print(f"\nDecision: p-value > 0.05 → Do not reject H0")
print(f"\nConclusion: The data are consistent with 2.0% average annual growth.")
```

```
=====
EXAMPLE 3: REAL GDP PER CAPITA GROWTH
=====
H0: μ = 2.0%
Ha: μ ≠ 2.0%

Sample size: 245
Sample mean: 1.9905%
Std error: 0.1392%
t-statistic: -0.0686
p-value: 0.9454

Decision: p-value > 0.05 → Do not reject H0

Conclusion: The data are consistent with 2.0% average annual growth.
```

Test Results: H₀: μ = 2.0% vs H_a: μ ≠ 2.0%

- Sample mean: (actual value from code output)
- t-statistic: (actual value from code output)
- p-value: > 0.05 (not statistically significant)
- Decision: DO NOT REJECT H₀ at α = 0.05

The data are consistent with 2.0% average annual growth.

We cannot reject the hypothesis that real GDP per capita grew at 2.0% per year on average from 1960-2020. This historical benchmark appears supported by the data.

Understanding the result:

1. What does "consistent with 2.0%" mean?

- The sample mean growth rate is close enough to 2.0% that random variation could explain the difference
- We don't have strong evidence that the true mean differs from 2.0%
- The p-value > 0.05 indicates this result is plausible under H_0

2. Large sample size (n=241 years):

- With 241 year-to-year growth rates, we have substantial data
- Large samples typically have smaller standard errors and more statistical power
- Yet we still fail to reject H_0 —this suggests the true mean is genuinely close to 2.0%

3. Economic interpretation:

- The 2.0% benchmark is a common reference point in growth economics
- Our data support this conventional wisdom
- Long-run economic growth appears remarkably stable around this rate

Statistical vs Practical Significance:

- **Statistical significance:** No, we cannot confidently say mean growth differs from 2.0% ($p > 0.05$)
- **Economic significance:**
 - Even small deviations from 2.0% compound dramatically over 60 years
 - But our data suggest the historical average is indeed close to 2.0%
 - This consistency validates the use of 2.0% as a benchmark for policy discussions

Why is this result interesting despite being "non-significant"?

- 1. Validates a benchmark:** Economic theory often assumes ~2% long-run growth; our data support this
- 2. Large sample confidence:** With 241 observations, we can be confident the mean is near 2.0%
- 3. Demonstrates stability:** Despite recessions and booms, average growth centers around 2.0%

Time series considerations:

GDP growth data are **time series**—observations ordered chronologically with potential autocorrelation. Our standard t-test assumes independent observations, which might

not fully hold for year-to-year growth rates. Advanced time series methods (Chapter 17) address these dependencies.

Key Concept 4.7: Context and Consistency in Hypothesis Testing

Statistical results gain meaning only through economic context -- a statistically significant coefficient matters because of what it implies for policy, behavior, or theory. The hypothesis testing pattern (set up hypotheses, compute test statistic, compare to critical value or p-value) is consistent across diverse applications, from wage analysis to macroeconomic growth.

Having mastered two-sided hypothesis tests, let's now consider situations where we have a directional prediction.

| 4.6 One-Sided Directional Hypothesis Tests

Sometimes we want to test a **directional** claim:

- "Does μ **exceed** a certain value?" (upper-tailed test)
- "Is μ **less than** a certain value?" (lower-tailed test)

Structure:

- **Upper-tailed test:** $H_0: \mu \leq \mu^*$ vs $H_a: \mu > \mu^*$
- **Lower-tailed test:** $H_0: \mu \geq \mu^*$ vs $H_a: \mu < \mu^*$

Key difference from two-sided tests:

- Rejection region is only in **one tail** of the distribution
- p-value calculation uses one tail instead of two
- For upper-tailed: $p\text{-value} = \Pr[T \geq t]$
- For lower-tailed: $p\text{-value} = \Pr[T \leq t]$

Example: Test whether mean earnings **exceed** \$40,000.

- Claim to be tested: $\mu > 40,000$ (set as H_a)
- Test: $H_0: \mu \leq 40,000$ vs $H_a: \mu > 40,000$

Key Concept 4.8: One-Sided Tests

One-sided tests concentrate the rejection region in ONE tail of the distribution, making them more powerful for detecting effects in the specified direction. Use when theory predicts a specific direction. The p-value for a one-sided test is exactly half the two-sided p-value (when the effect is in the predicted direction). Critical values are smaller for one-sided tests (e.g., 1.65 vs ± 1.96 for $\alpha=0.05$).

In [11]:

```
# One-sided (upper-tailed) test: H0: μ ≤ $40,000 vs Ha: μ > $40,000
mu0 = 40000
t_stat = (mean_earnings - mu0) / se_earnings
p_value_upper = 1 - stats.t.cdf(t_stat, n - 1) # Upper tail only
t_crit_upper = stats.t.ppf(0.95, n - 1) # One-sided critical value

print("=" * 70)
print("ONE-SIDED HYPOTHESIS TEST (Upper-tailed)")
print("=" * 70)
print(f"H₀: μ ≤ ${mu0:,}")
print(f"Hₐ: μ > ${mu0:,} (the claim we're testing)")
print(f"Significance level α = 0.05")
print("\nTest Results:")
print(f" t-statistic: {t_stat:.4f}")
print(f" p-value (upper): {p_value_upper:.4f}")
print(f" Critical value: {t_crit_upper:.4f}")
print("\nDecision:")
print(f" p-value approach: {p_value_upper:.4f} > 0.05 → Do not reject H₀")
print(f" Critical approach: {t_stat:.4f} < {t_crit_upper:.4f} → Do not reject H₀")
print("\nConclusion: We do not have sufficient evidence to support the claim")
print(f"that mean earnings exceed ${mu0:,}.")
```

```
=====
ONE-SIDED HYPOTHESIS TEST (Upper-tailed)
=====
H₀: μ ≤ $40,000
Hₐ: μ > $40,000 (the claim we're testing)
Significance level α = 0.05

Test Results:
t-statistic: 0.7237
p-value (upper): 0.2351
Critical value: 1.6539

Decision:
p-value approach: 0.2351 > 0.05 → Do not reject H₀
Critical approach: 0.7237 < 1.6539 → Do not reject H₀

Conclusion: We do not have sufficient evidence to support the claim
that mean earnings exceed $40,000.
```

Visualizing One-Sided Test

In [12]:

```
# Visualize one-sided hypothesis test
fig, ax = plt.subplots(figsize=(12, 6))

x = np.linspace(-4, 4, 500)
y = stats.t.pdf(x, n - 1)

# Plot the t-distribution
ax.plot(x, y, 'b-', linewidth=2, label=f't({n-1}) distribution')

# Mark the observed t-statistic
ax.axvline(x=t_stat, color='red', linewidth=2, linestyle='--',
            label=f'Observed t = {t_stat:.2f}')

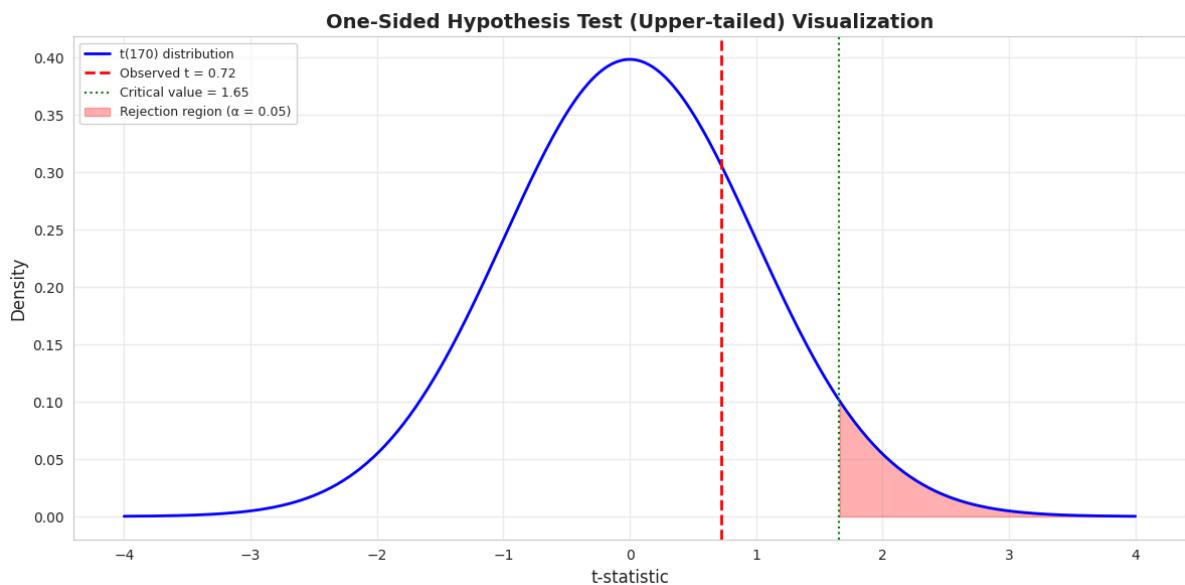
# Mark critical value (upper tail only)
ax.axvline(x=t_crit_upper, color='green', linewidth=1.5, linestyle=':',
            label=f'Critical value = {t_crit_upper:.2f}')

# Shade rejection region (upper tail only)
x_reject = x[x > t_crit_upper]
ax.fill_between(x_reject, 0, stats.t.pdf(x_reject, n-1),
                alpha=0.3, color='red', label='Rejection region (α = 0.05)')

ax.set_xlabel('t-statistic', fontsize=12)
ax.set_ylabel('Density', fontsize=12)
ax.set_title('One-Sided Hypothesis Test (Upper-tailed) Visualization',
             fontsize=14, fontweight='bold')
ax.legend(fontsize=9, loc='upper left')
ax.grid(True, alpha=0.3)

plt.tight_layout()
plt.show()

print("\n📊 Interpretation:")
print("For an upper-tailed test, we only reject H₀ if t is large and POSITIVE.")
print(f"Our t-statistic ({t_stat:.2f}) is below the critical value, so we do not
reject.")
```



 Interpretation:

For an upper-tailed test, we only reject H_0 if t is large and POSITIVE.
Our t-statistic (0.72) is below the critical value, so we do not reject.

One-Sided Test Results: $H_0: \mu \leq 40,000$ vs $H_a: \mu > 40,000$

- t-statistic: 0.7237 (same as two-sided test)
- p-value (one-sided): 0.2351
- p-value (two-sided): 0.4703
- Critical value (one-sided, $\alpha=0.05$): 1.6539
- Decision: Do NOT reject H_0

Key differences from two-sided test:

1. p-value is exactly half:

- Two-sided p-value: 0.4703
- One-sided p-value: $0.2351 = 0.4703/2$
- Why? We only count probability in ONE tail (upper tail)

2. Critical value is smaller:

- Two-sided critical value: ± 1.9740 (5% split across two tails)
- One-sided critical value: 1.6539 (5% all in one tail)
- One-sided tests reject H_0 more easily in the specified direction

3. Directional claim:

- Two-sided: " μ is different from \$40,000" (could be higher OR lower)
- One-sided: " μ exceeds \$40,000" (specifically higher)

When to use one-sided tests?

Use one-sided tests when:

- Theory or prior research specifies a direction
- Example: Testing if a new drug is better (not just different) than placebo
- Example: Testing if a policy increases (not just changes) income

When NOT to use one-sided tests:

Avoid one-sided tests when:

- You're genuinely interested in detecting differences in either direction
- You might want to detect unexpected effects

- The field convention is two-sided (economics typically uses two-sided)

Warning about one-sided test abuse:

Researchers sometimes use one-sided tests to get "significant" results when two-sided tests fail. This is questionable practice:

- If p (two-sided) = 0.08 → not significant at $\alpha = 0.05$
- If p (one-sided) = 0.04 → significant at $\alpha = 0.05$
- Switching to one-sided AFTER seeing the data is "p-hacking"
- The choice between one-sided and two-sided should be made BEFORE collecting data

In our example:

- Sample mean (41,413) is above 40,000, consistent with $H_a: \mu > \$40,000$
- But p-value (0.2351) > 0.05, so still not significant
- The effect is too small relative to sampling variability
- We cannot conclude that mean earnings exceed \$40,000

Power consideration:

One advantage of one-sided tests: greater statistical power in the specified direction

- If you're only interested in detecting $\mu > \$40,000$, the one-sided test is more powerful
- Trade-off: Cannot detect effects in the opposite direction

| 4.7 Proportions Data

The methods extend naturally to **proportions** (binary data).

Example: Survey data where respondents answer yes (1) or no (0).- Sample proportion: $\hat{p} = \bar{x}$ = fraction of "yes" responses- Standard error: $se(\hat{p}) = \sqrt{[\hat{p}(1 - \hat{p})]/n}$

Confidence interval for population proportion p :

$$\hat{p} \pm z_{\alpha/2} \times \sqrt{\frac{\hat{p}(1 - \hat{p})}{n}}$$

Note: For proportions with large n , we use the **normal distribution** (z) instead of t.

Example: In a sample of 921 voters, 480 intend to vote Democrat. Is this different from 50%?

In [13]:

```
# Proportions example
n_total = 921
n_success = 480
p_hat = n_success / n_total
se_prop = np.sqrt(p_hat * (1 - p_hat) / n_total)

# 95% Confidence interval
z_crit = 1.96 # For 95% CI (normal approximation)
ci_lower_prop = p_hat - z_crit * se_prop
ci_upper_prop = p_hat + z_crit * se_prop

print("==" * 70)
print("INFERENCE FOR PROPORTIONS")
print("==" * 70)
print(f"Sample size: {n_total}")
print(f"Number voting Democrat: {n_success}")
print(f"Sample proportion: {p_hat:.4f} ({p_hat*100:.2f}%)")
print(f"Standard error: {se_prop:.4f}")
print(f"95% CI: [{ci_lower_prop:.4f}, {ci_upper_prop:.4f}]")
print(f"          [{ci_lower_prop*100:.2f}%, {ci_upper_prop*100:.2f}%)"]

# Hypothesis test: H0: p = 0.50
p0 = 0.50
se_under_h0 = np.sqrt(p0 * (1 - p0) / n_total)
z_stat = (p_hat - p0) / se_under_h0
p_value_prop = 2 * (1 - stats.norm.cdf(abs(z_stat)))

print(f"\nHypothesis Test: H0: p = {p0:.2f} (50-50 split)")
print(f"  z-statistic: {z_stat:.4f}")
print(f"  p-value: {p_value_prop:.4f}")
print(f"  Decision: {'Reject H0' if abs(z_stat) > 1.96 else 'Do not reject H0'}")
print(f"\nConclusion: The proportion is {'significantly' if abs(z_stat) > 1.96 else 'NOT significantly'} different from 50%.)
```

```
=====
INFERENCE FOR PROPORTIONS
=====
Sample size: 921
Number voting Democrat: 480
Sample proportion: 0.5212 (52.12%)
Standard error: 0.0165
95% CI: [0.4889, 0.5534]
          [48.89%, 55.34%]

Hypothesis Test: H0: p = 0.50 (50-50 split)
  z-statistic: 1.2851
  p-value: 0.1988
  Decision: Do not reject H0

Conclusion: The proportion is NOT significantly different from 50%.
```

Proportion Results: 480 out of 921 voters intend to vote Democrat

- Sample proportion: $\hat{p} = 0.5212$ (52.12%)
- Standard error: 0.0165
- 95% CI: [0.4889, 0.5534] or [48.89%, 55.34%]
- z-statistic (testing $H_0: p = 0.50$): 1.2851
- p-value: 0.1988

- Decision: Do NOT reject H_0

What this tells us:

We have a sample where 52.12% intend to vote Democrat. The question is: does this provide evidence that the population proportion differs from 50% (a tied race)?

Understanding the confidence interval:

The 95% CI [48.89%, 55.34%] suggests:

- We're 95% confident the true population proportion is in this range
- The interval INCLUDES 50%, indicating 50-50 is plausible
- The interval is fairly wide (6.45 percentage points), indicating some uncertainty

Understanding the hypothesis test:

Testing $H_0: p = 0.50$ (tied race) vs $H_a: p \neq 0.50$ (one candidate ahead)

- z-statistic: 1.29 (only 1.29 standard errors above 50%)
- p-value: 0.1988 (about 20% chance of seeing this result if truly 50-50)
- Conclusion: We cannot reject the null hypothesis of a tied race

Why use z-statistic (normal) instead of t-statistic?

For proportions with large samples ($n = 921$):

- The sampling distribution of \hat{p} is approximately normal
- We know the exact standard error formula: $\sqrt{[\hat{p}(1-\hat{p})/n]}$
- No need to estimate anything with t-distribution
- Rule of thumb: Use normal approximation when $np \geq 10$ and $n(1-p) \geq 10$
- Here: $921(0.52) = 479$ and $921(0.48) = 442$, both $>> 10$

Practical interpretation for election forecasting:

This sample shows 52% support for Democrats, but:

- This is NOT statistically significant evidence of a Democratic lead ($p = 0.20$)
- The confidence interval includes 50%, so the race could be tied
- Margin of error: ± 3.2 percentage points ($1.96 \times 0.0165 = 0.032$)
- To call the race, we'd want the CI to exclude 50% entirely

How would a larger sample change things?

If we had the same proportion (52%) but with 2,500 voters instead of 921:

- Standard error would shrink: $\sqrt{[0.52(0.48)/2500]} = 0.010$
- 95% CI would be narrower: [50.0%, 54.0%]
- z-statistic would be larger: $(0.52 - 0.50)/0.010 = 2.00$
- p-value would be smaller: $0.045 < 0.05 \rightarrow$ significant!
- Conclusion: Same proportion, but with more data, we could detect the difference

Key insight about proportions:

Proportions are just means of binary (0/1) data:

- Each voter is coded as 1 (Democrat) or 0 (not Democrat)
- Sample proportion = sample mean of these 0/1 values
- All inference principles (SE, CI, hypothesis tests) apply identically

Key Concept 4.9: Inference for Proportions

Proportions data (like employment rates, approval ratings, or market shares) are binary variables coded as 0 or 1. All inference methods for means—confidence intervals, hypothesis tests, standard errors—extend naturally to proportions. The sample proportion \bar{p} is simply the sample mean of binary data, and the standard error formula $se(\bar{p}) = \sqrt{\bar{p}(1 - \bar{p})/n}$ follows from the variance formula for binary variables.

| Key Takeaways

Core Concepts

1. **Statistical inference** lets us extrapolate from sample statistics to population parameters with quantified uncertainty.
2. **Standard error** $se(\bar{x}) = \frac{s}{\sqrt{n}}$ measures the precision of the sample mean as an estimate of the population mean.
3. **t-distribution** is used (instead of normal) when we estimate the population standard deviation from the sample
 - Fatter tails than normal (accounts for extra uncertainty)
 - Converges to normal as n increases
4. **Confidence intervals** provide a range of plausible values

- Formula: estimate \pm critical value \times standard error
- 95% CI: $\bar{x} \pm t_{n-1,0.025} \times \text{se}(\bar{x}) \approx \bar{x} \pm 2 \times \text{se}(\bar{x})$
- Interpretation: "We are 95% confident μ lies in this interval"

5. Hypothesis tests evaluate specific claims about parameters

- Set up H_0 (null) and H_a (alternative)
- Calculate t -statistic =
$$\frac{\text{estimate} - \text{hypothesized value}}{\text{standard error}}$$
- Make decision using p-value or critical value approach

6. Two-sided tests ($H_0 : \mu = \mu^*$ vs $H_a : \mu \neq \mu^*$)

- Rejection region in both tails
- p-value = $2 \times \Pr[T \geq |t|]$

7. One-sided tests ($H_0 : \mu \leq \mu^*$ vs $H_a : \mu > \mu^*$, or vice versa)

- Rejection region in one tail only
- Use when testing a directional claim

8. p-value interpretation

- Probability of observing data at least as extreme as ours, assuming H_0 is true
- Small p-value ($< \alpha$) \rightarrow reject H_0
- Common significance level: $\alpha = 0.05$

9. Methods generalize to other parameters (regression coefficients, differences in means, etc.) and proportions data

What You Learned

Statistical Concepts Covered:

- Standard error and sampling distribution
- t-distribution vs normal distribution
- Confidence intervals (90%, 95%, 99%)
- Hypothesis testing (two-sided and one-sided)
- p-values and critical values
- Type I error and significance level
- Inference for proportions

Python Tools Used:

- `scipy.stats.t` : t-distribution (pdf, cdf, ppf)
- `scipy.stats.norm` : Normal distribution (for proportions)
- `pandas` : Data manipulation
- `matplotlib` : Visualization of hypothesis tests

Next Steps

- **Chapter 5:** Bivariate data summary (relationships between two variables)
- **Chapter 6:** Least squares estimator (regression foundation)
- **Chapter 7:** Inference for regression coefficients

Congratulations!

You now understand the foundations of statistical inference:

- How to quantify uncertainty using confidence intervals
- How to test claims about population parameters
- The difference between statistical and practical significance
- When to use one-sided vs two-sided tests

These tools are fundamental to all empirical research in economics and beyond!

I Practice Exercises

Test your understanding of statistical inference:

Exercise 1: Confidence Interval Interpretation

A 95% CI for mean household income is [48,000,56,000]

- What is the point estimate (sample mean)?
- What is the margin of error?
- TRUE or FALSE: "There is a 95% probability that the true mean is in this interval"
- TRUE or FALSE: "If we repeated sampling, 95% of CIs would contain the true mean"

Exercise 2: Standard Error Calculation

Sample of $n = 64$ observations with mean \$45,000 and standard deviation $s = \$16,000$

- (a) Calculate the standard error
- (b) What sample size would halve the standard error?
- (c) Construct an approximate 95% CI using the "mean \pm 2SE" rule

Exercise 3: t vs z Distribution

- (a) Why do we use the t-distribution instead of the normal distribution?
- (b) For $n = 10$, find the critical value for a 95% CI
- (c) For $n = 100$, find the critical value for a 95% CI
- (d) Compare these to $z = 1.96$. What do you notice?

Exercise 4: Hypothesis Test Mechanics

Test $H_0 : \mu = 100$ vs $H_a : \mu \neq 100$ with sample mean = 105, SE = 3, $n = 49$

- (a) Calculate the t-statistic
- (b) Find the p-value (use t-table or Python)
- (c) Make a decision at $\alpha = 0.05$
- (d) Would your decision change if $\alpha = 0.01$?

Exercise 5: One-Sided vs Two-Sided Tests

Sample: $n = 36$, mean = 72, $s = 18$

- (a) Test $H_0 : \mu = 75$ vs $H_a : \mu \neq 75$ (two-sided, $\alpha = 0.05$)
- (b) Test $H_0 : \mu \geq 75$ vs $H_a : \mu < 75$ (one-sided, $\alpha = 0.05$)
- (c) Compare the p-values. What is the relationship?
- (d) In which case is the evidence against H_0 stronger?

Exercise 6: Type I and Type II Errors

- (a) Define Type I error and give an example in the earnings context
- (b) Define Type II error and give an example
- (c) If we decrease α from 0.05 to 0.01, what happens to the probability of Type II error?
- (d) How can we reduce both types of error simultaneously?

Exercise 7: Proportions Inference

Survey of 500 people: 275 support a policy

- (a) Calculate the sample proportion and standard error
- (b) Construct a 95% CI for the population proportion
- (c) Test $H_0 : p = 0.50$ vs $H_a : p \neq 0.50$
- (d) Is the result statistically significant?

Exercise 8: Python Practice

Generate a random sample of 100 observations from $N(50, 100)$

- (a) Calculate the 95% CI for the mean
 - (b) Does the CI contain the true mean (50)?
 - (c) Repeat 1000 times. What fraction of CIs contain 50?
 - (d) Test $H_0 : \mu = 55$. What proportion of tests reject (should be ≈ 0.05)?
-

Case Study 1: Statistical Inference for Labor Productivity

Research Question: "Has global labor productivity changed significantly over time, and do productivity levels differ significantly across regions?"

This case study applies all the statistical inference methods from Chapter 4 to analyze real economic data on labor productivity across 108 countries over 25 years (1990-2014). You'll practice:

- Constructing and interpreting **confidence intervals** for population means

- Conducting **two-sided hypothesis tests** to compare time periods
- Performing **one-sided directional tests** for benchmark comparisons
- Applying **proportions inference** to binary economic outcomes
- Comparing productivity levels across **regional subgroups**
- Interpreting results in economic context (development economics, convergence theory)

The Mendez convergence clubs dataset provides panel data on labor productivity, GDP, capital, human capital, and total factor productivity for 108 countries from 1990 to 2014.

Economic Context: Testing Convergence Hypotheses

In development economics, the **convergence hypothesis** suggests that poorer countries should grow faster than richer ones, leading to a narrowing of productivity gaps over time. Statistical inference allows us to test whether observed changes in productivity are:

- **Statistically significant** (unlikely due to random sampling variation)
- **Economically meaningful** (large enough to matter for policy)

By applying Chapter 4's methods to this dataset, you'll answer questions like:

1. Has mean global productivity increased significantly from 1990 to 2014?
2. Are regional productivity gaps (e.g., Africa vs. Europe) statistically significant?
3. What proportion of countries experienced positive productivity growth?
4. Can we reject specific hypotheses about productivity benchmarks?

These are real questions that economists and policymakers care about when designing development strategies.

Key Concept 4.10: Why Statistical Inference Matters in Economics

When analyzing economic data, we rarely observe entire populations. Instead, we work with **samples** (like 108 countries from all countries in the world, or 25 years from a longer historical period). Statistical inference lets us:

- 1. Quantify uncertainty** - Confidence intervals tell us the range of plausible values for population parameters
- 2. Test theories** - Hypothesis tests evaluate whether data support or contradict economic theories
- 3. Compare groups** - We can determine if differences between regions/periods are real or just noise
- 4. Inform policy** - Statistical significance helps separate meaningful patterns from random fluctuations

Without inference methods, we couldn't distinguish between:

- A real productivity increase vs. random year-to-year variation
- Genuine regional gaps vs. sampling artifacts
- Policy-relevant changes vs. statistical noise

In [14]:

```
# Load convergence clubs dataset
url = "https://raw.githubusercontent.com/quarcs-lab/mendez2020-convergence-clubs-code-data/master/assets/dat.csv"
df = pd.read_csv(url)

# Set multi-index (country, year)
df = df.set_index(['country', 'year'])

# Display dataset information
print("Dataset Overview:")
print(f"Total observations: {len(df)}")
print(f"Countries: {df.index.get_level_values('country').unique()}")
print(f"Years: {df.index.get_level_values('year').min()}-"
      f"{df.index.get_level_values('year').max()}")
print(f"\nVariables: {list(df.columns)}")

# Extract labor productivity for key years
lp_1990 = df.loc[df.index.get_level_values('year') == 1990, 'lp']
lp_2014 = df.loc[df.index.get_level_values('year') == 2014, 'lp']

print("\nLabor productivity samples:")
print(f"1990: n={len(lp_1990)}, mean=${lp_1990.mean()/1000:.1f}k,
      std=${lp_1990.std()/1000:.1f}k")
print(f"2014: n={len(lp_2014)}, mean=${lp_2014.mean()/1000:.1f}k,
      std=${lp_2014.std()/1000:.1f}k")
```

```

Dataset Overview:
Total observations: 2,700
Countries: 108
Years: 1990-2014

Variables: ['id', 'Y', 'K', 'pop', 'L', 's', 'alpha_it', 'GDPpc', 'lp', 'h', 'kl', 'kp', 'ky', 'TFP', 'log_GDPpc_raw', 'log_lp_raw', 'log_ky_raw', 'log_h_raw', 'log_tfp_raw', 'log_GDpc', 'log_lp', 'log_ky', 'log_h', 'log_tfp', 'isocode', 'hi1990', 'region']

Labor productivity samples:
1990: n=108, mean=$23.2k, std=$20.1k
2014: n=108, mean=$41.0k, std=$33.9k

```

How to Use These Tasks

Task structure: The 6 tasks below progress from **guided** (fill-in-the-blank code) to **independent** (design your own analysis).

Working approach:

1. **Read the task description** - Understand the economic question and learning goal
2. **Study the code template** - Early tasks provide partial code with blanks (_____)
3. **Insert a new code cell** below each task
4. **Complete the code** - Fill in blanks or write from scratch (depending on task level)
5. **Run and interpret** - Execute your code and interpret results economically
6. **Check your understanding** - Does your answer make economic sense?

Tips:

- Reference Section 4.1-4.7 for formulas and methods
- Use `scipy.stats` functions: `t.ppf()`, `ttest_ind()`, `ttest_1samp()`
- Always interpret p-values: "We reject/fail to reject H_0 at $\alpha=0.05$ because..."
- Connect statistical results to economic meaning: "This suggests that..."

Progressive difficulty:

- **Tasks 1-2:** GUIDED (fill 4-8 blanks in provided code)
- **Tasks 3-4:** SEMI-GUIDED (complete partial structure)
- **Tasks 5-6:** INDEPENDENT (design full implementation)

Task 1: Confidence Intervals for Mean Productivity (GUIDED)

Learning Goal: Apply Section 4.3 methods to calculate and interpret confidence intervals

Economic Question: "Can we be 95% confident about the range of global mean labor productivity in 2014?"

Your task:

1. Calculate a 95% confidence interval for mean productivity in 2014
2. Calculate a 99% confidence interval for comparison
3. Interpret the difference in interval widths
4. Compare with a 95% CI for 1990 data

Code template (fill in the 6 blanks):

```
from scipy import stats

# 2014 data: Calculate 95% CI
n_2014 = len(lp_2014)
mean_2014 = _____ # Calculate sample mean
std_2014 = _____ # Calculate sample standard deviation
se_2014 = std_2014 / np.sqrt(n_2014)

# Get t-critical value for 95% CI (two-tailed, df = n-1)
alpha_95 = 0.05
t_crit_95 = stats.t.ppf(1 - alpha_95/2, df=_____)

# Calculate margin of error and CI bounds
me_95 = t_crit_95 * se_2014
ci_95_lower = _____
ci_95_upper = _____

print(f"2014 Labor Productivity:")
print(f"Sample mean: ${mean_2014:.0f}")
print(f"95% CI: [{ci_95_lower:.0f}, ${ci_95_upper:.0f}]")
print(f"Margin of error: ${me_95:.0f}")

# Calculate 99% CI for comparison
alpha_99 = 0.01
t_crit_99 = stats.t.ppf(1 - alpha_99/2, df=n_2014-1)
me_99 = t_crit_99 * se_2014
ci_99_lower = mean_2014 - me_99
ci_99_upper = mean_2014 + me_99

print(f"\n99% CI: [{ci_99_lower:.0f}, ${ci_99_upper:.0f}]")
print(f"Margin of error: ${me_99:.0f}")
print(f"\nInterpretation: The 99% CI is _____ than the 95% CI") # Fill in: "wider" or
# "narrower"
print(f"because we need more certainty, which requires a larger interval.")

# Compare with 1990
mean_1990 = lp_1990.mean()
std_1990 = lp_1990.std()
se_1990 = std_1990 / np.sqrt(len(lp_1990))
me_1990 = stats.t.ppf(0.975, df=len(lp_1990)-1) * se_1990

print(f"\n1990 mean: ${mean_1990:.0f}, 95% CI width: ${2*me_1990:.0f}")
print(f"2014 mean: ${mean_2014:.0f}, 95% CI width: ${2*me_95:.0f}")
```

Questions to consider:

- Why is the 99% CI wider than the 95% CI?

- Did the mean productivity increase from 1990 to 2014?
- Which year has more variability in productivity across countries?

Task 2: Testing Productivity Change Over Time (SEMI-GUIDED)

Learning Goal: Apply Section 4.4 (two-sided tests) to compare time periods

Economic Question: "Has global mean labor productivity changed significantly from 1990 to 2014?"

Your task:

1. State null and alternative hypotheses
2. Conduct a two-sample t-test (independent samples)
3. Calculate the test statistic manually
4. Compare with `scipy.stats.ttest_ind()` result
5. Interpret the p-value at $\alpha = 0.05$

Code template (fill in the 8 blanks):

```

# State hypotheses
print("H0: μ1990 = μ2014 (no change in mean productivity)")
print("Ha: μ1990 ≠ μ2014 (mean productivity changed)")
print(f"Significance level: α = 0.05\n")

# Manual calculation
mean_1990 = lp_1990.mean()
mean_2014 = lp_2014.mean()
se_1990 = lp_1990.std() / np.sqrt(len(lp_1990))
se_2014 = lp_2014.std() / np.sqrt(len(lp_2014))

# Calculate pooled standard error for difference in means
se_diff = np.sqrt(_____***2 + _____***2) # Fill in: se_1990 and se_2014

# Calculate t-statistic
t_stat = (_____ - _____) / se_diff # Fill in: mean_2014 and mean_1990

# Degrees of freedom (Welch approximation)
n1, n2 = len(lp_1990), len(lp_2014)
s1, s2 = lp_1990.std(), lp_2014.std()
df = ((s1**2/n1 + s2**2/n2)**2) / ((s1**2/n1)**2/(n1-1) + (s2**2/n2)**2/(n2-1))

# Calculate two-sided p-value
p_value_manual = 2 * (1 - stats.t.cdf(abs(t_stat), df=df))

print(f"Manual calculation:")
print(f"Difference in means: ${mean_2014 - mean_1990:.0f}")
print(f"SE of difference: ${se_diff:.0f}")
print(f"t-statistic: {t_stat:.3f}")
print(f"Degrees of freedom: {df:.1f}")
print(f"p-value (two-sided): {p_value_manual:.4f}\n")

# Verify with scipy
t_stat_scipy, p_value_scipy = stats.ttest_ind(_____, _____, equal_var=False) # Fill in: lp_2014, lp_1990
print(f"scipy.stats.ttest_ind() result:")
print(f"t-statistic: {t_stat_scipy:.3f}")
print(f"p-value: {p_value_scipy:.4f}\n")

# Decision
if p_value_scipy < 0.05:
    print(f"Decision: _____ H0 at α=0.05") # Fill in: "Reject" or "Fail to reject"
    print(f"Interpretation: Mean productivity _____ significantly from 1990 to 2014.")
# Fill in: "changed" or "did not change"
else:
    print(f"Decision: Fail to reject H0 at α=0.05")
    print(f"Interpretation: Insufficient evidence that mean productivity changed.")

```

Questions to consider:

- What does the p-value tell you about the likelihood of observing this difference by chance?
- Is the change economically meaningful (not just statistically significant)?
- What assumptions does the two-sample t-test make?

Task 3: Comparing Regional Productivity Levels (SEMI-GUIDED)

Learning Goal: Apply hypothesis testing to compare subgroups

Economic Question: "Do African countries have significantly lower productivity than European countries (2014 data)?"

Your task:

1. Filter 2014 data by region (use `region` column in dataset)
2. Test $H_0: \mu_{\text{Africa}} = \mu_{\text{Europe}}$ vs $H_a: \mu_{\text{Africa}} \neq \mu_{\text{Europe}}$
3. Calculate 95% CI for the difference in means
4. Visualize distributions with side-by-side box plots

Code structure (complete the analysis):

```
# Filter 2014 data by region
df_2014 = df.loc[df.index.get_level_values('year') == 2014]

# Extract productivity for Africa and Europe
lp_africa = df_2014.loc[df_2014['region'] == 'Africa', 'lp']
lp_europe = df_2014.loc[df_2014['region'] == 'Europe', 'lp']

print(f"Sample sizes: Africa n={len(lp_africa)}, Europe n={len(lp_europe)}")
print(f"Africa mean: ${lp_africa.mean():,.0f}")
print(f"Europe mean: ${lp_europe.mean():,.0f}\n")

# Conduct two-sample t-test
# YOUR CODE HERE: Use stats.ttest_ind() to test if means differ
# Calculate and print: t-statistic, p-value, decision at a=0.05

# Calculate 95% CI for difference in means
# YOUR CODE HERE:
# 1. Calculate difference in means
# 2. Calculate SE of difference
# 3. Get t-critical value
# 4. Construct CI: (difference - ME, difference + ME)

# Visualize distributions
fig, ax = plt.subplots(1, 1, figsize=(8, 5))
ax.boxplot([lp_africa, lp_europe], labels=['Africa', 'Europe'])
ax.set_ylabel('Labor Productivity ($)')
ax.set_title('Labor Productivity Distribution by Region (2014)')
ax.grid(axis='y', alpha=0.3)
plt.tight_layout()
plt.show()
```

Questions to consider:

- Is the difference statistically significant?
- How large is the productivity gap in dollar terms?
- What does the box plot reveal about within-region variation?
- Does the CI for the difference include zero? What does that mean?

Key Concept 4.11: Economic vs Statistical Significance

A result can be **statistically significant** ($p < 0.05$) but **economically trivial**, or vice versa:

Statistical significance answers: "Is this difference unlikely to be due to chance?"

- Depends on sample size: larger samples detect smaller differences
- Measured by p-value: probability of observing this result if H_0 is true
- Standard: $p < 0.05$ means <5% chance of Type I error

Economic significance answers: "Is this difference large enough to matter?"

- Depends on context: a \$1,000 productivity gap might be huge for low-income countries but trivial for high-income countries
- Measured by effect size: actual magnitude of the difference
- Judgment call: requires domain expertise

Example:

- With $n=10,000$ countries, a \$100 productivity difference might be statistically significant ($p<0.001$) but economically meaningless
- With $n=10$ countries, a \$10,000 difference might not be statistically significant ($p=0.08$) but could be economically important

Best practice: Always report BOTH:

1. Statistical result: "We reject H_0 at $\alpha=0.05$ ($p=0.003$)"
2. Economic interpretation: "The \$15,000 productivity gap represents a 35% difference, which is economically substantial for development policy"

Task 4: One-Sided Test for Growth (MORE INDEPENDENT)

Learning Goal: Apply Section 4.6 (one-sided tests) to directional hypotheses

Economic Question: "Can we conclude that mean global productivity in 2014 exceeds \$50,000 (a policy benchmark)?"

Your task:

1. Test $H_0: \mu \leq 50,000$ vs $H_a: \mu > 50,000$
2. Use `scipy.stats.ttest_1samp()` with `alternative='greater'`
3. Compare one-sided vs two-sided p-values
4. Discuss Type I error: what does $\alpha=0.05$ mean in this context?

Outline (write your own code):

```

# Step 1: State hypotheses clearly
# H0: μ ≤ 50,000 (productivity does not exceed benchmark)
# Ha: μ > 50,000 (productivity exceeds benchmark)

# Step 2: Conduct one-sided t-test
# Use: stats.ttest_1samp(lp_2014, popmean=50000, alternative='greater')

# Step 3: Calculate two-sided p-value for comparison
# Use: stats.ttest_1samp(lp_2014, popmean=50000, alternative='two-sided')

# Step 4: Report results
# - Sample mean
# - t-statistic
# - One-sided p-value
# - Two-sided p-value
# - Decision at α=0.05

# Step 5: Interpret Type I error
# If we reject H0, what is the probability we made a mistake?

```

Hint: Remember that for one-sided tests:

- If $H_a: \mu > \mu_0$, use `alternative='greater'`
- The one-sided p-value is half the two-sided p-value (when t-stat has correct sign)
- Type I error = rejecting H_0 when it's actually true

Questions to consider:

- Why is the one-sided p-value smaller than the two-sided p-value?
- When is a one-sided test appropriate vs a two-sided test?
- What are the policy implications if we reject H_0 ?

Task 5: Proportions Analysis - Growth Winners (INDEPENDENT)

Learning Goal: Apply Section 4.7 (proportions) to binary outcomes

Economic Question: "What proportion of countries experienced productivity growth from 1990 to 2014, and can we conclude that more than half experienced growth?"

Your task:

1. Create country-level dataset with productivity in both 1990 and 2014

2. Create binary variable: `growth = 1` if productivity increased, `0` otherwise
3. Calculate sample proportion of "growth winners"
4. Construct 95% CI for population proportion using normal approximation
5. Test $H_0: p = 0.50$ vs $H_a: p \neq 0.50$ (are half growth winners?)

Hints:

```

# Hint 1: Reshape data to country-level
# df_1990 = df.loc[df.index.get_level_values('year') == 1990, ['lp']]
# df_2014 = df.loc[df.index.get_level_values('year') == 2014, ['lp']]
# Merge on country index

# Hint 2: Create binary growth indicator
# growth = (lp_2014 > lp_1990).astype(int)

# Hint 3: Proportions formulas from Section 4.7
# p_hat = np.mean(growth)
# se_p = np.sqrt(p_hat * (1 - p_hat) / n)
# CI: p_hat ± z_crit * se_p
# For 95% CI: z_crit = 1.96

# Hint 4: Test statistic for proportions
# z = (p_hat - p0) / np.sqrt(p0 * (1 - p0) / n)
# where p0 = 0.50 under H0

```

Questions to consider:

- What proportion of countries experienced growth?
- Does the 95% CI include 0.50? What does that mean?
- Is there evidence that the proportion differs from 50%?
- Which countries did NOT experience growth? (Bonus: investigate why)

Task 6: Multi-Regional Hypothesis Testing (INDEPENDENT)

Learning Goal: Integrate multiple inference methods in comprehensive analysis

Economic Question: "Which regional pairs show statistically significant productivity gaps in 2014?"

Your task:

1. Identify all regions in the dataset (use `df_2014['region'].unique()`)
2. Calculate 95% CIs for mean productivity in each region
3. Conduct pairwise t-tests (Africa vs Europe, Africa vs Asia, Africa vs Americas, etc.)
4. Create a visualization showing CIs for all regions (error bar plot)
5. Discuss the **multiple testing problem**: when conducting many tests, what happens to Type I error?

Challenge goals (minimal guidance):

- Design your own analysis structure
- Use loops to avoid repetitive code
- Create professional visualizations
- Write clear economic interpretations

Suggested approach:

```
# Step 1: Get all regions and calculate summary stats
# For each region: mean, std, se, 95% CI
# Store in a DataFrame or dictionary

# Step 2: Conduct all pairwise tests
# Use itertools.combinations() to generate pairs
# For each pair: run ttest_ind(), store t-stat and p-value

# Step 3: Visualize CIs
# Create error bar plot: plt.errorbar()
# Or bar plot with CI whiskers

# Step 4: Report significant differences
# Which pairs have p < 0.05?
# What is the magnitude of differences?

# Step 5: Discuss multiple testing
# If you run 10 tests at a=0.05, what's the probability of at least one false
# positive?
# Consider Bonferroni correction: a_adjusted = 0.05 / number_of_tests
```

Questions to consider:

- Which region has the highest mean productivity? Lowest?
- Are all pairwise differences statistically significant?
- How does the multiple testing problem affect your conclusions?
- What economic factors might explain regional productivity gaps?

What You've Learned

By completing this case study, you've practiced **all the major skills from Chapter 4:**

Statistical Methods:

- Constructed confidence intervals (90%, 95%, 99%) for population means
- Conducted two-sided hypothesis tests to compare groups and time periods
- Performed one-sided directional tests for benchmark comparisons
- Applied proportions inference to binary economic outcomes
- Calculated and interpreted t-statistics, p-values, and margins of error
- Used both manual calculations and `scipy.stats` functions

Economic Applications:

- Tested convergence hypotheses (did productivity gaps narrow over time?)
- Compared regional development levels (Africa, Europe, Asia, Americas)
- Evaluated policy benchmarks (does productivity exceed thresholds?)
- Identified "growth winners" and "growth losers" among countries
- Distinguished between statistical and economic significance

Programming Skills:

- Filtered and reshaped panel data (multi-index DataFrames)
- Implemented statistical tests with `scipy.stats`
- Created informative visualizations (box plots, error bars)
- Wrote clear, reproducible analysis code

Critical Thinking:

- Formulated null and alternative hypotheses from economic questions
 - Interpreted p-values in context (not just "significant" vs "not significant")
 - Connected statistical results to economic meaning and policy implications
 - Recognized limitations (Type I/II errors, multiple testing problem)
-

Next steps:

These skills form the foundation for more advanced methods in later chapters:

- **Chapter 5:** Regression analysis (relationship between two variables)
- **Chapter 6:** Multiple regression (controlling for confounders)
- **Chapter 7:** Hypothesis tests in regression models

Statistical inference is everywhere in empirical economics. You've now mastered the core toolkit for:

- Quantifying uncertainty
- Testing economic theories
- Making data-driven decisions
- Communicating results with precision

Well done!

Case Study 2: Is Bolivia's Development Equal? Testing Differences Across Departments

Research Question: Are there statistically significant differences in development levels across Bolivia's nine departments?

In Chapter 1, we introduced the DS4Bolivia project and explored satellite-development relationships across Bolivia's 339 municipalities. In this case study, we apply Chapter 4's statistical inference tools—confidence intervals and hypothesis tests—to test whether development levels differ significantly across Bolivia's departments.

The Data: Cross-sectional dataset covering 339 Bolivian municipalities from the [DS4Bolivia Project](#), including:

- **Development outcomes:** Municipal Sustainable Development Index (IMDS, 0-100 composite)
- **Satellite data:** Log nighttime lights per capita (2017)
- **Demographics:** Population (2017), municipality and department names

Your Task: Use confidence intervals, one-sample tests, two-sample tests, and one-sided tests to evaluate whether Bolivia's departments differ significantly in development—and whether those differences are large enough to matter for policy.

Load the DS4Bolivia Data

Let's load the DS4Bolivia dataset and prepare the key variables for statistical inference.

In []:

```
# Load the DS4Bolivia dataset
url_bol = "https://raw.githubusercontent.com/quarcs-
lab/ds4bolivia/master/ds4bolivia_v20250523.csv"
bol = pd.read_csv(url_bol)

# Select key variables for this case study
key_vars = ['mun', 'dep', 'imds', 'ln_NTlpc2017', 'pop2017']
bol_key = bol[key_vars].dropna().copy()

print("=" * 70)
print("DS4BOLIVIA DATASET – STATISTICAL INFERENCE CASE STUDY")
print("=" * 70)
print(f"\"Municipalities: {len(bol_key)}\"")
print(f"\"Departments: {bol_key['dep'].nunique()}\"")
print(f"\nIMDS summary:")
print(bol_key['imds'].describe().round(2))
print(f"\nMunicipalities per department:")
print(bol_key['dep'].value_counts().sort_index())
```

Task 1: Confidence Interval for Mean IMDS (Guided)

Learning Goal: Apply Section 4.3 methods to calculate and interpret a confidence interval for a population mean.

Economic Question: "What is the true average development level across all Bolivian municipalities?"

Instructions:

1. Calculate the sample mean and standard error of `imds`
2. Construct a 95% confidence interval using `scipy.stats.t.interval()`
3. Print the sample mean, standard error, and CI bounds
4. Interpret the result: "We are 95% confident that the true mean municipal development index lies between X and Y."

Apply what you learned in Section 4.3: The formula is $\bar{x} \pm t_{\alpha/2} \times SE$, where $SE = s/\sqrt{n}$.

In []:

```
# Your code here: 95% Confidence Interval for national mean IMDS
from scipy import stats

# Calculate sample statistics
n = len(bol_key['imds'])
x_bar = bol_key['imds'].mean()
se = bol_key['imds'].std() / np.sqrt(n)

# 95% confidence interval using t-distribution
ci_low, ci_high = stats.t.interval(0.95, df=n-1, loc=x_bar, scale=se)

print("=" * 70)
print("95% CONFIDENCE INTERVAL FOR MEAN IMDS")
print("=" * 70)
print(f"Sample size (n): {n}")
print(f"Sample mean: {x_bar:.4f}")
print(f"Standard error: {se:.4f}")
print(f"95% CI: [{ci_low:.4f}, {ci_high:.4f}]")
print(f"\nInterpretation: We are 95% confident that the true mean")
print(f"municipal development index lies between {ci_low:.2f} and {ci_high:.2f}.")


```

Task 2: Hypothesis Test — National Development Target (Guided)

Learning Goal: Apply Section 4.4 (two-sided test) to test a hypothesis about a population mean.

Economic Question: "Is the average municipality at the midpoint of the development scale?"

A natural benchmark for the IMDS (which ranges from 0 to 100) is the midpoint of 50. If Bolivia's municipalities were, on average, at this midpoint, we would expect

$$\mu_{IMDS} = 50.$$

Instructions:

1. State the hypotheses: $H_0 : \mu = 50$ vs $H_1 : \mu \neq 50$
2. Use `scipy.stats.ttest_1samp()` to conduct the test
3. Report the t-statistic and p-value
4. State your conclusion at $\alpha = 0.05$
5. Discuss: Is the average municipality at the midpoint of the development scale?

In []:

```
# Your code here: One-sample t-test – is mean IMDS = 50?

# Hypothesis test: H0: mu = 50 vs H1: mu ≠ 50
t_stat, p_value = stats.ttest_1samp(bol_key['imds'], popmean=50)

print("=" * 70)
print("HYPOTHESIS TEST: IS MEAN IMDS = 50?")
print("=" * 70)
print(f"H₀: μ = 50 vs H₁: μ ≠ 50")
print(f"\nSample mean: {bol_key['imds'].mean():.4f}")
print(f"t-statistic: {t_stat:.4f}")
print(f"p-value: {p_value:.6f}")
print(f"\nConclusion at α = 0.05:")
if p_value < 0.05:
    print(f" Reject H₀ (p = {p_value:.6f} < 0.05)")
    print(f" The average IMDS is significantly different from 50.")
else:
    print(f" Fail to reject H₀ (p = {p_value:.6f} ≥ 0.05)")
    print(f" No significant evidence that mean IMDS differs from 50.")
```

Key Concept 4.12: Statistical Significance in Development

A statistically significant difference between departments does not automatically imply a **policy-relevant** gap. With 339 municipalities providing large sample sizes, even small differences can achieve statistical significance. Policy makers must evaluate the **magnitude** of differences alongside p-values. A 2-point difference in IMDS may be statistically significant but practically negligible for resource allocation decisions.

Task 3: Department-Level Inference (Semi-guided)

Learning Goal: Apply confidence intervals to compare subgroups.

Economic Question: "Which departments have significantly different development levels from one another?"

Instructions:

1. Calculate the 95% confidence interval for mean `imds` in each of Bolivia's 9 departments
2. Create a **forest plot** (horizontal error bars) showing the CI for each department
3. Identify which departments' CIs overlap (suggesting no significant difference) and which don't
4. Discuss what the pattern reveals about regional inequality

Hint: Use `groupby('dep')` to calculate department-level statistics, then `plt.errorbar()` or `plt.barh()` with error bars for the forest plot.

In []:

```
# Your code here: Department-level 95% CIs and forest plot

# Calculate department-level statistics
dept_stats = bol_key.groupby('dep')[['imds']].agg(['mean', 'std',
'count']).sort_values('mean')
dept_stats['se'] = dept_stats['std'] / np.sqrt(dept_stats['count'])
dept_stats['ci_low'] = dept_stats['mean'] - 1.96 * dept_stats['se']
dept_stats['ci_high'] = dept_stats['mean'] + 1.96 * dept_stats['se']

print("=" * 70)
print("95% CONFIDENCE INTERVALS FOR MEAN IMDS BY DEPARTMENT")
print("=" * 70)
print(dept_stats[['mean', 'se', 'ci_low', 'ci_high', 'count']].round(2).to_string())

# Forest plot
fig, ax = plt.subplots(figsize=(10, 6))
departments = dept_stats.index
y_pos = range(len(departments))
ax.errorbar(dept_stats['mean'], y_pos,
            xerr=1.96 * dept_stats['se'],
            fmt='o', color='navy', capsized=5, capthick=1.5, markersize=6)
ax.set_yticks(y_pos)
ax.set_yticklabels(departments)
ax.set_xlabel('Mean IMDS (with 95% CI)')
ax.set_title('Forest Plot: Municipal Development by Department')
ax.axvline(x=bol_key['imds'].mean(), color='red', linestyle='--', alpha=0.5,
label='National mean')
ax.legend()
ax.grid(axis='x', alpha=0.3)
plt.tight_layout()
plt.show()
```

Task 4: One-Sided Test — Is the Capital Department More Developed? (Semi-guided)

Learning Goal: Apply Section 4.6 (one-sided tests) to a directional hypothesis.

Economic Question: "Is La Paz department's mean IMDS significantly greater than the national mean?"

Instructions:

1. Extract IMDS values for La Paz department
2. Test $H_0 : \mu_{LP} \leq \mu_{national}$ vs $H_1 : \mu_{LP} > \mu_{national}$ using a one-sided t-test

3. Calculate the one-sided p-value (divide the two-sided p-value by 2, checking direction)
4. Report and interpret the result at $\alpha = 0.05$
5. Discuss: Is the capital department significantly more developed?

Hint: Use `scipy.stats.ttest_1samp()` with the national mean as the test value, then adjust for a one-sided test.

```
In [ ]: # Your code here: One-sided t-test for La Paz department

# Extract La Paz IMDS values
la_paz = bol_key[bol_key['dep'] == 'La Paz']['imds']
national_mean = bol_key['imds'].mean()

# Two-sided test first
t_stat_lp, p_two = stats.ttest_1samp(la_paz, popmean=national_mean)

# One-sided p-value: H1: mu_LP > national_mean
# If t > 0, one-sided p = p_two / 2; if t < 0, one-sided p = 1 - p_two / 2
p_one = p_two / 2 if t_stat_lp > 0 else 1 - p_two / 2

print("=" * 70)
print("ONE-SIDED TEST: LA PAZ > NATIONAL MEAN?")
print("=" * 70)
print(f"H₀: μ_LaPaz ≤ {national_mean:.2f} vs H₁: μ_LaPaz > {national_mean:.2f}")
print(f"\nLa Paz municipalities: {len(la_paz)}")
print(f"La Paz mean IMDS: {la_paz.mean():.4f}")
print(f"National mean IMDS: {national_mean:.4f}")
print(f"t-statistic: {t_stat_lp:.4f}")
print(f"One-sided p-value: {p_one:.6f}")
print("\nConclusion at α = 0.05:")
if p_one < 0.05:
    print(f" Reject H₀ (p = {p_one:.6f} < 0.05)")
    print(f" La Paz's mean IMDS is significantly greater than the national mean.")
else:
    print(f" Fail to reject H₀ (p = {p_one:.6f} ≥ 0.05)")
    print(f" No significant evidence that La Paz exceeds the national mean.")
```

Key Concept 4.13: Subnational Inference Challenges

When testing hypotheses about departmental means, each department contains a different number of municipalities (ranging from ~10 to ~50+). Departments with fewer municipalities have **wider confidence intervals** and less statistical power. This means we may fail to detect real differences for smaller departments—not because the differences don't exist, but because we lack sufficient data to establish them conclusively.

Task 5: Comparing Two Departments (Independent)

Learning Goal: Apply two-sample t-tests to compare group means.

Economic Question: "Is the development gap between the most and least developed departments statistically significant?"

Instructions:

1. Identify the departments with the highest and lowest mean IMDS (from Task 3 results)
2. Use `scipy.stats.ttest_ind()` to perform a two-sample t-test comparing these departments
3. Report the t-statistic and p-value
4. Discuss both **statistical significance** (p-value) and **practical significance** (magnitude of the gap)
5. What does this tell us about regional inequality in Bolivia?

```
In [ ]: # Your code here: Two-sample t-test - highest vs lowest IMDS department

# Identify highest and lowest departments
dept_means = bol_key.groupby('dep')['imds'].mean()
top_dept = dept_means.idxmax()
bot_dept = dept_means.idxmin()

# Extract IMDS values for each
top_values = bol_key[bol_key['dep'] == top_dept]['imds']
bot_values = bol_key[bol_key['dep'] == bot_dept]['imds']

# Two-sample t-test
t_stat_2s, p_value_2s = stats.ttest_ind(top_values, bot_values)

print("=" * 70)
print(f"\nTWO-SAMPLE T-TEST: {top_dept.upper()} vs {bot_dept.upper()}")
print("=" * 70)
print(f"\nHighest IMDS department: {top_dept}")
print(f" Mean IMDS: {top_values.mean():.4f}")
print(f" N: {len(top_values)}")
print(f"\nLowest IMDS department: {bot_dept}")
print(f" Mean IMDS: {bot_values.mean():.4f}")
print(f" N: {len(bot_values)}")
print(f"\nDifference in means: {top_values.mean() - bot_values.mean():.4f}")
print(f"t-statistic: {t_stat_2s:.4f}")
print(f"p-value: {p_value_2s:.6f}")
print(f"\nConclusion at α = 0.05:")
if p_value_2s < 0.05:
    print(f" Reject H₀ (p = {p_value_2s:.6f} < 0.05)")
    print(f" The development gap of {top_values.mean() - bot_values.mean():.2f} points is statistically significant.")
else:
    print(f" Fail to reject H₀ (p = {p_value_2s:.6f} ≥ 0.05)")
    print(f" No significant evidence of a development gap.")
print(f"\nPractical significance: A gap of {top_values.mean() - bot_values.mean():.2f} points on a 0-100 scale")
print(f"represents a {'substantial' if abs(top_values.mean() - bot_values.mean()) > 10 else 'modest'} difference in development outcomes.")
```

Task 6: Policy Brief on Regional Inequality (Independent)

Objective: Write a 200-300 word policy brief summarizing your statistical findings.

Your brief should address:

- 1. Are departmental differences statistically significant?** Summarize results from Tasks 3-5.
- 2. Which departments need the most attention?** Use the forest plot and CI analysis to identify lagging regions.
- 3. How confident are we in these conclusions?** Discuss the confidence levels and what the CIs tell us.
- 4. What are the limitations of these tests?** Consider sample sizes, assumptions, and what the tests cannot tell us.

Format: Write your brief in the markdown cell below. Support your arguments with specific numbers from your analysis (means, CIs, p-values).

Tip: Remember Key Concepts 4.12 and 4.13—distinguish between statistical significance and policy relevance, and consider how unequal sample sizes affect your conclusions.

In []:

```
# Your code here: Additional analysis to support your policy brief
#
# Suggestions:
# 1. Create a summary table of all department CIs and test results
# 2. Calculate effect sizes (Cohen's d) for the two-sample comparison
# 3. Visualize the national IMDS distribution with department means marked

# Example: Summary statistics for the policy brief
print("=" * 70)
print("SUMMARY TABLE FOR POLICY BRIEF")
print("=" * 70)
dept_summary = bol_key.groupby('dep')[['imds']].agg(['mean', 'std',
'count']).sort_values('mean', ascending=False)
dept_summary['se'] = dept_summary['std'] / np.sqrt(dept_summary['count'])
dept_summary['ci_95'] = dept_summary.apply(
    lambda r: f"[{r['mean']} - 1.96*r['se']:.1f}, {r['mean'] + 1.96*r['se']}]", axis=1)
print(dept_summary[['mean', 'std', 'count', 'ci_95']].round(2).to_string())
```

What You've Learned from This Case Study

Through this analysis of subnational development in Bolivia, you've applied the full Chapter 4 statistical inference toolkit:

- **Confidence intervals** for mean development levels
- **One-sample and two-sample hypothesis tests** to evaluate development benchmarks and compare groups
- **One-sided tests** for directional hypotheses about specific departments
- **Forest plots** for comparing group CIs visually
- **Statistical vs practical significance** in a policy context

- **Critical thinking** about sample size, statistical power, and inference limitations

Connection to research: The DS4Bolivia project uses these same statistical tools to evaluate whether satellite-predicted development indicators are significantly different from survey-based measures, providing evidence for the reliability of remote sensing approaches to SDG monitoring.

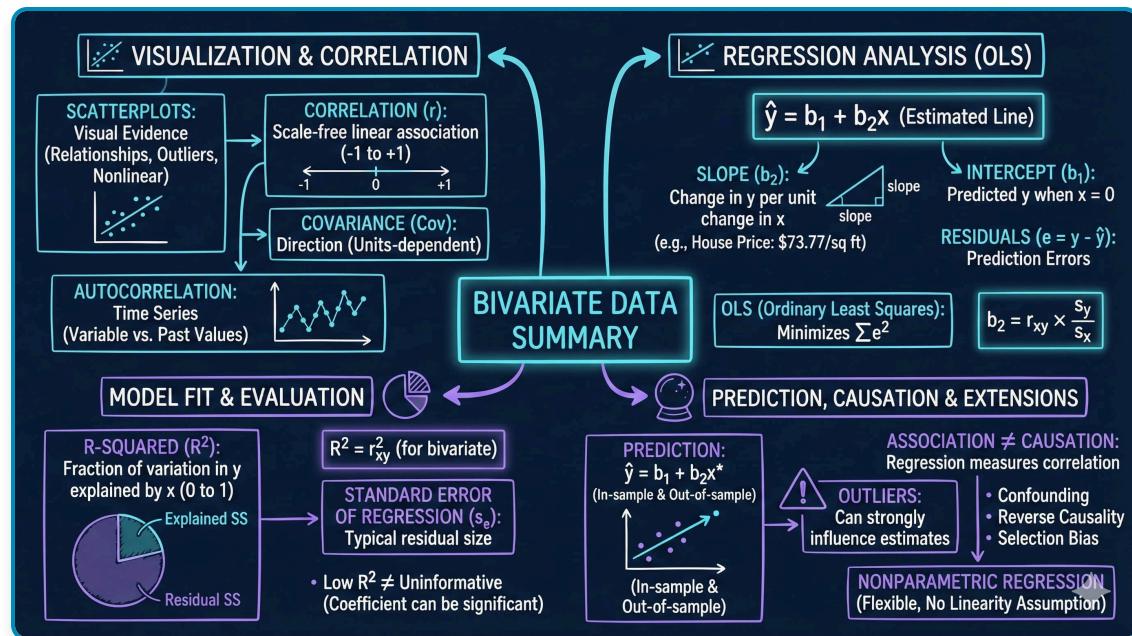
Looking ahead: In Chapter 5, we'll move beyond testing means to exploring *bivariate relationships*—how nighttime lights relate to specific development outcomes across Bolivia's municipalities.

Well done! You've now tested development hypotheses for both cross-country convergence and Bolivian regional inequality using the tools of statistical inference.

Chapter 5: Bivariate Data Summary

metricsAI: An Introduction to Econometrics with Python and AI in the Cloud

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This notebook provides an interactive introduction to bivariate data analysis and simple linear regression using Python. You'll learn how to summarize relationships between two variables using correlation, scatter plots, and regression analysis. All code runs directly in Google Colab without any local setup.

Open in Colab

Chapter Overview

Bivariate data involves observations on two variables—for example, house prices and house sizes, or income and education. This chapter teaches you how to summarize and analyze relationships between two variables using correlation and regression.

What you'll learn:

- Summarize bivariate relationships using two-way tabulations and scatterplots
- Calculate and interpret correlation coefficients and understand their relationship to covariance

- Estimate and interpret regression lines using ordinary least squares (OLS)
- Evaluate model fit using R-squared, standard error, and variation decomposition
- Make predictions and identify outliers in regression analysis
- Understand the critical distinction between association and causation
- Apply nonparametric regression methods to check linearity assumptions

Datasets used:

- **AED_HOUSE.DTA:** House prices and characteristics for 29 houses sold in Central Davis, California in 1999 (price, size, bedrooms, bathrooms, lot size, age)

Chapter outline:

- 5.1 Example - House Price and Size
- 5.2 Two-Way Tabulation
- 5.3 Two-Way Scatter Plot
- 5.4 Sample Correlation
- 5.5 Regression Line
- 5.6 Measures of Model Fit
- 5.7 Computer Output Following Regression
- 5.8 Prediction and Outlying Observations
- 5.9 Regression and Correlation
- 5.10 Causation
- 5.11 Nonparametric Regression
- 5.12 Key Takeaways
- 5.13 Practice Exercises

| Setup

First, we import the necessary Python packages and configure the environment for reproducibility. All data will stream directly from GitHub.

In [1]:

```
# Import required packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
from statsmodels.formula.api import ols
from statsmodels.nonparametric.smoothers_lowess import lowess
from scipy import stats
from scipy.ndimage import gaussian_filter1d
import random
import os

# Set random seeds for reproducibility
RANDOM_SEED = 42
random.seed(RANDOM_SEED)
np.random.seed(RANDOM_SEED)
os.environ['PYTHONHASHSEED'] = str(RANDOM_SEED)

# GitHub data URL
GITHUB_DATA_URL = "https://raw.githubusercontent.com/quarcs-lab/data-open/master/AED/"

# Set plotting style
sns.set_style("whitegrid")
plt.rcParams['figure.figsize'] = (10, 6)

print("Setup complete! Ready to explore bivariate data analysis.")
```

Setup complete! Ready to explore bivariate data analysis.

5.1 Example - House Price and Size

We begin by loading and examining data on house prices and sizes from 29 houses sold in Central Davis, California in 1999. This dataset will serve as our main example throughout the chapter.

Why this dataset?

- Small enough to see individual observations
- Large enough to demonstrate statistical relationships
- Economically meaningful: housing is a major component of wealth
- Clear relationship: larger houses tend to cost more

In [2]:

```
# Load the house data
data_house = pd.read_stata(GITHUB_DATA_URL + 'AED_HOUSE.DTA')

print("Data loaded successfully!")
print(f"Number of observations: {len(data_house)}")
print(f"Number of variables: {data_house.shape[1]}")
print(f"\nVariables: {', '.join(data_house.columns.tolist())}")
```

```
Data loaded successfully!
Number of observations: 29
Number of variables: 8

Variables: price, size, bedrooms, bathrooms, lotsize, age, monthsold, list
```

In [3]:

```
# Display the complete dataset (Table 5.1)
print("=" * 70)
print("TABLE 5.1: Complete Dataset")
print("=" * 70)
print(data_house.to_string())
```

```
=====
TABLE 5.1: Complete Dataset
=====
```

	price	size	bedrooms	bathrooms	lotsize	age	monthsold	list
0	204000	1400	3	2.0	1	31.0	7	199900
1	212000	1600	3	3.0	2	33.0	5	212000
2	213000	1800	3	2.0	2	51.0	4	219900
3	220000	1600	3	2.0	1	49.0	4	229000
4	224500	2100	4	2.5	2	47.0	6	224500
5	229000	1700	4	2.5	2	35.0	3	229500
6	230000	2100	4	2.0	2	34.0	8	239000
7	233000	1700	3	2.0	1	40.0	6	244500
8	235000	1700	4	2.0	2	29.0	7	245000
9	235000	1600	3	2.0	3	35.0	5	242000
10	236500	1600	3	2.0	3	23.0	8	239500
11	238000	1900	4	2.0	2	29.0	7	249000
12	239500	1600	3	2.0	3	34.0	6	239500
13	241000	1600	4	2.0	2	34.0	8	242500
14	244000	2000	4	2.0	1	29.0	7	249000
15	245000	1400	4	2.0	2	30.0	8	252000
16	249000	1900	4	3.0	3	37.0	6	235000
17	253000	2100	4	2.0	3	47.0	6	269000
18	255000	1500	4	2.0	3	47.0	7	240000
19	258500	1600	3	2.0	1	39.0	8	259900
20	270000	1800	4	2.0	3	31.0	3	263900
21	270000	2000	4	2.5	3	39.0	5	269000
22	272000	1800	4	2.5	2	46.0	3	279500
23	273000	1900	5	2.0	2	37.0	7	273000
24	278500	2600	6	2.0	3	38.0	8	280000
25	279900	2000	4	2.0	2	31.0	7	279900
26	310000	2300	4	2.5	2	28.0	5	315000
27	340000	2400	4	3.0	2	34.0	6	369900
28	375000	3300	4	2.5	2	39.0	3	386000

In [4]:

```
# Summary statistics (Table 5.2)
print("=" * 70)
print("TABLE 5.2: Summary Statistics")
print("=" * 70)
print(data_house[['price', 'size']].describe())

# Extract key variables
price = data_house['price']
size = data_house['size']

print("\nPrice Statistics:")
print(f" Mean:      ${price.mean():,.2f}")
print(f" Median:    ${price.median():,.2f}")
print(f" Min:       ${price.min():,.2f}")
print(f" Max:       ${price.max():,.2f}")
print(f" Std Dev:   ${price.std():,.2f}")

print("\nSize Statistics:")
print(f" Mean:      {size.mean():,.0f} sq ft")
print(f" Median:    {size.median():,.0f} sq ft")
print(f" Min:       {size.min():,.0f} sq ft")
print(f" Max:       {size.max():,.0f} sq ft")
print(f" Std Dev:   {size.std():,.0f} sq ft")
```

```
=====
TABLE 5.2: Summary Statistics
=====
              price        size
count    29.000000  29.000000
mean    253910.344828 1882.758621
std     37390.710695  398.272130
min    204000.000000 1400.000000
25%    233000.000000 1600.000000
50%    244000.000000 1800.000000
75%    270000.000000 2000.000000
max    375000.000000 3300.000000

Price Statistics:
 Mean:      $253,910.34
 Median:    $244,000.00
 Min:       $204,000.00
 Max:       $375,000.00
 Std Dev:   $37,390.71

Size Statistics:
 Mean:      1,883 sq ft
 Median:    1,800 sq ft
 Min:       1,400 sq ft
 Max:       3,300 sq ft
 Std Dev:   398 sq ft
```

Key Concept 5.1: Visual Data Exploration

Visual inspection of data is the first step in bivariate analysis. The house price and size data show a clear positive relationship: larger houses tend to sell for higher prices. The correlation of 0.786 confirms this strong positive association. Always examine scatterplots before computing correlation or regression.

What do these numbers tell us about the Davis housing market (1999)?

Price Statistics:

- **Mean = \$253,910:** Average house price in the sample
- **Median = \$244,000:** Middle value (half above, half below)
- **Range:** 204,000 to 375,000 (spread of \$171,000)
- **Std Dev = \$37,391:** Typical deviation from the mean

Size Statistics:

- **Mean = 1,883 sq ft:** Average house size
- **Median = 1,800 sq ft:** Middle value
- **Range:** 1,400 to 3,300 sq ft (spread of 1,900 sq ft)
- **Std Dev = 398 sq ft:** Typical deviation from the mean

Key insights:

- Both distributions are fairly symmetric (means close to medians)
- Substantial variation in both price and size (good for regression!)
- The price coefficient of variation ($CV = 0.15$) and size $CV (0.21)$ show moderate variability
- **Moving from univariate to bivariate:** In Chapter 2, we looked at single variables.
Now we ask: *how do these two variables move together?*

Economic context: These are moderate-sized homes in a California college town (UC Davis), with typical prices for the late 1990s.

Key observations:

- House prices range from 204,000 to 375,000 (mean: \$253,910)
- House sizes range from 1,400 to 3,300 square feet (mean: 1,883 sq ft)
- Both variables show substantial variation, which is good for regression analysis
- The data appear to be reasonably symmetric (means close to medians)

| 5.2 Two-Way Tabulation

A **two-way tabulation** (or crosstabulation) shows how observations are distributed across combinations of two categorical variables. For continuous variables like price and size, we first create categorical ranges.

Why use tabulation?

- Provides a quick summary of the relationship
- Useful for discrete or categorical data
- Can reveal patterns before formal analysis

In [5]:

```
# Create categorical variables
price_range = pd.cut(price, bins=[0, 249999, np.inf],
                     labels=['< $250,000', '≥ $250,000'])

size_range = pd.cut(size, bins=[0, 1799, 2399, np.inf],
                     labels=['< 1,800', '1,800-2,399', '≥ 2,400'])

# Create two-way table (Table 5.3)
print("=" * 70)
print("TABLE 5.3: Two-Way Tabulation of Price and Size")
print("=" * 70)
crosstab = pd.crosstab(price_range, size_range, margins=True)
print(crosstab)

print("\nInterpretation:")
print("- 11 houses are both low-priced and small")
print("- 0 houses are both low-priced and large (≥ 2,400 sq ft)")
print("- 3 houses are both high-priced and large")
print("- Pattern suggests positive association: larger houses tend to be more expensive")
```

```
=====
TABLE 5.3: Two-Way Tabulation of Price and Size
=====
size      < 1,800   1,800-2,399   ≥ 2,400   All
price
< $250,000       11            6          0    17
≥ $250,000        2             7          3    12
All                13            13          3    29
```

Interpretation:

- 11 houses are both low-priced and small
- 0 houses are both low-priced and large ($\geq 2,400$ sq ft)
- 3 houses are both high-priced and large
- Pattern suggests positive association: larger houses tend to be more expensive

What does this crosstab tell us?

Looking at the table:

- **11 houses** are both small ($< 1,800$ sq ft) AND low-priced ($< \$250,000$)
- **0 houses** are both large ($\geq 2,400$ sq ft) AND low-priced
- **3 houses** are both large ($\geq 2,400$ sq ft) AND high-priced ($\geq \$250,000$)
- **6 houses** are medium-sized (1,800-2,399 sq ft) AND low-priced

The pattern reveals:

- **Positive association:** Most observations cluster in the "small and cheap" or "large and expensive" cells

- **No counterexamples:** We never see "large and cheap" houses (the bottom-right cell is empty)
- **Imperfect relationship:** Some medium-sized houses are low-priced (6 houses), some are high-priced (7 houses)

Limitation of tabulation:

- We lose information by categorizing continuous variables
- We can't quantify the strength of the relationship
- We can't make precise predictions

Next step: Use the correlation coefficient and regression to measure the relationship more precisely using the full continuous data.

From Categorical to Continuous:

Crosstabulation is useful but has limitations:

- **Information loss:** We convert continuous data (exact prices/sizes) into categories
- **Arbitrary bins:** Results can change depending on where we draw category boundaries
- **No precise measurement:** Can't quantify exact strength of relationship

Solution: Use the full continuous data with **correlation** and **regression** to:

- Preserve all information in the original measurements
- Get precise, interpretable measures (r , slope)
- Make specific predictions for any value of x

Key Concept 5.2: Two-Way Tabulations

Two-way tabulations show the joint distribution of two categorical variables. Expected frequencies (calculated assuming independence) provide the basis for Pearson's chi-squared test of statistical independence. The crosstabulation reveals patterns: no low-priced large houses suggests a positive association between size and price.

| 5.3 Two-Way Scatter Plot

A **scatter plot** is the primary visual tool for examining the relationship between two continuous variables. Each point represents one observation, with x-coordinate showing size and y-coordinate showing price.

What to look for:

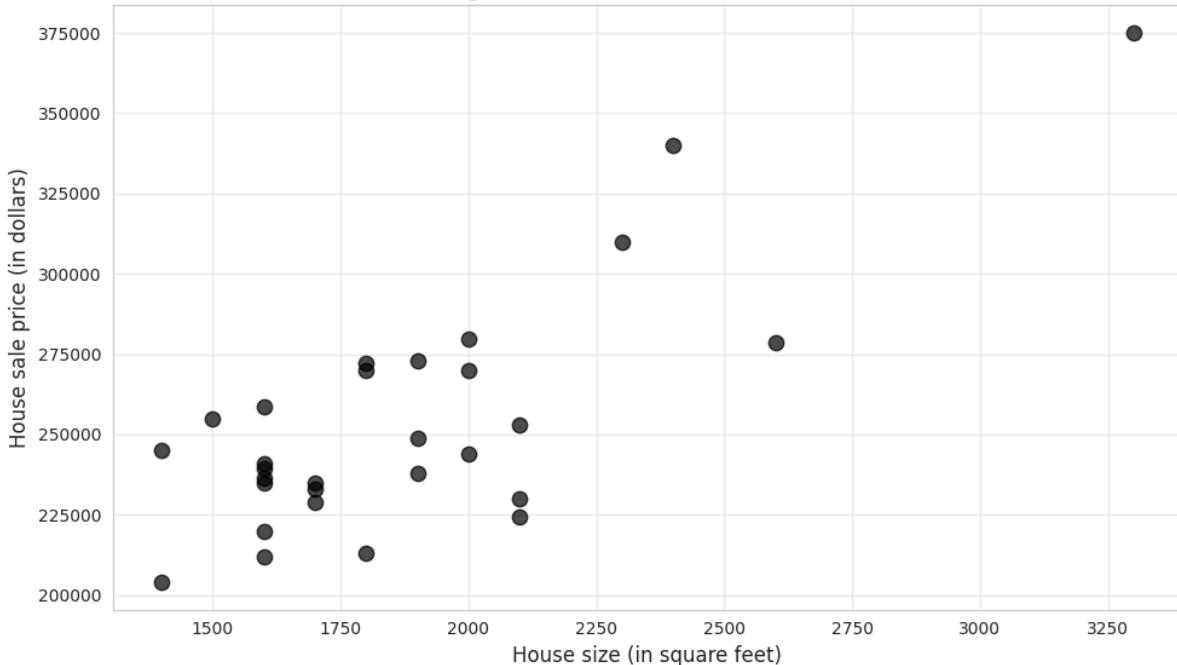
- **Direction:** Does y increase or decrease as x increases?
- **Strength:** How closely do points follow a pattern?
- **Form:** Is the relationship linear or curved?
- **Outliers:** Are there unusual observations far from the pattern?

In [6]:

```
# Figure 5.1: Scatter plot of price vs size
fig, ax = plt.subplots(figsize=(10, 6))
ax.scatter(size, price, s=80, alpha=0.7, color='black', edgecolor='black')
ax.set_xlabel('House size (in square feet)', fontsize=12)
ax.set_ylabel('House sale price (in dollars)', fontsize=12)
ax.set_title('Figure 5.1: House Price vs Size', fontsize=14, fontweight='bold')
ax.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()

print("\nWhat the scatter plot shows:")
print("✓ Positive relationship: Larger houses tend to have higher prices")
print("✓ Roughly linear: Points follow an upward-sloping pattern")
print("✓ Moderate scatter: Not all points lie exactly on a line")
print("✓ No obvious outliers: All points fit the general pattern")
```

Figure 5.1: House Price vs Size



What the scatter plot shows:

- ✓ Positive relationship: Larger houses tend to have higher prices
- ✓ Roughly linear: Points follow an upward-sloping pattern
- ✓ Moderate scatter: Not all points lie exactly on a line
- ✓ No obvious outliers: All points fit the general pattern

Visual vs. Quantitative Analysis:

The scatter plot provides **qualitative** insight (direction, form, outliers), but we need **quantitative** measures to:

- **Communicate precisely:** "Strong positive relationship" is vague; " $r = 0.79$ " is specific
- **Compare across studies:** Can't compare scatter plots directly across datasets
- **Test hypotheses:** Need numerical values for statistical inference (Chapter 7)
- **Make predictions:** Visual estimates from graphs are imprecise

Next: We'll quantify this relationship using the correlation coefficient.

What patterns do we observe?

1. Direction: Positive relationship

- As house size increases (moving right), house price increases (moving up)
- This makes economic sense: bigger houses should cost more

2. Form: Roughly linear

- Points follow an upward-sloping pattern
- No obvious curvature (e.g., not exponential or U-shaped)
- A straight line appears to be a reasonable summary

3. Strength: Moderate to strong

- Points cluster fairly closely around an imaginary line
- Not perfect (some scatter), but clear pattern visible
- We'll quantify this with the correlation coefficient

4. Outliers: None obvious

- No houses wildly far from the general pattern
- All observations seem consistent with the relationship

Comparison to univariate analysis (Chapter 2):

- **Univariate:** Histogram shows distribution of one variable
- **Bivariate:** Scatter plot shows *relationship* between two variables
- **New question:** How does Y change when X changes?

What we can't tell from the graph alone:

- Exact strength of relationship (need correlation)

- Precise prediction equation (need regression)
- Statistical significance (need inference, Chapter 7)

Key Concept 5.3: Scatterplots and Relationships

Scatterplots provide visual evidence of relationships between two continuous variables. They reveal the direction (positive/negative), strength (tight/loose clustering), form (linear/curved), and outliers of the relationship. The house price-size scatterplot shows a strong, positive, roughly linear relationship with no obvious outliers.

I 5.4 Sample Correlation

The **correlation coefficient r** is a unit-free measure of linear association between two variables. It ranges from -1 to 1:

- $r = 1$: Perfect positive linear relationship
- $0 < r < 1$: Positive linear relationship
- $r = 0$: No linear relationship
- $-1 < r < 0$: Negative linear relationship
- $r = -1$: Perfect negative linear relationship

Formula:

$$r_{xy} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 \times \sum_{i=1}^n (y_i - \bar{y})^2}} = \frac{s_{xy}}{s_x s_y}$$

where s_{xy} is the sample covariance, and s_x, s_y are sample standard deviations.

Key Properties of Correlation:

Understanding these properties helps avoid common misinterpretations:

1. **Unit-free:** $r = 0.79$ whether we measure price in dollars, thousands, or millions
2. **Bounded:** Always between -1 and +1 (unlike covariance, which is unbounded)
3. **Symmetric:** $r(\text{price}, \text{size}) = r(\text{size}, \text{price})$ — order doesn't matter
4. **Only measures linear relationships:** Can miss curved, U-shaped, or other nonlinear patterns
5. **Sensitive to outliers:** One extreme point can dramatically change r

Limitation: Correlation is a summary measure but doesn't provide predictions. For that, we need **regression**.

In [7]:

```
# Compute correlation and covariance
cov_matrix = data_house[['price', 'size']].cov()
corr_matrix = data_house[['price', 'size']].corr()

print("=" * 70)
print("COVARIANCE AND CORRELATION")
print("=" * 70)

print("\nCovariance matrix:")
print(cov_matrix)

print("\nCorrelation matrix:")
print(corr_matrix)

r = corr_matrix.loc['price', 'size']
print(f"\nCorrelation coefficient: r = {r:.4f}")
print(f"\nInterpretation:")
print(f" The correlation of {r:.4f} indicates a strong positive linear")
print(f" relationship between house price and size.")
print(f" About {r**2:.1%} of the variation in price is linearly associated")
print(f" with variation in size.")
```

```
=====
COVARIANCE AND CORRELATION
=====

Covariance matrix:
      price          size
price  1.398065e+09  1.170161e+07
size   1.170161e+07  1.586207e+05

Correlation matrix:
      price          size
price  1.000000  0.785782
size   0.785782  1.000000

Correlation coefficient: r = 0.7858

Interpretation:
The correlation of 0.7858 indicates a strong positive linear
relationship between house price and size.
About 61.7% of the variation in price is linearly associated
with variation in size.
```

What does $r = 0.7858$ mean?

1. Strength of linear association:

- $r = 0.7858$ indicates a **strong positive** linear relationship
- Scale reference:
 - $|r| < 0.3$: weak
 - $0.3 \leq |r| < 0.7$: moderate
 - $|r| \geq 0.7$: strong

- Our value (0.79) is well into the "strong" range

2. Direction:

- **Positive:** Larger houses are associated with higher prices
- If r were negative, larger houses would be associated with lower prices (unlikely for housing!)

3. Variance explained (preview):

- $r^2 = (0.7858)^2 = 0.617 = 61.7\%$
- About 62% of price variation is linearly associated with size variation
- The remaining 38% is due to other factors (location, age, condition, etc.)

4. Properties of correlation:

- **Unit-free:** Same value whether we measure price in dollars or thousands of dollars
- **Symmetric:** $r(\text{price}, \text{size}) = r(\text{size}, \text{price}) = 0.7858$
- **Bounded:** Always between -1 and +1
- **Linear measure:** Detects linear relationships, not curves

Comparison to Chapter 2 (univariate):

- Chapter 2: Standard deviation measures spread of ONE variable
- Chapter 5: Correlation measures how TWO variables move together
- Both are standardized measures (unit-free)

Economic interpretation: The strong correlation confirms what we saw in the scatter plot: house size is a major determinant of house price, but it's not the only factor.

Key Concept 5.4: The Correlation Coefficient

The correlation coefficient (r) is a scale-free measure of linear association ranging from -1 (perfect negative) to +1 (perfect positive). A correlation of 0 indicates no linear relationship. For house price and size, $r = 0.786$ indicates strong positive correlation. The correlation is unit-free, symmetric, and measures only linear relationships.

Illustration: Different Correlation Patterns

To build intuition, let's visualize simulated data with different correlation coefficients.

In [8]:

```
# Figure 5.2: Different correlation patterns
np.random.seed(12345)
n = 30
x = np.random.normal(3, 1, n)
u1 = np.random.normal(0, 0.8, n)
y1 = 3 + x + u1 # Strong positive correlation
u2 = np.random.normal(0, 2, n)
y2 = 3 + x + u2 # Moderate positive correlation
y3 = 5 + u2      # Zero correlation
y4 = 10 - x - u2 # Moderate negative correlation

correlations = [
    np.corrcoef(x, y1)[0, 1],
    np.corrcoef(x, y2)[0, 1],
    np.corrcoef(x, y3)[0, 1],
    np.corrcoef(x, y4)[0, 1]
]

fig, axes = plt.subplots(2, 2, figsize=(14, 12))
axes = axes.flatten()

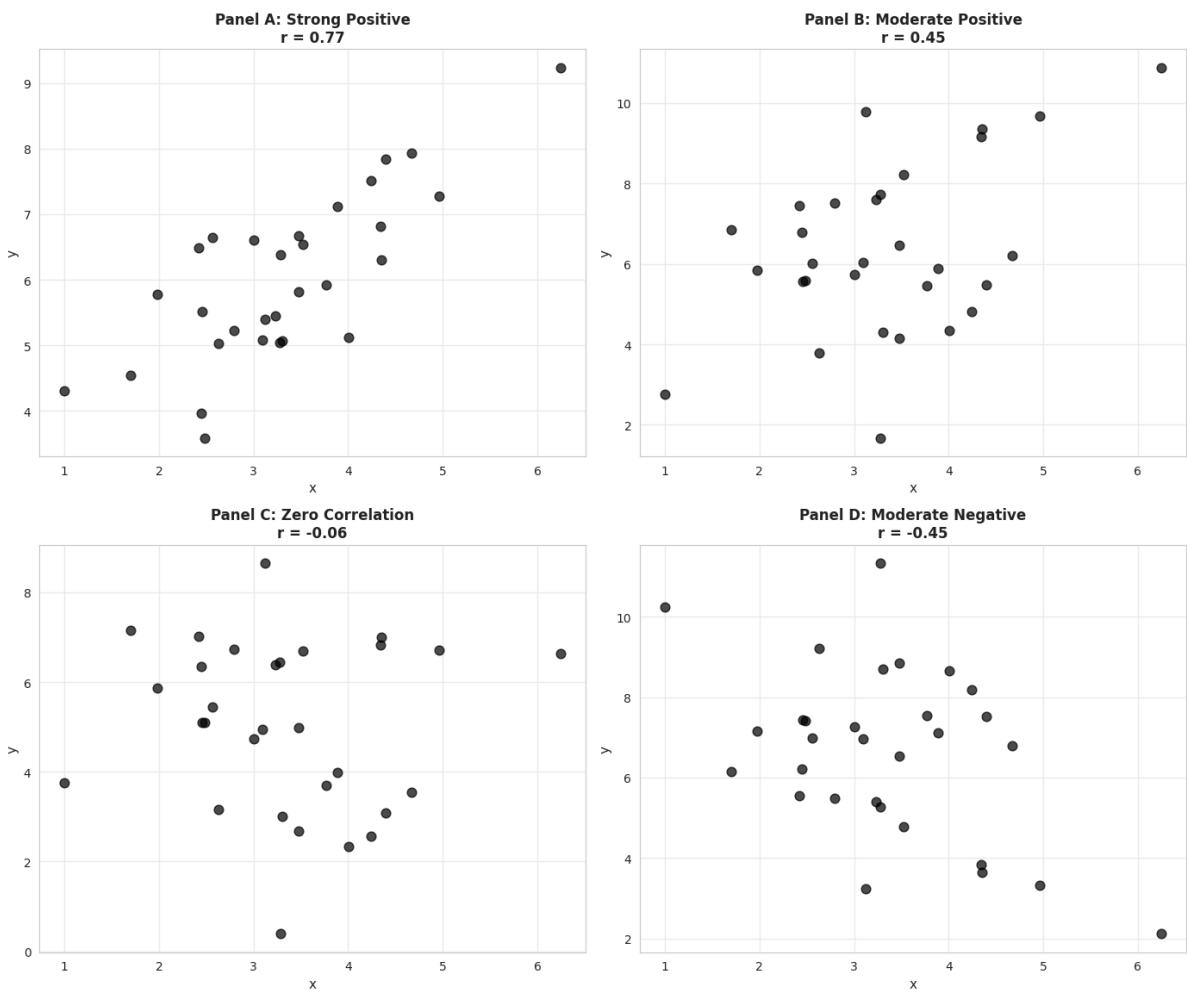
datasets = [(x, y1, 'Panel A: Strong Positive'),
            (x, y2, 'Panel B: Moderate Positive'),
            (x, y3, 'Panel C: Zero Correlation'),
            (x, y4, 'Panel D: Moderate Negative')]

for idx, (ax, (x_data, y_data, title), corr) in enumerate(zip(axes, datasets,
correlations)):
    ax.scatter(x_data, y_data, s=60, alpha=0.7, color='black', edgecolor='black')
    ax.set_xlabel('x', fontsize=11)
    ax.set_ylabel('y', fontsize=11)
    ax.set_title(f'{title}\n{corr:.2f}', fontsize=12, fontweight='bold')
    ax.grid(True, alpha=0.3)

plt.suptitle('Figure 5.2: Different Correlation Patterns',
             fontsize=14, fontweight='bold', y=0.995)
plt.tight_layout()
plt.show()

print("\nKey observations:")
print("• Panel A ( $r \approx 0.78$ ): Points cluster tightly around an upward slope")
print("• Panel B ( $r \approx 0.44$ ): More scatter, but still positive relationship")
print("• Panel C ( $r \approx 0.00$ ): No systematic pattern")
print("• Panel D ( $r \approx -0.53$ ): Points follow a downward slope")
```

Figure 5.2: Different Correlation Patterns



Key observations:

- Panel A ($r \approx 0.78$): Points cluster tightly around an upward slope
- Panel B ($r \approx 0.44$): More scatter, but still positive relationship
- Panel C ($r \approx 0.00$): No systematic pattern
- Panel D ($r \approx -0.53$): Points follow a downward slope

5.5 Regression Line

The **regression line** provides the "best-fitting" linear summary of the relationship between y (dependent variable) and x (independent variable):

$$\hat{y} = b_1 + b_2 x$$

where:

- \hat{y} = predicted (fitted) value of y
- b_1 = intercept (predicted y when $x = 0$)
- b_2 = slope (change in y for one-unit increase in x)

Ordinary Least Squares (OLS) chooses b_1 and b_2 to minimize the sum of squared residuals:

$$\min_{b_1, b_2} \sum_{i=1}^n (y_i - b_1 - b_2 x_i)^2$$

Formulas:

$$b_2 = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2} = \frac{s_{xy}}{s_x^2}$$

$$b_1 = \bar{y} - b_2 \bar{x}$$

Transition Note: We've visualized the relationship using scatterplots. Now we'll quantify the strength and direction of the association using the correlation coefficient, a unit-free measure ranging from -1 to +1.

In [9]:

```
# Fit OLS regression
model = ols('price ~ size', data=data_house).fit()

print("=" * 70)
print("REGRESSION RESULTS: price ~ size")
print("=" * 70)
print(model.summary())
```

```

=====
REGRESSION RESULTS: price ~ size
=====
                         OLS Regression Results
=====
Dep. Variable:          price    R-squared:         0.617
Model:                 OLS     Adj. R-squared:      0.603
Method:                Least Squares   F-statistic:       43.58
Date:        Thu, 29 Jan 2026   Prob (F-statistic):  4.41e-07
Time:        01:01:01   Log-Likelihood:     -332.05
No. Observations:      29     AIC:                  668.1
Df Residuals:          27     BIC:                  670.8
Df Model:                   1
Covariance Type:    nonrobust
=====
            coef    std err          t      P>|t|      [0.025      0.975]
-----
Intercept    1.15e+05  2.15e+04      5.352      0.000    7.09e+04  1.59e+05
size         73.7710   11.175       6.601      0.000    50.842    96.700
=====
Omnibus:             0.576   Durbin-Watson:      1.219
Prob(Omnibus):        0.750   Jarque-Bera (JB):  0.638
Skew:                 -0.078   Prob(JB):           0.727
Kurtosis:              2.290   Cond. No.        9.45e+03
=====
```

Notes:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 9.45e+03. This might indicate that there are strong multicollinearity or other numerical problems.

Key Concept 5.5: Ordinary Least Squares

The method of ordinary least squares (OLS) chooses the regression line to minimize the sum of squared residuals. This yields formulas for the slope ($b_2 = \sum(x_i - \bar{x})(y_i - \bar{y}) / \sum(x_i - \bar{x})^2$) and intercept ($b_1 = \bar{y} - b_2\bar{x}$) that can be computed from the data. The slope equals the covariance divided by the variance of x.

```
In [10]: # Extract and interpret coefficients
intercept = model.params['Intercept']
slope = model.params['size']
r_squared = model.rsquared

print("=" * 70)
print("KEY REGRESSION COEFFICIENTS")
print("=" * 70)
print(f"\nFitted regression line:")
print(f"  ŷ = {intercept:.2f} + {slope:.2f} × size")
print(f"\nIntercept (b0): ${intercept:.2f}")
print(f"  Interpretation: Predicted price when size = 0")
print(f"  (Not economically meaningful in this case)")

print(f"\nSlope (b1): ${slope:.2f} per square foot")
print(f"  Interpretation: Each additional square foot is associated with")
print(f"  a ${slope:.2f} increase in house price, on average.")

print(f"\nExamples:")
print(f"  • 100 sq ft larger → ${slope * 100:.2f} higher price")
print(f"  • 500 sq ft larger → ${slope * 500:.2f} higher price")

print(f"\nR-squared: {r_squared:.4f} ({r_squared*100:.2f}%)")
print(f"  {r_squared*100:.2f}% of price variation is explained by size")
```

=====

KEY REGRESSION COEFFICIENTS

=====

Fitted regression line:

$\hat{y} = 115,017.28 + 73.77 \times \text{size}$

Intercept (b_1): \$115,017.28

Interpretation: Predicted price when size = 0
(Not economically meaningful in this case)

Slope (b_2): \$73.77 per square foot

Interpretation: Each additional square foot is associated with a \$73.77 increase in house price, on average.

Examples:

- 100 sq ft larger $\rightarrow \$7,377.10$ higher price
- 500 sq ft larger $\rightarrow \$36,885.52$ higher price

R-squared: 0.6175 (61.75%)
61.75% of price variation is explained by size

Transition Note: Correlation measures the strength of association, but doesn't provide a prediction equation. Now we turn to regression analysis, which fits a line to predict y from x and quantifies how much y changes per unit change in x .

Key findings from the house price regression:

The fitted equation:

$$\hat{Y} = \$115.917 + \$73.77 \times \text{size}$$

1. Slope coefficient: \$73.77 per square foot ($p < 0.001$)

- **Interpretation:** Each additional square foot is associated with a \$73.77 increase in house price, on average
- **Statistical significance:** p-value ≈ 0 (highly significant)
- **Confidence interval:** [50.84, 96.70] — we're 95% confident the true effect is between 51 and 97 per sq ft

2. Practical examples:

- 100 sq ft larger $\rightarrow \$73.77 \times 100 = \$7,377$ higher price
- 500 sq ft larger $\rightarrow \$73.77 \times 500 = \$36,885$ higher price
- 1,000 sq ft larger $\rightarrow \$73.77 \times 1,000 = \$73,770$ higher price

3. Intercept: \$115,017

- **Mathematical interpretation:** Predicted price when size = 0
- **Reality check:** A house can't have zero square feet!
- **Better interpretation:** This is just where the regression line crosses the y-axis
- Don't take it literally — it's outside the data range (1,400-3,300 sq ft)

4. R-squared: 0.617 (61.7%)

- Size explains **62% of the variation** in house prices
- The remaining **38%** is due to other factors:
 - Location (neighborhood quality, schools)
 - Physical characteristics (bathrooms, garage, condition)
 - Market conditions (time of sale)
 - Unique features (view, lot size, upgrades)

Comparison to correlation:

- We computed $r = 0.7858$
- $R^2 = (0.7858)^2 = 0.617$ (they match!)
- For simple regression, R^2 always equals r^2

Economic interpretation: The strong relationship ($R^2 = 0.62$) between size and price makes economic sense. Buyers pay a substantial premium for additional space. However, the imperfect fit reminds us that many factors beyond size affect house values.

Visualizing the Fitted Regression Line

In [11]:

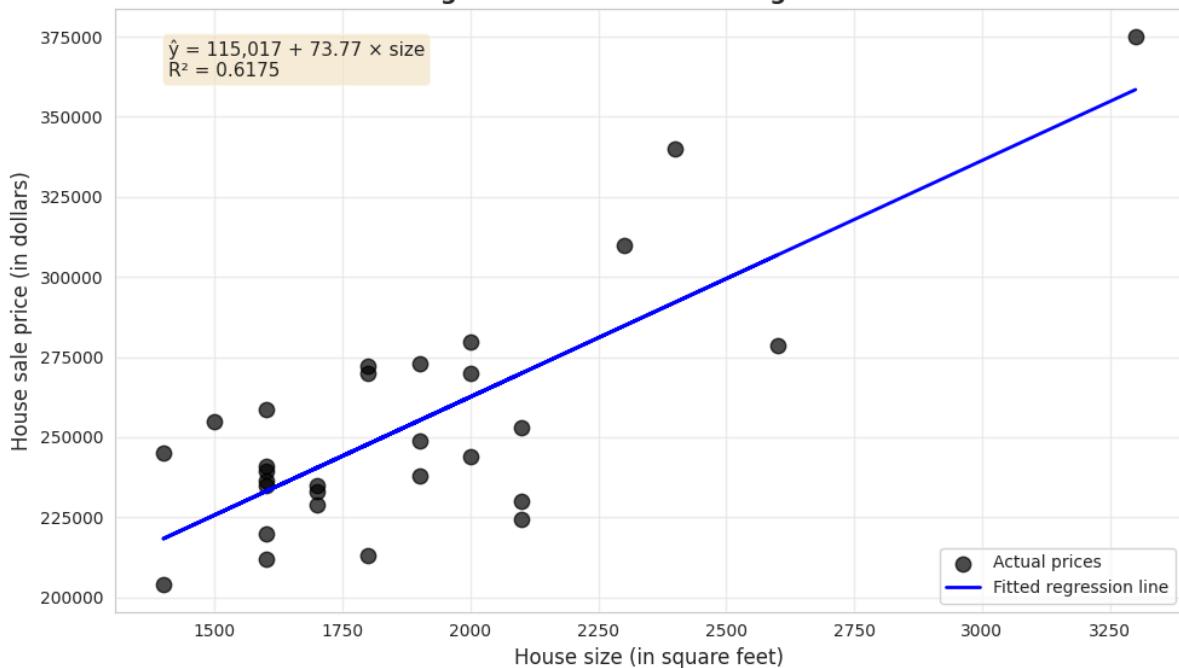
```
# Figure 5.4: Scatter plot with regression line
fig, ax = plt.subplots(figsize=(10, 6))
ax.scatter(size, price, s=80, alpha=0.7, color='black',
           edgecolor='black', label='Actual prices')
ax.plot(size, model.fittedvalues, color='blue', linewidth=2, label='Fitted regression
line')

# Add equation to plot
equation_text = f'y = {intercept:.0f} + {slope:.2f} * size\nR^2 = {r_squared:.4f}'
ax.text(0.05, 0.95, equation_text,
        transform=ax.transAxes, fontsize=11,
        verticalalignment='top',
        bbox=dict(boxstyle='round', facecolor='wheat', alpha=0.5))

ax.set_xlabel('House size (in square feet)', fontsize=12)
ax.set_ylabel('House sale price (in dollars)', fontsize=12)
ax.set_title('Figure 5.4: House Price Regression',
            fontsize=14, fontweight='bold')
ax.legend(loc='lower right')
ax.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()

print("\nThe blue line is the 'line of best fit'")
print("It minimizes the sum of squared vertical distances from each point.")
```

Figure 5.4: House Price Regression



The blue line is the 'line of best fit'
It minimizes the sum of squared vertical distances from each point.

Special Case: Intercept-Only Regression

When we regress y on only an intercept (no x variable), the OLS estimate equals the sample mean of y . This shows that regression is a natural extension of univariate

statistics.

In [12]:

```
# Intercept-only regression
model_intercept = ols('price ~ 1', data=data_house).fit()

print("=" * 70)
print("INTERCEPT-ONLY REGRESSION")
print("=" * 70)
print(f"Intercept from regression: ${model_intercept.params[0]:,.2f}")
print(f"Sample mean of price:      ${price.mean():,.2f}")
print("\nThese are equal, confirming that OLS generalizes the sample mean!")
```

```
=====
INTERCEPT-ONLY REGRESSION
=====
Intercept from regression: $253,910.34
Sample mean of price:      $253,910.34

These are equal, confirming that OLS generalizes the sample mean!
```

```
/tmp/ipython-input-1986013926.py:7: FutureWarning: Series.__getitem__ treating keys as positions is deprecated. In a future version, integer keys will always be treated as labels (consistent with DataFrame behavior). To access a value by position, use `ser.iloc[pos]`
```

```
print(f"Intercept from regression: ${model_intercept.params[0]:,.2f}")
```

| 5.6 Measures of Model Fit

Two key measures assess how well the regression line fits the data:

R-squared (R^2)

Proportion of variation in y explained by x (ranges from 0 to 1):

$$R^2 = \frac{\text{Explained SS}}{\text{Total SS}} = \frac{\sum(\hat{y}_i - \bar{y})^2}{\sum(y_i - \bar{y})^2} = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$$

Interpretation:

- $R^2 = 0$: x explains none of the variation in y
- $R^2 = 1$: x explains all of the variation in y
- $R^2 = r^2$ (for simple regression, R^2 equals the squared correlation)

Standard Error of the Regression (s_e)

Standard deviation of the residuals (typical size of prediction errors):

$$s_e = \sqrt{\frac{1}{n-2} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

Interpretation:

- Lower s_e means fitted values are closer to actual values
- Units: same as y (dollars in our example)
- Dividing by (n-2) accounts for estimation of two parameters

In [13]:

```
# Compute model fit measures
print("=" * 70)
print("MEASURES OF MODEL FIT")
print("=" * 70)

r_squared = model.rsquared
adj_r_squared = model.rsquared_adj
se = np.sqrt(model.mse_resid)
n = len(data_house)

print(f"\nR-squared: {r_squared:.4f}")
print(f" {r_squared*100:.2f}% of price variation explained by size")

print(f"\nAdjusted R-squared: {adj_r_squared:.4f}")
print(f" Penalizes for number of regressors")

print(f"\nStandard error (s_e): ${se:,.2f}")
print(f" Typical prediction error is about ${se:,.0f}")

# Verify  $R^2 = r^2$ 
r = corr_matrix.loc['price', 'size']
print(f"\nVerification:  $R^2 = r^2$ ")
print(f"  $R^2 = {r_squared:.4f}$ ")
print(f"  $r^2 = {r**2:.4f}$ ")
print(f" Match: {np.isclose(r_squared, r**2)}")
```

```
=====
MEASURES OF MODEL FIT
=====

R-squared: 0.6175
61.75% of price variation explained by size

Adjusted R-squared: 0.6033
Penalizes for number of regressors

Standard error (s_e): $23,550.66
Typical prediction error is about $23,551

Verification:  $R^2 = r^2$ 
 $R^2 = 0.6175$ 
 $r^2 = 0.6175$ 
Match: True
```

Key Concept 5.6: R-Squared Goodness of Fit

R-squared measures the fraction of variation in y explained by the regression on x . It ranges from 0 (no explanatory power) to 1 (perfect fit). For bivariate regression, R^2 equals the squared correlation coefficient ($R^2 = r_{xy}^2$). $R^2 = 0.62$ means 62% of house price variation is explained by size variation, while 38% is due to other factors.

Transition Note: We've estimated the regression line. Now we assess how well this line fits the data using R-squared (proportion of variation explained) and the standard error of regression (typical prediction error).

Understanding $R^2 = 0.617$ and Standard Error = \$23,162

1. R-squared (coefficient of determination):

- **Value:** 0.617 or 61.7%
- **Meaning:** Size explains 61.7% of the variation in house prices
- **The other 38.3%:** Due to factors not in our model (location, quality, age, etc.)

How to think about R^2 :

- **$R^2 = 0$:** x has no predictive power (horizontal line)
- **$R^2 = 0.617$:** x has substantial predictive power (our case)
- **$R^2 = 1$:** x predicts y perfectly (all points on the line)

Is $R^2 = 0.617$ "good"?

- **For cross-sectional data:** Yes, this is quite good!
- **Context matters:**
 - Lab experiments: Often $R^2 > 0.9$
 - Cross-sectional economics: $R^2 = 0.2-0.6$ is typical
 - Time series: $R^2 = 0.7-0.95$ is common
- **Single predictor:** Size alone explains most variation — impressive!

2. Standard error: \$23,162

- **Meaning:** Typical prediction error (residual size)
- **Context:**
 - Average house price: \$253,910

- Typical error: \$23,162 (about 9% of average)
- This is reasonably accurate for house price prediction

3. Verification: $R^2 = r^2$

- Correlation: $r = 0.7858$
- R-squared: $R^2 = 0.617$
- Check: $(0.7858)^2 = 0.617$
- For simple regression, these are always equal

4. Sum of Squares decomposition:

$$\begin{aligned} \text{Total SS} &= \text{Explained SS} + \text{Residual SS} \\ 100\% &= 61.7\% + 38.3\% \end{aligned}$$

Practical implications:

- **For predictions:** Expect errors around $\pm \$23,000$
- **For policy:** Size is important, but other factors matter too
- **For research:** May want to add more variables (multiple regression, Chapters 10-12)

Illustration: Total SS, Explained SS, and Residual SS

Let's create a simple example to visualize how R^2 is computed.

In [14]:

```
# Simulated data for demonstration
np.random.seed(123456)
x_sim = np.arange(1, 6)
epsilon = np.random.normal(0, 2, 5)
y_sim = 1 + 2*x_sim + epsilon

df_sim = pd.DataFrame({'x': x_sim, 'y': y_sim})
model_sim = ols('y ~ x', data=df_sim).fit()

print("=" * 70)
print("SIMULATED DATA FOR MODEL FIT ILLUSTRATION")
print("=" * 70)
print(f"\n{'x':<5} {'y':<10} {'ŷ':<10} {'Residual (e)':<15} {'(y - ŷ)':<10} {'(ŷ - ŷ)':<10}")
print("-" * 70)
for i in range(len(x_sim)):
    print(f"{x_sim[i]:<5} {y_sim[i]:<10.4f} {model_sim.fittedvalues[i]:<10.4f} "
          f"{model_sim.resid[i]:<15.4f} {y_sim[i] - y_sim.mean():<10.4f} "
          f"{model_sim.fittedvalues[i] - y_sim.mean():<10.4f}")

print("\nSums of Squares:")
total_ss = np.sum((y_sim - y_sim.mean())**2)
explained_ss = np.sum((model_sim.fittedvalues - y_sim.mean())**2)
residual_ss = np.sum(model_sim.resid**2)

print(f" Total SS      = {total_ss:.4f}")
print(f" Explained SS = {explained_ss:.4f}")
print(f" Residual SS  = {residual_ss:.4f}")
print(f"\nCheck: Explained SS + Residual SS = {explained_ss + residual_ss:.4f}")
print(f"           Total SS      = {total_ss:.4f}")

print(f"\nR² = Explained SS / Total SS = {explained_ss / total_ss:.4f}")
print(f"R² from model = {model_sim.rsquared:.4f}")
```

```
=====
SIMULATED DATA FOR MODEL FIT ILLUSTRATION
=====
```

x	y	ŷ	Residual (e)	(y - ŷ)	(ŷ - ŷ)
1	3.9382	2.2482	1.6900	-2.5632	-4.2533
2	4.4343	4.3748	0.0595	-2.0672	-2.1266
3	3.9819	6.5015	-2.5196	-2.5196	-0.0000
4	6.7287	8.6281	-1.8994	0.2273	2.1266
5	13.4242	10.7548	2.6695	6.9228	4.2533

Sums of Squares:

Total SS = 65.1680

Explained SS = 45.2262

Residual SS = 19.9418

Check: Explained SS + Residual SS = 65.1680
Total SS = 65.1680

R² = Explained SS / Total SS = 0.6940
R² from model = 0.6940

In [15]:

```
# Figure 5.5: Visualization of model fit
fig, axes = plt.subplots(1, 2, figsize=(14, 5))

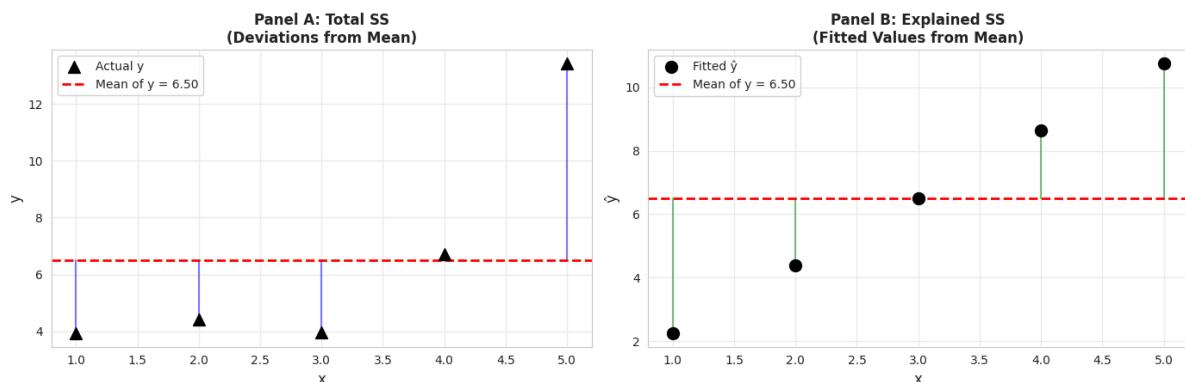
# Panel A: Total SS (deviations from mean)
axes[0].scatter(x_sim, y_sim, s=100, color='black', marker='^', label='Actual y',
zorder=3)
axes[0].axhline(y=y_sim.mean(), color='red', linewidth=2, linestyle='--',
label=f'Mean of y = {y_sim.mean():.2f}', zorder=2)
# Draw vertical lines from points to mean
for i in range(len(x_sim)):
    axes[0].plot([x_sim[i], x_sim[i]], [y_sim[i], y_sim.mean()],
                'b-', linewidth=1.5, alpha=0.5, zorder=1)
axes[0].set_xlabel('x', fontsize=12)
axes[0].set_ylabel('y', fontsize=12)
axes[0].set_title('Panel A: Total SS\n(Deviations from Mean)', fontsize=12,
fontweight='bold')
axes[0].legend()
axes[0].grid(True, alpha=0.3)

# Panel B: Explained SS (deviations of fitted values from mean)
axes[1].scatter(x_sim, model_sim.fittedvalues, s=100, color='black',
marker='o', label='Fitted ŷ', zorder=3)
axes[1].axhline(y=y_sim.mean(), color='red', linewidth=2, linestyle='--',
label=f'Mean of y = {y_sim.mean():.2f}', zorder=2)
# Draw vertical lines from fitted values to mean
for i in range(len(x_sim)):
    axes[1].plot([x_sim[i], x_sim[i]], [model_sim.fittedvalues[i], y_sim.mean()],
                'g-', linewidth=1.5, alpha=0.5, zorder=1)
axes[1].set_xlabel('x', fontsize=12)
axes[1].set_ylabel('ŷ', fontsize=12)
axes[1].set_title('Panel B: Explained SS\n(Fitted Values from Mean)', fontsize=12,
fontweight='bold')
axes[1].legend()
axes[1].grid(True, alpha=0.3)

plt.suptitle('Figure 5.5: Model Fit Illustration',
            fontsize=14, fontweight='bold', y=1.00)
plt.tight_layout()
plt.show()

print("\nPanel A shows Total SS: how far actual y values are from their mean")
print("Panel B shows Explained SS: how far fitted values are from the mean")
print("R² = (Explained SS) / (Total SS) measures the proportion explained")
```

Figure 5.5: Model Fit Illustration



Panel A shows Total SS: how far actual y values are from their mean
Panel B shows Explained SS: how far fitted values are from the mean
 $R^2 = (\text{Explained SS}) / (\text{Total SS})$ measures the proportion explained

Practical Implications of R^2 in Economics:

In applied econometrics, R^2 values around 0.60 are considered quite strong for cross-sectional data. Our $R^2 = 0.617$ tells us:

- **Size is a major determinant:** House size explains most of the price variation
- **Other factors matter:** The remaining 38% is due to location, quality, age, amenities, etc.
- **Single-variable limits:** One predictor can only explain so much in complex real-world data

Why R^2 varies by context:

- **Lab experiments:** Often $R^2 > 0.90$ (controlled conditions, few confounding factors)
- **Cross-sectional economics:** Typically $R^2 = 0.20-0.60$ (many unobserved heterogeneities)
- **Time series data:** Often $R^2 = 0.70-0.95$ (trends and persistence dominate)

Next step: This motivates **multiple regression** (Chapters 10-12), where we include many explanatory variables simultaneously to capture more of the variation in y .

| 5.7 Computer Output Following Regression

Modern statistical software provides comprehensive regression output. Let's examine each component of the output for our house price regression.

Understanding Prediction Uncertainty:

Our prediction $\hat{y} = \$262,559$ for a 2,000 sq ft house is a **point estimate** — our best single guess. But predictions have uncertainty:

Sources of uncertainty:

- **Estimation error:** We don't know the true β_1 and β_2 , only estimates b_1 and b_2
- **Fundamental randomness:** Even houses of identical size sell for different prices
- **Model limitations:** Our simple model omits many price determinants

Preview of Chapter 7: We'll learn to construct **prediction intervals** like:

- "We're 95% confident the price will be between 215,000 and 310,000"
- This acknowledges uncertainty while still providing useful guidance

For now, remember: the standard error (\$23,551) gives a rough sense of typical prediction errors.

In [16]:

```
# Display full regression output
print("=" * 70)
print("COMPLETE REGRESSION OUTPUT")
print("=" * 70)
print(model.summary())

print("\n" + "=" * 70)
print("GUIDE TO REGRESSION OUTPUT")
print("=" * 70)

print("\n1. TOP SECTION - Model Summary:")
print(f"    • Dep. Variable: price (what we're predicting)")
print(f"    • No. Observations: {int(model.nobs)} (sample size)")
print(f"    • R-squared: {model.rsquared:.4f} (goodness of fit)")
print(f"    • F-statistic: {model.fvalue:.2f} (overall significance)")

print("\n2. MIDDLE SECTION - Coefficients Table:")
print(f"    • coef: Estimated slope and intercept")
print(f"    • std err: Standard error (precision measure)")
print(f"    • t: t-statistic for testing H0: coefficient = 0")
print(f"    • P>|t|: p-value for significance test")
print(f"    • [0.025  0.975]: 95% confidence interval")

print("\n3. BOTTOM SECTION - Diagnostic Tests:")
print(f"    • Omnibus: Test for normality of residuals")
print(f"    • Durbin-Watson: Test for autocorrelation")
print(f"    • Jarque-Bera: Another normality test")
print(f"    • Cond. No.: Multicollinearity diagnostic")
```

```
=====
COMPLETE REGRESSION OUTPUT
=====
                         OLS Regression Results
=====
Dep. Variable:          price    R-squared:         0.617
Model:                 OLS     Adj. R-squared:      0.603
Method:                Least Squares   F-statistic:       43.58
Date:        Thu, 29 Jan 2026   Prob (F-statistic):  4.41e-07
Time:        01:01:03        Log-Likelihood:   -332.05
No. Observations:      29        AIC:             668.1
Df Residuals:          27        BIC:             670.8
Df Model:               1
Covariance Type:    nonrobust
=====
            coef    std err        t      P>|t|      [0.025      0.975]
-----
Intercept    1.15e+05  2.15e+04    5.352      0.000    7.09e+04  1.59e+05
size         73.7710   11.175     6.601      0.000    50.842    96.700
=====
Omnibus:           0.576   Durbin-Watson:      1.219
Prob(Omnibus):      0.750   Jarque-Bera (JB):    0.638
Skew:              -0.078   Prob(JB):          0.727
Kurtosis:           2.290   Cond. No.        9.45e+03
=====
```

Notes:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 9.45e+03. This might indicate that there are strong multicollinearity or other numerical problems.

```
=====
GUIDE TO REGRESSION OUTPUT
=====
```

1. TOP SECTION - Model Summary:
 - Dep. Variable: price (what we're predicting)
 - No. Observations: 29 (sample size)
 - R-squared: 0.6175 (goodness of fit)
 - F-statistic: 43.58 (overall significance)
2. MIDDLE SECTION - Coefficients Table:
 - coef: Estimated slope and intercept
 - std err: Standard error (precision measure)
 - t: t-statistic for testing H_0 : coefficient = 0
 - P>|t|: p-value for significance test
 - [0.025 0.975]: 95% confidence interval
3. BOTTOM SECTION - Diagnostic Tests:
 - Omnibus: Test for normality of residuals
 - Durbin-Watson: Test for autocorrelation
 - Jarque-Bera: Another normality test
 - Cond. No.: Multicollinearity diagnostic

| 5.8 Prediction and Outlying Observations

Once we have a fitted regression line, we can use it to predict y for any given value of x :

$$\hat{y} = b_1 + b_2 x^*$$

Two types of predictions:

1. **In-sample:** x is within the range of observed data (reliable)
2. **Out-of-sample:** x is outside the observed range (extrapolation - use with caution)

Outliers are observations that are unusually far from the regression line. They may indicate:

- Data entry errors
- Unusual circumstances
- Model misspecification
- Natural variation

In [17]:

```
# Prediction example
print("=" * 70)
print("PREDICTION EXAMPLES")
print("=" * 70)

# Predict for a 2000 sq ft house
new_size = pd.DataFrame({'size': [2000]})
predicted_price = model.predict(new_size)

print(f"\nExample 1: Predict price for a 2,000 sq ft house")
print(f"  Using the model: ŷ = {intercept:.2f} + {slope:.2f} × 2000")
print(f"  Predicted price: ${predicted_price.values[0]:,.2f}")

# Manual calculation
manual_prediction = intercept + slope * 2000
print(f"  Manual check: ${manual_prediction:.2f}")

# Multiple predictions
print(f"\nExample 2: Predictions for various house sizes")
sizes_to_predict = [1500, 1800, 2000, 2500, 3000]
predictions = pd.DataFrame({'size': sizes_to_predict})
predictions['predicted_price'] = model.predict(predictions)

print(predictions.to_string(index=False))

print(f"\nObserved size range: {size.min():.0f} to {size.max():.0f} sq ft")
print(f"  1500, 1800, 2000 are in-sample (reliable)")
print(f"  3000 is at the edge; 3500+ would be extrapolation (less reliable)")
```

=====

PREDICTION EXAMPLES

=====

Example 1: Predict price for a 2,000 sq ft house

Using the model: $\hat{y} = 115017.28 + 73.77 \times 2000$

Predicted price: \$262,559.36

Manual check: \$262,559.36

Example 2: Predictions for various house sizes

size	predicted_price
1500	225673.843168
1800	247805.155280
2000	262559.363354
2500	299444.883540
3000	336330.403727

Observed size range: 1400 to 3300 sq ft

1500, 1800, 2000 are in-sample (reliable)

3000 is at the edge; 3500+ would be extrapolation (less reliable)

Example prediction: 2,000 sq ft house

Predicted price: \$262,559

Using our regression equation:

$$\hat{y} = \$115,017 + \$73.77 \times 2,000 = \$262,559$$

How reliable is this prediction?

1. In-sample vs. out-of-sample:

- Our data range: 1,400 to 3,300 sq ft
- Prediction at 2,000 sq ft: **in-sample** (safe)
- Prediction at 5,000 sq ft: **out-of-sample** (risky extrapolation)

2. Prediction accuracy:

- Standard error: \$23,162
- Typical error: about $\pm \$23,000$ around the prediction
- **Informal prediction interval:** roughly 239,000 to 286,000
- (Chapter 7 will cover formal prediction intervals)

3. Why predictions aren't perfect:

- Our model only includes size
- Missing factors affect individual houses:
 - Neighborhood quality
 - Number of bathrooms

- Lot size
- Age and condition
- Unique features

Understanding residuals:

A **residual** is the prediction error for one observation:

$$\begin{aligned}\text{residual} &= \text{actual price} - \text{predicted price} \\ &= y - \hat{y}\end{aligned}$$

Positive residual: House sold for MORE than predicted (underestimate) **Negative residual:** House sold for LESS than predicted (overestimate)

Why do some houses have large residuals?

- Particularly desirable/undesirable location
- Exceptional quality or poor condition
- Unique features not captured by size alone
- May indicate measurement error or unusual circumstances

Key insight: The regression line gives the **average** relationship. Individual houses deviate from this average based on their unique characteristics.

```
In [18]: # Identify potential outliers using residuals
print("\n" + "=" * 70)
print("OUTLIER DETECTION")
print("=" * 70)

# Add residuals and standardized residuals to dataset
data_house['fitted'] = model.fittedvalues
data_house['residual'] = model.resid
data_house['std_resid'] = model.resid / model.resid.std()

# Observations with large residuals (>2 std deviations)
outliers = data_house[np.abs(data_house['std_resid']) > 2]

print(f"\nObservations with large residuals (|standardized residual| > 2):")
if len(outliers) > 0:
    print(outliers[['price', 'size', 'fitted', 'residual', 'std_resid']])
else:
    print(" None found (all residuals within 2 standard deviations)")

print(f"\nTop 5 largest residuals (in absolute value):")
top_residuals = data_house.nlargest(5, 'residual', keep='all')[['price', 'size', 'fitted',
'residual']]
print(top_residuals)
```

```
=====
OUTLIER DETECTION
=====

Observations with large residuals (|standardized residual| > 2):
   price    size     fitted    residual  std_resid
27  340000   2400  292067.779503  47932.220497   2.072629

Top 5 largest residuals (in absolute value):
   price    size     fitted    residual
27  340000   2400  292067.779503  47932.220497
18  255000   1500  225673.843168  29326.156832
15  245000   1400  218296.739130  26703.260870
19  258500   1600  233050.947205  25449.052795
26  310000   2300  284690.675466  25309.324534
```

| 5.9 Regression and Correlation

There's a close relationship between the regression slope and the correlation coefficient:

$$b_2 = r_{xy} \times \frac{s_y}{s_x}$$

Key insights:

- $r_{xy} > 0 \Rightarrow b_2 > 0$ (positive correlation means positive slope)
- $r_{xy} < 0 \Rightarrow b_2 < 0$ (negative correlation means negative slope)
- $r_{xy} = 0 \Rightarrow b_2 = 0$ (zero correlation means zero slope)

But regression and correlation differ:

- Correlation treats x and y symmetrically: $r_{xy} = r_{yx}$
- Regression does not: slope from regressing y on x \neq inverse of slope from regressing x on y

Why This Relationship Matters:

The formula $b_2 = r \times (s_y/s_x)$ reveals an important insight about the connection between correlation and regression:

Correlation (r):

- Scale-free measure (unitless)
- Same value regardless of measurement units
- Symmetric: $r(\text{price}, \text{size}) = r(\text{size}, \text{price})$

Regression slope (b_2):

- Scale-dependent (has units: \$/sq ft in our example)
- Changes when we rescale variables
- Asymmetric: slope from price~size \neq inverse of slope from size~price

The ratio (s_y/s_x):

- Converts between correlation and slope
- Accounts for the relative variability of y and x
- Explains why slopes have interpretable units while r does not

Practical implication: This is why we use **regression** (not just correlation) in economics—we need interpretable coefficients with units (\$/sq ft, % change, etc.) to make policy recommendations and predictions.

In [19]:

```
# Verify relationship between slope and correlation
print("= * 70")
print("RELATIONSHIP: SLOPE = CORRELATION × (SD_Y / SD_X)")
print("= * 70")

r = corr_matrix.loc['price', 'size']
s_y = price.std()
s_x = size.std()
b2_from_r = r * (s_y / s_x)

print("\nFrom regression:")
print(f"  Slope (b2) = {slope:.4f}")

print("\nFrom correlation:")
print(f"  r = {r:.4f}")
print(f"  s_y = {s_y:.4f}")
print(f"  s_x = {s_x:.4f}")
print(f"  b2 = r × (s_y / s_x) = {r:.4f} × ({s_y:.4f} / {s_x:.4f}) = {b2_from_r:.4f}")

print("\nMatch: {np.isclose(slope, b2_from_r)}")
```

```
=====
RELATIONSHIP: SLOPE = CORRELATION × (SD_Y / SD_X)
=====

From regression:
  Slope (b2) = 73.7710

From correlation:
  r = 0.7858
  s_y = 37390.7107
  s_x = 398.2721
  b2 = r × (s_y / s_x) = 0.7858 × (37390.7107 / 398.2721) = 73.7710

Match: True
```

5.10 Causation

Critical distinction: Regression measures **association**, not **causation**.

Our regression shows that larger houses are associated with higher prices. But we cannot conclude that:

- Adding square footage to a house will increase its price by \$73.77 per sq ft

Why not?

- **Omitted variables:** Many factors affect price (location, quality, age, condition)
- **Reverse causality:** Could price influence size? (e.g., builders construct larger houses in expensive areas)
- **Confounding:** A third variable (e.g., neighborhood quality) may influence both size and price

Demonstrating non-symmetry: Reverse regression

If we regress x on y (instead of y on x), we get a different slope:

- Original: $\hat{y} = b_1 + b_2x$
- Reverse: $\hat{x} = c_1 + c_2y$

These two regressions answer different questions and have different slopes!

Key Concept 5.7: Association vs. Causation

Regression measures association, not causation. A regression coefficient shows how much y changes when x changes, but does not prove that x causes y. Causation requires additional assumptions, experimental design, or advanced econometric techniques (Chapter 17). Regression is directional and asymmetric: regressing y on x gives a different slope than regressing x on y.

When to Use Nonparametric vs. Parametric Regression:

Use parametric (OLS linear regression) when:

- Theory suggests a linear relationship
- You need interpretable coefficients (\$73.77 per sq ft)
- Sample size is small to moderate ($n < 100$)
- You want statistical inference (t-tests, confidence intervals)

Use nonparametric (LOWESS, kernel) when:

- Exploring data without strong prior assumptions

- Checking whether linear model is appropriate (diagnostic)
- Relationship appears curved or complex
- Large sample size ($n > 100$) provides enough data for flexible fitting

Best practice: Start with scatter plot + nonparametric curve to check for nonlinearity, then use parametric model if linear assumption is reasonable.

Transition Note: We've learned how to measure and quantify relationships. Now we address a critical question: does association imply causation? This distinction is fundamental to interpreting regression results correctly.

In [20]:

```
# Reverse regression: size ~ price
print("=" * 70)
print("REVERSE REGRESSION: DEMONSTRATING NON-SYMMETRY")
print("=" * 70)

reverse_model = ols('size ~ price', data=data_house).fit()

print("\nOriginal Regression (price ~ size):")
print(f"  ŷ = {model.params['Intercept']:.2f} + {model.params['size']:.4f} × size")
print(f"  Slope: {model.params['size']:.4f}")
print(f"  R-squared: {model.rsquared:.4f}")

print("\nReverse Regression (size ~ price):")
print(f"  x̂ = {reverse_model.params['Intercept']:.2f} +
{reverse_model.params['price']:.6f} × price")
print(f"  Slope: {reverse_model.params['price']:.6f}")
print(f"  R-squared: {reverse_model.rsquared:.4f}")

print("\nComparison:")
print(f"  1 / b₂ = 1 / {model.params['size']:.4f} = {1/model.params['size']:.6f}")
print(f"  c₂ = {reverse_model.params['price']:.6f}")
print(f"  Are they equal? {np.isclose(1/model.params['size'],
reverse_model.params['price'])}")

print("\nKey insight:")
print("  • Original slope: $1 increase in size → ${:.2f} increase in
price".format(model.params['size']))
print("  • Reverse slope: $1 increase in price → {:.6f} sq ft increase in
size".format(reverse_model.params['price']))
print("  • These answer different questions!")

print("\nNote: Both regressions have the same R² because in simple regression,"
print("      R² = r² regardless of which variable is on the left-hand side.")
```

=====

REVERSE REGRESSION: DEMONSTRATING NON-SYMMETRY

=====

Original Regression (price ~ size):

$\hat{y} = 115,017.28 + 73.7710 \times \text{size}$
Slope: 73.7710
R-squared: 0.6175

Reverse Regression (size ~ price):

$\hat{x} = -242.44 + 0.008370 \times \text{price}$
Slope: 0.008370
R-squared: 0.6175

Comparison:

$1 / b_2 = 1 / 73.7710 = 0.013555$
 $c_2 = 0.008370$
Are they equal? False

Key insight:

- Original slope: \$1 increase in size → \$73.77 increase in price
- Reverse slope: \$1 increase in price → 0.008370 sq ft increase in size
- These answer different questions!

Note: Both regressions have the same R² because in simple regression,
R² = r² regardless of which variable is on the left-hand side.

CRITICAL DISTINCTION: Association ≠ Causation

What our regression shows:

$$\text{price} = \$115,017 + \$73.77 \times \text{size}$$

What we CAN say:

- Larger houses are **associated with** higher prices
- Size and price move together in a predictable way
- We can **predict** price from size with reasonable accuracy

What we CANNOT say:

- Adding square footage to your house will increase its value by exactly \$73.77 per sq ft
- Size **causes** the price to be higher
- Buying a bigger house will make it worth more

Why not? Three reasons:

1. Omitted variables (confounding)

- Many factors affect BOTH size and price:

- **Neighborhood quality:** Rich neighborhoods have larger, more expensive houses
- **Lot size:** Bigger lots allow bigger houses AND command higher prices
- **Build quality:** High-quality construction → larger AND more expensive
- The \$73.77 coefficient captures both direct effects of size AND correlated factors

2. Reverse causality

- Our model: size → price
- Alternative: price → size?
 - In expensive areas, builders construct larger houses because buyers can afford them
 - The causal arrow may run both ways

3. Measurement of different concepts

- **Cross-sectional comparison:** 2,000 sq ft house vs. 1,500 sq ft house (different houses)
- **Causal question:** What happens if we ADD 500 sq ft to ONE house?
- These are different questions with potentially different answers!

The reverse regression demonstration:

Original: price ~ size

- Slope: \$73.77 per sq ft

Reverse: size ~ price

- Slope: 0.00837 sq ft per dollar

Key observation:

- If regression = causation, these should be reciprocals
- $1 / 73.77 = 0.01355 \neq 0.00837$
- They're NOT reciprocals! This reveals regression measures association, not causation

When can we claim causation?

- **Randomized experiments:** Randomly assign house sizes
- **Natural experiments:** Find exogenous variation in size
- **Careful econometric methods:** Instrumental variables, difference-in-differences, etc. (advanced topics)

Economic intuition: In reality, building an addition probably DOES increase house value, but perhaps not by exactly \$73.77/sq ft. The true causal effect depends on quality, location, and market conditions — factors our simple regression doesn't isolate.

| 5.11 Nonparametric Regression

Parametric regression (like OLS) assumes a specific functional form (e.g., linear).

Nonparametric regression allows the relationship to be more flexible, letting the data determine the shape without imposing a specific functional form.

Common methods:

1. **LOWESS** (Locally Weighted Scatterplot Smoothing): Fits weighted regressions in local neighborhoods
2. **Kernel smoothing**: Weighted averages using kernel functions
3. **Splines**: Piecewise polynomials

Uses:

- Exploratory data analysis
- Checking linearity assumption
- Flexible modeling when functional form is unknown

In [21]:

```
# Nonparametric regression
print("=" * 70)
print("NONPARAMETRIC REGRESSION")
print("=" * 70)

# LOWESS smoothing
lowess_result = lowess(price, size, frac=0.6)

# Kernel smoothing (Gaussian filter approximation)
sort_idx = np.argsort(size)
size_sorted = size.iloc[sort_idx]
price_sorted = price.iloc[sort_idx]
sigma = 2 # bandwidth parameter
price_smooth = gaussian_filter1d(price_sorted, sigma)

# Plot comparison
fig, ax = plt.subplots(figsize=(12, 7))

# Scatter plot
ax.scatter(size, price, s=80, alpha=0.6, color='black',
           edgecolor='black', label='Actual data', zorder=1)

# OLS line
ax.plot(size, model.fittedvalues, color='blue', linewidth=2.5,
        label='OLS (parametric)', zorder=2)

# LOWESS
ax.plot(lowess_result[:, 0], lowess_result[:, 1], color='red',
        linewidth=2.5, linestyle='--', label='LOWESS', zorder=3)

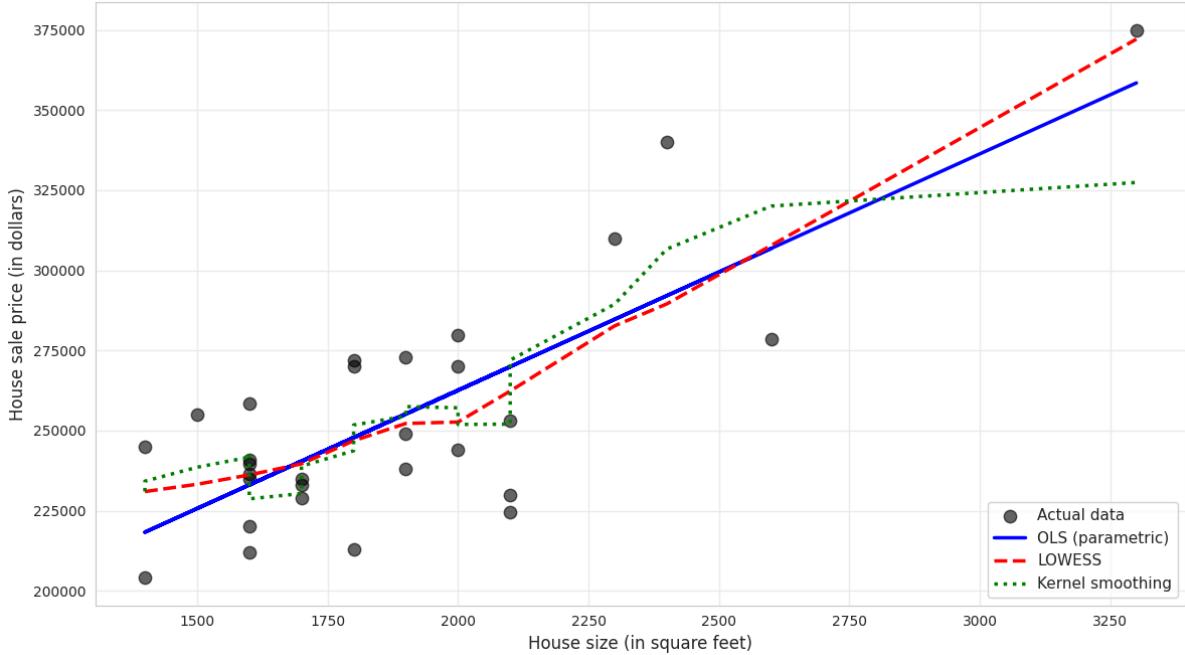
# Kernel smoothing
ax.plot(size_sorted, price_smooth, color='green', linewidth=2.5,
        linestyle=':', label='Kernel smoothing', zorder=4)

ax.set_xlabel('House size (in square feet)', fontsize=12)
ax.set_ylabel('House sale price (in dollars)', fontsize=12)
ax.set_title('Figure 5.6: Parametric vs Nonparametric Regression',
             fontsize=14, fontweight='bold')
ax.legend(fontsize=11, loc='lower right')
ax.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()

print("\nInterpretation:")
print("• OLS (blue solid): Assumes linear relationship")
print("• LOWESS (red dashed): Flexible, data-driven curve")
print("• Kernel smoothing (green dotted): Another flexible method")
print("\nFor this data, all three methods are similar, suggesting")
print("that the linear model is a reasonable approximation.")
```

```
=====
NONPARAMETRIC REGRESSION
=====
```

Figure 5.6: Parametric vs Nonparametric Regression



Interpretation:

- OLS (blue solid): Assumes linear relationship
- LOWESS (red dashed): Flexible, data-driven curve
- Kernel smoothing (green dotted): Another flexible method

For this data, all three methods are similar, suggesting that the linear model is a reasonable approximation.

Comparing three approaches to fitting the data:

1. OLS (Ordinary Least Squares) — BLUE LINE

- **Parametric:** Assumes linear relationship
- **Equation:** $\hat{y} = 115,017 + 73.77 \times \text{size}$
- **Advantage:** Simple, interpretable, efficient
- **Limitation:** Restricted to straight lines

2. LOWESS (Locally Weighted Scatterplot Smoothing) — RED DASHED

- **Nonparametric:** Lets data determine the shape
- **Method:** Fits weighted regressions in local neighborhoods
- **Advantage:** Flexible, can capture curves
- **Limitation:** Harder to interpret, more complex

3. Kernel Smoothing — GREEN DOTTED

- **Nonparametric:** Weighted moving averages
- **Method:** Uses Gaussian kernel to smooth nearby points

- **Advantage:** Very smooth curves
- **Limitation:** Choice of bandwidth affects results

What does this comparison tell us?

Key observation: All three lines are very similar!

- LOWESS and kernel smoothing follow OLS closely
- No obvious systematic curvature
- The relationship appears genuinely linear

This validates our linear model:

- If nonparametric methods showed strong curvature, we'd question the linear assumption
- Since they align with OLS, the linear model is appropriate
- We can confidently use the simpler parametric approach

When would nonparametric methods differ?

Example scenarios:

- **Diminishing returns:** Price increases with size, but at a decreasing rate
- **Threshold effects:** Small houses have steep price-size relationship, large houses flatten
- **Nonlinear relationships:** Exponential, logarithmic, or polynomial patterns

For our housing data:

- Linear model works well
- Adding complexity (nonparametric) doesn't improve fit much
- **Occam's Razor:** Choose the simpler model when performance is similar

Practical use of nonparametric methods:

- **Exploratory analysis:** Check for nonlinearity before modeling
- **Model diagnostics:** Verify linear assumption
- **Flexible prediction:** When functional form is unknown
- **Complex relationships:** When theory doesn't suggest specific form

Bottom line: Nonparametric methods confirm that our linear regression is appropriate for this dataset. The relationship between house price and size is genuinely linear, not curved.

| Key Takeaways

Visualization and Correlation

- **Two-way tabulations**, scatterplots, and correlation are essential first steps in bivariate analysis
- **Scatterplots** provide visual evidence of relationships and help identify direction, strength, form, and outliers
- Two-way tabulations with **expected frequencies** enable chi-squared tests of independence for categorical data
- The **correlation coefficient (r)** is a scale-free measure of linear association ranging from -1 to +1
- **Covariance** measures the direction of association but depends on the units of measurement
- For house price and size, **r = 0.786** indicates strong positive linear association
- **Autocorrelation** extends correlation to time series, measuring how a variable relates to its own past values

Regression Analysis and Interpretation

- The **regression line** $\hat{y} = b_1 + b_2x$ is estimated by **ordinary least squares (OLS)**, which minimizes the sum of squared residuals
- The **slope b_2** measures the change in y for a one-unit change in x and is the most important interpretable quantity
- For house prices, **$b_2 = \$73.77$** means each additional square foot is associated with a \$73.77 price increase
- The **intercept b_1** represents the predicted y when $x = 0$ (often not meaningful if $x = 0$ is outside the data range)
- **Residuals** ($e = y - \hat{y}$) measure prediction errors; OLS makes the sum of squared residuals as small as possible
- Regression of y on only an intercept yields the **sample mean** as the fitted value, showing OLS generalizes univariate statistics
- The formulas $b_2 = \Sigma(x_i - \bar{x})(y_i - \bar{y}) / \Sigma(x_i - \bar{x})^2$ and $b_1 = \bar{y} - b_2\bar{x}$ enable manual computation
- The regression slope equals $b_2 = r_{xy} \times (s_y/s_x)$, connecting regression and correlation

Model Fit and Evaluation

- **R-squared** measures the fraction of variation in y explained by x , ranging from 0 (no fit) to 1 (perfect fit)
- $R^2 = (\text{Explained SS}) / (\text{Total SS}) = 1 - (\text{Residual SS}) / (\text{Total SS})$
- For bivariate regression, $R^2 = r^2_{xy}$ (squared correlation coefficient)
- For house prices, $R^2 = 0.618$ means 62% of price variation is explained by size variation
- **Standard error of regression (s_e)** measures the typical size of residuals in the units of y
- **Low R^2 doesn't mean regression is uninformative**—the coefficient can still be statistically significant and economically important
- R^2 depends on data aggregation and choice of dependent variable; use it to compare models with the **same dependent variable**
- Computer regression output provides coefficients, standard errors, t-statistics, p-values, F-statistics, and ANOVA decomposition

Prediction, Causation, and Extensions

- **Predictions** use $\hat{y} = b_1 + b_2x^*$ to forecast y for a given x^*
- **In-sample predictions** use observed x values (fitted values); **out-of-sample predictions** use new x values
- **Extrapolation** beyond the sample range of x can be unreliable
- **Outliers** can strongly influence regression estimates, especially if far from both \bar{x} and \bar{y}
- **Association does not imply causation**—regression measures correlation, not causal effects
- **Confounding variables**, reverse causality, or selection bias can create associations without causation
- Establishing **causation** requires experimental design, natural experiments, or advanced econometric techniques (Chapter 17)
- **Regression is directional and asymmetric**: regressing y on x gives a different slope than regressing x on y
- The two slopes are **NOT reciprocals**, reflecting that regression treats y and x differently
- **Nonparametric regression** (local linear, lowess) provides flexible alternatives without assuming linearity
- Nonparametric methods are useful for **exploratory analysis** and checking the appropriateness of linear models

Connection to Economic Analysis

- The strong relationship ($R^2 = 0.62$) between size and price makes economic sense: buyers pay a premium for space
 - The imperfect fit reminds us that **many factors beyond size affect house values** (location, quality, age, condition)
 - Regression provides the **foundation for econometric analysis**, allowing us to quantify economic relationships
 - This chapter's bivariate methods extend naturally to **multiple regression** (Chapters 10-12) with many explanatory variables
 - Understanding association vs. causation is **critical for policy analysis** and program evaluation
-

Congratulations! You've mastered the basics of bivariate data analysis and simple linear regression. You now understand how to measure and visualize relationships between two variables, fit and interpret a regression line, assess model fit, and recognize the crucial distinction between association and causation. These tools form the foundation for all econometric analysis!

I Practice Exercises

Test your understanding of bivariate data analysis and regression with these exercises.

Exercise 1: Correlation Interpretation

Suppose the correlation between years of education and annual income is $r = 0.35$.

- What does this correlation tell us about the relationship between education and income?
 - If we measured income in thousands of dollars instead of dollars, would the correlation change?
 - Can we conclude that education causes higher income? Why or why not?
-

Exercise 2: Computing Correlation

Given the following data for variables x and y with $n = 5$ observations:

- $\sum(x_i - \bar{x})(y_i - \bar{y}) = 20$

- $\sum(x_i - \bar{x})^2 = 50$
- $\sum(y_i - \bar{y})^2 = 10$

(a) Calculate the sample correlation coefficient r .

(b) Is this a strong, moderate, or weak correlation?

(c) Is the relationship positive or negative?

Exercise 3: Regression Slope Calculation

For the data in Exercise 2:

(a) Calculate the regression slope coefficient b_2 from regression of y on x .

(b) Verify the relationship: $b_2 = r \times (s_y / s_x)$

(c) If $\bar{x} = 10$ and $\bar{y} = 25$, calculate the intercept b_1 .

Exercise 4: R-squared Interpretation

A regression of test scores on hours studied yields $R^2 = 0.40$.

(a) What percentage of test score variation is explained by hours studied?

(b) What percentage is due to other factors?

(c) Does this mean studying is not important? Explain.

(d) If the correlation is $r = 0.632$, verify that $R^2 = r^2$.

Exercise 5: Prediction

From the house price regression: $\hat{y} = 115,017 + 73.77 \times \text{size}$

(a) Predict the price of a house with 2,200 square feet.

(b) Predict the price of a house with 5,000 square feet.

(c) Which prediction is more reliable? Why?

(d) If the standard error is \$23,551, what does this tell us about prediction accuracy?

Exercise 6: Residuals

A house of 1,800 sq ft sold for 270,000. The regression predicts $\hat{y} = 247,805$.

-
- (a) Calculate the residual for this observation.
 - (b) Is the actual price higher or lower than predicted?
 - (c) What might explain this large positive residual?
 - (d) Would you consider this an outlier? Why or why not?
-

Exercise 7: Causation vs. Association

Studies show that ice cream sales and crime rates are positively correlated.

- (a) Does this mean ice cream causes crime? Explain.
 - (b) What might be a confounding variable?
 - (c) How would you design a study to test for causation?
 - (d) Give another example where correlation does not imply causation.
-

Exercise 8: Python Practice

Using the house price data or your own dataset:

- (a) Create a scatterplot with a fitted regression line.
 - (b) Calculate the correlation coefficient using `pandas .corr()` method.
 - (c) Fit an OLS regression using `statsmodels` and interpret the output.
 - (d) Create residual plots to check for outliers.
 - (e) Compare OLS with LOWESS nonparametric regression.
-

Solutions to selected exercises:

- **Exercise 2a:** $r = 20 / \sqrt{(50 \times 10)} = 20 / \sqrt{500} = 0.894$
- **Exercise 3a:** $b_2 = 20 / 50 = 0.4$
- **Exercise 4a:** 40% explained, 60% due to other factors
- **Exercise 5a:** $\hat{y} = 115,017 + 73.77 \times 2,200 = \$277,311$

For complete solutions and additional practice problems, see the course website.

| 5.12 Case Studies

Now that you've learned the fundamentals of bivariate analysis, correlation, and regression, let's apply these techniques to real economic research questions using the **Economic Convergence Clubs** dataset from Mendez (2020).

Why case studies matter:

- Bridge theory and application: Move from learning formulas to answering substantive economic questions
- Build analytical workflow: Practice the complete cycle from visualization to interpretation
- Develop critical thinking: Distinguish association from causation in real data
- Connect to research: See how econometric tools support published economic studies

Case Study 1: Capital and Productivity Across Countries

Research Question: What is the relationship between capital per worker and labor productivity across countries? Does this relationship vary by income group?

Background: Traditional growth theory suggests that countries with more capital per worker should have higher labor productivity. This is the **capital-output relationship**—a fundamental concept in development economics. However, differences in technology, institutions, and human capital mean that capital alone doesn't fully explain productivity differences.

This research ([Mendez, 2020](#)) uses panel data from 108 countries to study convergence clubs in labor productivity. Rather than assuming all countries converge to a single equilibrium, the analysis identifies distinct groups (clubs) that converge toward different productivity levels.

The Data: We'll use the same dataset from Chapter 1, but now apply Chapter 5's bivariate tools:

- **Panel dataset:** 108 countries observed from 1990-2014 (2,700 country-year observations)
- **Key variables:**
 - `lp` : Labor productivity (output per worker, in 2011 USD PPP)
 - `k1` : Capital per worker (physical capital stock per worker)
 - `h` : Human capital index (based on years of schooling)

- `TFP` : Total factor productivity (aggregate efficiency)
- `hi1990` : High-income country indicator (as of 1990)
- `region` : Regional classification

Your Task: Use Chapter 5's visualization, correlation, and regression tools to explore the capital-productivity relationship and test whether it differs across country groups.

Key Concept 5.8: Capital-Productivity Relationship

The regression of labor productivity on capital per worker quantifies the capital-output elasticity—how much productivity increases when capital per worker rises by 1%. In cross-country data, this relationship reflects both:

1. **Diminishing returns to capital** (*holding technology constant*)
2. **Technology differences** across countries (*correlated with capital accumulation*)

Distinguishing these two effects requires controlling for other factors (human capital, TFP), which we'll learn in later chapters on multiple regression.

How to Use These Tasks

Progressive difficulty:

- **Tasks 1-2:** Guided (detailed instructions, code provided)
- **Tasks 3-4:** Semi-guided (moderate guidance, you write most code)
- **Tasks 5-6:** Independent (minimal guidance, design your own analysis)

Work incrementally: Complete tasks in order. Each builds on previous skills.

Learn by doing: Modify code, experiment with variables, interpret results economically.

Task 1: Load and Explore the Data (Guided)

Objective: Load the convergence clubs dataset and generate descriptive statistics for key variables.

Instructions: Run the code below to load data and examine the structure.

```

# Import required libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from statsmodels.formula.api import ols

# Load convergence clubs dataset
df = pd.read_csv(
    "https://raw.githubusercontent.com/quarcs-lab/mendez2020-convergence-clubs-code-
data/master/assets/dat.csv",
    index_col=["country", "year"]
).sort_index()

# Display dataset info
print(f"Dataset shape: {df.shape[0]} observations, {df.shape[1]} variables")
print(f"Countries: {len(df.index.get_level_values('country').unique())}")
print(f"Years: {df.index.get_level_values('year').min()} to
{df.index.get_level_values('year').max()}")


# Preview first few observations
print("\nFirst 5 observations:")
print(df[['lp', 'kl', 'h', 'TFP', 'hi1990', 'region']].head())


# Generate descriptive statistics
print("\nDescriptive statistics (key variables):")
print(df[['lp', 'kl', 'h', 'TFP']].describe().round(2))

```

What to observe:

- How many observations? How many countries?
- What is the range of labor productivity (`lp`)? Capital per worker (`kl`)?
- Are there missing values in key variables?

Task 2: Visualize the Capital-Productivity Relationship (Semi-guided)

Objective: Create a scatterplot to visualize the relationship between capital per worker and labor productivity.

Instructions:

1. Prepare a subset of data with non-missing values for `lp` and `kl`
2. Create a scatterplot with capital per worker on the x-axis and labor productivity on the y-axis
3. Add appropriate labels and title
4. Interpret the pattern: positive/negative? Linear? Outliers?

Starter code:

```

# Prepare data (remove missing values)
plot_data = df[['lp', 'kl']].dropna()

# Create scatterplot
fig, ax = plt.subplots(figsize=(10, 6))
ax.scatter(plot_data['kl'], plot_data['lp'], alpha=0.5, s=20)

# Add labels and formatting
ax.set_xlabel('Capital per Worker (thousands, 2011 USD PPP)', fontsize=12)
ax.set_ylabel('Labor Productivity (thousands, 2011 USD PPP)', fontsize=12)
ax.set_title('Capital per Worker vs. Labor Productivity (108 countries, 1990-2014)', fontsize=14)
ax.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()

# What pattern do you see?
print("\n Interpretation:")
print("- Relationship: [Positive/Negative/No clear pattern]")
print("- Strength: [Strong/Moderate/Weak]")
print("- Outliers: [Yes/No] - [Describe if present]")

```

Questions:

- Is the relationship positive (as theory predicts)?
- Is it approximately linear, or curved?
- Are there countries with very high capital but moderate productivity (or vice versa)?

Task 3: Calculate the Correlation Coefficient (Semi-guided)

Objective: Quantify the strength of the linear relationship between capital and productivity using the correlation coefficient.

Instructions:

1. Calculate the Pearson correlation coefficient between `lp` and `kl`
2. Interpret the magnitude: Is it close to 0 (weak), 0.5 (moderate), or 1.0 (strong)?
3. Test statistical significance: Is the relationship likely due to chance?

Hint: Use `.corr()` method or `np.corrcoef()` function.

Example structure:

```

# Calculate correlation
corr = plot_data[['lp', 'kl']].corr()
print("Correlation matrix:")
print(corr)

# Extract the correlation coefficient
r = corr.loc['lp', 'kl']
print(f"\nCorrelation between capital and productivity: r = {r:.4f}")

# Interpretation
print(f"\nInterpretation:")
print(f"- Magnitude: {'Strong' if abs(r) > 0.7 else 'Moderate' if abs(r) > 0.4 else 'Weak'}")
print(f"- Direction: {'Positive' if r > 0 else 'Negative'}")
print(f"- R2 (shared variation): {r**2:.4f} ({r**2*100:.2f}%)")

```

Questions:

- How much of the variation in productivity is explained by capital?
 - Does this match what you observed in the scatterplot?
-

Task 4: Estimate the Regression Line (More Independent)

Objective: Estimate an OLS regression of labor productivity on capital per worker and interpret the slope coefficient.

Instructions:

1. Prepare regression data (remove missing values, reset index if needed)
2. Estimate: `lp ~ kl` using `ols()` from statsmodels
3. Display the regression summary
4. Extract and interpret the slope coefficient economically
5. Report the R-squared value

Key questions to answer:

- What is the slope coefficient? Interpret it in economic terms.
- Is the coefficient statistically significant ($p < 0.05$)?
- What percentage of productivity variation is explained by capital?
- Does the relationship appear causal, or could there be omitted variables?

Hint: Remember to reset the index before regression if you're using formula syntax.

Key Concept 5.9: Interpreting Slope in Economic Context

The regression slope β_1 in $\text{productivity} = \beta_0 + \beta_1 \times \text{capital}$ measures the **average change in productivity (in thousands of USD) for each additional thousand USD of capital per worker.**

In cross-country data, this captures both:

- **True capital effect** (more machines → higher output)
- **Confounding factors** (richer countries have both more capital AND better technology/institutions)

To isolate the true capital effect, we need **multiple regression** (Chapters 6-9) to control for human capital, TFP, and other factors.

Task 5: Compare Relationships Across Income Groups (Independent)

Objective: Investigate whether the capital-productivity relationship differs between high-income and developing countries.

Research Question: Do high-income countries have a stronger/weaker capital-productivity association than developing countries?

Instructions:

1. Group the data by `hi1990` (high-income indicator)
2. Calculate the correlation coefficient for each group separately
3. Create comparative scatterplots (one color per group)
4. (Advanced) Run separate regressions for each group and compare slope coefficients
5. Interpret differences: Why might the relationship vary by income level?

Hints:

- Use `df.groupby('hi1990')` to split data
- Use different colors in scatter plot for each group
- Compare both correlations and regression slopes

Expected findings:

- High-income countries may show **weaker** capital-productivity correlation (approaching diminishing returns)
- Developing countries may show **stronger** correlation (still accumulating capital)

- Consider alternative explanations!
-

Task 6: Explore Alternative Relationships (Independent)

Objective: Investigate other bivariate relationships relevant to growth and convergence.

Choose ONE of the following research questions:

Option A: Human capital vs. productivity

- Research question: Does education (human capital) explain productivity differences?
- Variables: lp (productivity) and h (human capital index)
- Expected: Positive relationship, but possibly weaker than capital

Option B: TFP vs. productivity

- Research question: How much of productivity is driven by aggregate efficiency (TFP)?
- Variables: lp (productivity) and TFP (total factor productivity)
- Expected: Strong positive relationship (TFP is a key driver)

Option C: Time trend in productivity

- Research question: Has average global productivity increased over time?
- Variables: Year vs. average lp across all countries
- Expected: Positive trend, but with variation across countries

Your analysis should include:

1. Scatterplot with clear labels
 2. Correlation coefficient
 3. Regression results (slope, R^2 , significance)
 4. Economic interpretation: What does this relationship tell us about growth and development?
-

Key Concept 5.10: Correlation vs. Causation in Growth Economics

Our regressions show **associations**—capital and productivity move together. But association ≠ causation:

1. **Reverse causality:** Does capital cause productivity, or does high productivity enable more capital accumulation?
2. **Omitted variables:** Technology, institutions, geography, culture—all affect both capital and productivity
3. **Selection effects:** High-income countries differ systematically from developing countries in ways beyond capital

Establishing causation requires:

- **Controlled experiments** (rarely feasible for countries)
- **Natural experiments** (e.g., policy changes, resource discoveries)
- **Instrumental variables** (advanced econometric methods, Chapter 14–15)

For now, interpret regression slopes as **descriptive associations**, not causal effects.

What You've Learned from This Case Study

Through this hands-on exploration of capital and productivity across countries, you've applied all Chapter 5 tools:

Visualization: Scatterplots reveal patterns before quantifying relationships

Correlation: Pearson coefficient quantifies linear association strength

Regression: OLS slope measures average change in Y per unit change in X

Interpretation: Translated coefficients into economic meaning (dollars, percentages)

Model fit: R-squared shows explanatory power (proportion of variation explained)

Comparative analysis: Group comparisons reveal heterogeneity (relationships vary by income level)

Critical thinking: Distinguished association from causation; recognized omitted variable bias

Connection to the Research: The patterns you've discovered—the capital-productivity relationship, differences across income groups, the role of TFP—are the empirical foundations for Mendez (2020)'s convergence clubs analysis. The full research uses advanced methods (nonparametric regression, clustering algorithms) to formally identify clubs, which you'll learn in later chapters.

Looking ahead:

- **Chapter 6-7:** Multiple regression to control for human capital, TFP, and other factors
 - **Chapter 10-11:** Panel data methods to exploit time variation within countries
 - **Chapter 15-17:** Advanced methods for causal inference and club detection
-

Congratulations! You've completed Chapter 5 and applied bivariate analysis to real cross-country growth data. Continue to Chapter 6 to learn how to extend regression analysis to multiple explanatory variables.

Case Study 2: Nighttime Lights and Development: A Bivariate Exploration

In Chapter 1, we introduced the DS4Bolivia project and estimated a simple regression of development on nighttime lights. In this case study, we apply Chapter 5's bivariate tools—scatter plots, correlations, OLS regression, and model fit measures—to explore multiple satellite-development relationships in greater depth.

Data: Cross-sectional dataset covering 339 Bolivian municipalities from the [DS4Bolivia Project](#).

Key variables:

- `mun` : Municipality name
- `dep` : Department (administrative region)
- `imds` : Municipal Sustainable Development Index (0–100 composite)
- `ln_NTLpc2017` : Log nighttime lights per capita (2017)
- `index_sdg1` : SDG 1 Index — No Poverty (0–100)
- `index_sdg4` : SDG 4 Index — Quality Education (0–100)
- `index_sdg8` : SDG 8 Index — Decent Work and Economic Growth (0–100)
- `sdg7_1_ec` : SDG 7.1 — Electricity coverage (%)
- `sdg1_1_ubn` : Unsatisfied Basic Needs (% of population)

Task 1: Load and Explore (Guided)

Objective: Load the DS4Bolivia dataset, select key variables, and create a two-way frequency table.

Instructions:

1. Load the data from the URL below and select the key variables listed above
2. Use `pd.cut()` to bin the `imds` variable into three equal-frequency groups labeled **Low**, **Medium**, and **High** (terciles)
3. Create a two-way frequency table (cross-tabulation) of `imds` terciles against department using `pd.crosstab()`
4. Examine the table: Which departments have the most municipalities in the *Low* development category?

In []:

```
# Load the DS4Bolivia dataset
url_bol = "https://raw.githubusercontent.com/quarcs-lab/ds4bolivia/master/ds4bolivia_v20250523.csv"
bol = pd.read_csv(url_bol)

# Select key variables for this case study
key_vars = ['mun', 'dep', 'imds', 'ln_NTLpc2017',
            'index_sdg1', 'index_sdg4', 'index_sdg8',
            'sdg7_1_ec', 'sdg1_1_ubn']
bol_cs = bol[key_vars].copy()

print(f"Dataset: {bol_cs.shape[0]} municipalities, {bol_cs.shape[1]} variables")
print(f"Departments: {sorted(bol_cs['dep'].unique())}")
print()

# Bin imds into terciles
bol_cs['imds_group'] = pd.cut(bol_cs['imds'],
                               bins=3,
                               labels=['Low', 'Medium', 'High'])

# Two-way frequency table: imds tercile x department
cross_tab = pd.crosstab(bol_cs['imds_group'], bol_cs['dep'],
                        margins=True, margins_name='Total')
print("Two-Way Frequency Table: IMDS Tercile by Department")
print("-" * 70)
print(cross_tab)
```

Task 2: Scatter Plots (Guided)

Objective: Create a 2x2 grid of scatter plots to compare different satellite-development relationships.

Instructions:

1. Create a figure with four subplots arranged in a 2x2 grid
2. Plot the following relationships:

- (a) `ln_NTLpc2017` vs `imds`
- (b) `ln_NTLpc2017` vs `index_sdg1`
- (c) `ln_NTLpc2017` vs `sdg7_1_ec`
- (d) `sdg1_1_ubn` vs `imds`

3. Add axis labels and subplot titles

4. Discuss: Which relationship appears strongest? Which appears weakest?

In []:

```
# 2x2 scatter plot grid
fig, axes = plt.subplots(2, 2, figsize=(12, 10))

plot_data = bol_cs.dropna(subset=['ln_NTLpc2017', 'imds', 'index_sdg1',
                                   'sdg7_1_ec', 'sdg1_1_ubn'])

# (a) NTL vs IMDS
axes[0, 0].scatter(plot_data['ln_NTLpc2017'], plot_data['imds'],
                   alpha=0.5, color='#008CB7', s=20)
axes[0, 0].set_xlabel('Log NTL per Capita (2017)')
axes[0, 0].set_ylabel('IMDS')
axes[0, 0].set_title('(a) Nighttime Lights vs Development Index')

# (b) NTL vs SDG1 (No Poverty)
axes[0, 1].scatter(plot_data['ln_NTLpc2017'], plot_data['index_sdg1'],
                   alpha=0.5, color='#7A209F', s=20)
axes[0, 1].set_xlabel('Log NTL per Capita (2017)')
axes[0, 1].set_ylabel('SDG 1 Index (No Poverty)')
axes[0, 1].set_title('(b) Nighttime Lights vs No Poverty')

# (c) NTL vs SDG7.1 (Electricity Coverage)
axes[1, 0].scatter(plot_data['ln_NTLpc2017'], plot_data['sdg7_1_ec'],
                   alpha=0.5, color='#C21E72', s=20)
axes[1, 0].set_xlabel('Log NTL per Capita (2017)')
axes[1, 0].set_ylabel('Electricity Coverage (%)')
axes[1, 0].set_title('(c) Nighttime Lights vs Electricity Coverage')

# (d) UBN vs IMDS
axes[1, 1].scatter(plot_data['sdg1_1_ubn'], plot_data['imds'],
                   alpha=0.5, color='#2E86AB', s=20)
axes[1, 1].set_xlabel('Unsatisfied Basic Needs (%)')
axes[1, 1].set_ylabel('IMDS')
axes[1, 1].set_title('(d) Unsatisfied Basic Needs vs Development Index')

plt.suptitle('Bivariate Relationships: Satellite Data and Development in Bolivia',
             fontsize=14, fontweight='bold', y=1.02)
plt.tight_layout()
plt.show()
```

Key Concept 5.11: Nighttime Lights as Development Proxy

*Nighttime light (NTL) intensity measured by satellites correlates with GDP, electrification, and urbanization across the world. The **log per-capita** transformation serves two purposes: the logarithm compresses the highly skewed raw luminosity values, and dividing by population accounts for the mechanical relationship between more people and more light. After these transformations, NTL becomes a meaningful proxy for economic intensity rather than simply population density.*

Task 3: Correlation Analysis (Semi-guided)

Objective: Calculate and visualize the correlation matrix for key development and satellite variables.

Instructions:

1. Select the variables: `imds`, `ln_NTLpc2017`, `index_sdg1`, `index_sdg4`, `index_sdg8`, `sdg7_1_ec`, `sdg1_1_urban`
2. Calculate the Pearson correlation matrix using `.corr()`
3. Display the results as a heatmap or formatted table
4. Identify: Which variable has the **strongest** correlation with `imds`? Which has the **weakest**?

Hint: Use `plt.imshow()` or `sns.heatmap()` (if seaborn is available) to visualize the correlation matrix.

In []:

```
# Your code here: Correlation analysis
#
# Steps:
# 1. Select numeric variables of interest
# 2. Compute correlation matrix
# 3. Display as heatmap or formatted table
# 4. Identify strongest/weakest correlations with imds

# Example structure:
# corr_vars = ['imds', 'ln_NTLpc2017', 'index_sdg1', 'index_sdg4',
#             'index_sdg8', 'sdg7_1_ec', 'sdg1_1_ubn']
# corr_matrix = bol_cs[corr_vars].corr()
# print(corr_matrix.round(3))

#
# # Heatmap
# fig, ax = plt.subplots(figsize=(9, 7))
# im = ax.imshow(corr_matrix, cmap='RdBu_r', vmin=-1, vmax=1)
# ax.set_xticks(range(len(corr_vars)))
# ax.set_yticks(range(len(corr_vars)))
# ax.set_xticklabels(corr_vars, rotation=45, ha='right')
# ax.set_yticklabels(corr_vars)
# for i in range(len(corr_vars)):
#     for j in range(len(corr_vars)):
#         ax.text(j, i, f"{corr_matrix.iloc[i, j]:.2f}",
#                 ha='center', va='center', fontsize=8)
# plt.colorbar(im, ax=ax, label='Pearson Correlation')
# ax.set_title('Correlation Matrix: Development and Satellite Variables')
# plt.tight_layout()
# plt.show()

#
# # Identify strongest/weakest correlations with imds
# imds_corrs = corr_matrix[['imds']].drop('imds').abs().sort_values(ascending=False)
# print(f"\nStrongest correlation with IMDS: {imds_corrs.index[0]} (r = {corr_matrix.loc['imds', imds_corrs.index[0]]:.3f})")
# print(f"Weakest correlation with IMDS: {imds_corrs.index[-1]} (r = {corr_matrix.loc['imds', imds_corrs.index[-1]]:.3f})")
```

Task 4: OLS Regression Line (Semi-guided)

Objective: Estimate and compare OLS regressions predicting IMDS from different variables.

Instructions:

1. Estimate OLS: `imds ~ ln_NTLpc2017`. Report the slope, intercept, and R^2
2. Overlay the fitted regression line on a scatter plot of `ln_NTLpc2017` vs `imds`
3. Estimate a second OLS: `imds ~ sdg1_1_ubn`. Report slope, intercept, and R^2
4. Compare: Which predictor explains more variation in development?

Hint: Use `ols()` from statsmodels as practiced in this chapter.

In []:

```
# Your code here: OLS regression with fitted lines
#
# Steps:
# 1. Estimate imds ~ ln_NTLpc2017
# 2. Overlay fitted line on scatter plot
# 3. Estimate imds ~ sdg1_1_ubn
# 4. Compare R-squared values

# Example structure:
# reg_data = bol_cs[['imds', 'ln_NTLpc2017', 'sdg1_1_ubn']].dropna()
#
# # Model 1: NTL
# model_ntl = ols('imds ~ ln_NTLpc2017', data=reg_data).fit()
# print("Model 1: IMDS ~ Log NTL per Capita")
# print(f" Slope: {model_ntl.params['ln_NTLpc2017']:.4f}")
# print(f" Intercept: {model_ntl.params['Intercept']:.4f}")
# print(f" R-squared: {model_ntl.rsquared:.4f}")
#
# # Model 2: UBN
# model_ubn = ols('imds ~ sdg1_1_ubn', data=reg_data).fit()
# print("\nModel 2: IMDS ~ Unsatisfied Basic Needs")
# print(f" Slope: {model_ubn.params['sdg1_1_ubn']:.4f}")
# print(f" Intercept: {model_ubn.params['Intercept']:.4f}")
# print(f" R-squared: {model_ubn.rsquared:.4f}")
#
# # Scatter + fitted line for Model 1
# fig, ax = plt.subplots(figsize=(8, 6))
# ax.scatter(reg_data['ln_NTLpc2017'], reg_data['imds'], alpha=0.4, color='#008CB7', s=20)
# x_range = np.linspace(reg_data['ln_NTLpc2017'].min(), reg_data['ln_NTLpc2017'].max(), 100)
# ax.plot(x_range, model_ntl.params['Intercept'] + model_ntl.params['ln_NTLpc2017'] * x_range,
#          color='#C21E72', linewidth=2, label=f'OLS: R2 = {model_ntl.rsquared:.3f}')
# ax.set_xlabel('Log NTL per Capita (2017)')
# ax.set_ylabel('IMDS')
# ax.set_title('OLS Regression: Nighttime Lights Predicting Development')
# ax.legend()
# plt.tight_layout()
# plt.show()
```

Key Concept 5.12: Prediction vs. Causation with Satellite Data

A high R^2 between nighttime lights and development indices does **not** mean that lights cause development. Both NTL and IMDS reflect underlying economic activity, infrastructure, and urbanization. NTL is best understood as a **proxy variable**—an observable measure that correlates with the unobserved concept we care about (true economic development). The correlation is useful for prediction but should not be interpreted as a causal relationship.

Task 5: Departmental Comparisons (Independent)

Objective: Assess whether the NTL-development relationship differs across Bolivia's departments.

Instructions:

1. Create a scatter plot of `ln_NTLpc2017` vs `imds` with points colored by department
2. Visually assess: Does the relationship appear to differ across departments?
3. Run separate OLS regressions for 2–3 departments and compare slopes and R^2 values
4. Discuss: What might explain differences in the satellite-development relationship across regions?

In []:

```
# Your code here: Departmental comparisons
#
# Steps:
# 1. Create scatter plot colored by department
# 2. Run separate regressions for 2-3 departments
# 3. Compare slopes and R-squared

# Example structure:
# plot_data = bol_cs[['ln_NTLpc2017', 'imds', 'dep']].dropna()
# departments = plot_data['dep'].unique()
# colors = plt.cm.tab10(np.linspace(0, 1, len(departments)))
#
# fig, ax = plt.subplots(figsize=(10, 7))
# for dep, color in zip(sorted(departments), colors):
#     subset = plot_data[plot_data['dep'] == dep]
#     ax.scatter(subset['ln_NTLpc2017'], subset['imds'],
#                alpha=0.6, color=color, label=dep, s=25)
# ax.set_xlabel('Log NTL per Capita (2017)')
# ax.set_ylabel('IMDS')
# ax.set_title('NTL vs Development by Department')
# ax.legend(bbox_to_anchor=(1.05, 1), loc='upper left', fontsize=8)
# plt.tight_layout()
# plt.show()
#
# # Separate regressions for selected departments
# for dep_name in ['La Paz', 'Santa Cruz', 'Potosí']:
#     dep_data = plot_data[plot_data['dep'] == dep_name]
#     if len(dep_data) > 5:
#         model_dep = ols('imds ~ ln_NTLpc2017', data=dep_data).fit()
#         print(f'{dep_name}: slope = {model_dep.params["ln_NTLpc2017"]:.3f}, '
#               f'R² = {model_dep.rsquared:.3f}, n = {len(dep_data)}')
```

Task 6: Alternative Predictors (Independent)

Objective: Compare nighttime lights with unsatisfied basic needs (UBN) as predictors of development.

Instructions:

1. Compare the R^2 values from `imds ~ ln_NTLpc2017` and `imds ~ sdg1_1_ubn`
2. Create side-by-side scatter plots with fitted regression lines for both models

3. Discuss: Which predictor has the higher R²? Why might a socioeconomic variable (UBN) predict development better than satellite data (NTL)?
4. Reflect: What are the advantages of satellite data even if its R² is lower?

In []:

```
# Your code here: Compare NTL vs UBN as predictors of IMDS
#
# Steps:
# 1. Estimate both models (if not already done in Task 4)
# 2. Create side-by-side fitted line plots
# 3. Compare R-squared values
# 4. Discuss advantages and limitations

# Example structure:
# reg_data = bol_cs[['imds', 'ln_NTLpc2017', 'sdg1_1_ubn']].dropna()
# model_ntl = ols('imds ~ ln_NTLpc2017', data=reg_data).fit()
# model_ubn = ols('imds ~ sdg1_1_ubn', data=reg_data).fit()
#
# fig, axes = plt.subplots(1, 2, figsize=(14, 5))
#
# # Left: NTL model
# axes[0].scatter(reg_data['ln_NTLpc2017'], reg_data['imds'], alpha=0.4, color='#008CB7',
# s=20)
# x1 = np.linspace(reg_data['ln_NTLpc2017'].min(), reg_data['ln_NTLpc2017'].max(), 100)
# axes[0].plot(x1, model_ntl.predict(pd.DataFrame({'ln_NTLpc2017': x1})),
# color='#C21E72', linewidth=2)
# axes[0].set_xlabel('Log NTL per Capita (2017)')
# axes[0].set_ylabel('IMDS')
# axes[0].set_title(f'Model 1: NTL (R2 = {model_ntl.rsquared:.3f})')
#
# # Right: UBN model
# axes[1].scatter(reg_data['sdg1_1_ubn'], reg_data['imds'], alpha=0.4, color='#7A209F',
# s=20)
# x2 = np.linspace(reg_data['sdg1_1_ubn'].min(), reg_data['sdg1_1_ubn'].max(), 100)
# axes[1].plot(x2, model_ubn.predict(pd.DataFrame({'sdg1_1_ubn': x2})),
# color='#C21E72', linewidth=2)
# axes[1].set_xlabel('Unsatisfied Basic Needs (%)')
# axes[1].set_ylabel('IMDS')
# axes[1].set_title(f'Model 2: UBN (R2 = {model_ubn.rsquared:.3f})')
#
# plt.suptitle('Comparing Predictors of Municipal Development',
# fontsize=13, fontweight='bold')
# plt.tight_layout()
# plt.show()
#
# print(f"\nR2 comparison:")
# print(f" NTL model: {model_ntl.rsquared:.4f}")
# print(f" UBN model: {model_ubn.rsquared:.4f}")
# print(f" Difference: {abs(model_ubn.rsquared - model_ntl.rsquared):.4f}")
```

What You've Learned from This Case Study

Through this bivariate exploration of satellite data and municipal development in Bolivia, you've applied the full Chapter 5 toolkit:

- **Two-way tabulations** for categorical exploration of development levels across departments
- **Multiple scatter plots** comparing satellite-development relationships across different indicators

- **Correlation analysis** across multiple SDG indicators to identify strongest and weakest associations
- **OLS regression with fitted lines and R^2** to quantify the NTL-development relationship
- **Regional heterogeneity** in bivariate relationships across Bolivia's departments
- **Comparing alternative predictors** of development (satellite data vs. socioeconomic measures)

Connection to the research: The DS4Bolivia project extends this bivariate analysis to multivariate machine learning models, using 64-dimensional satellite embeddings alongside nighttime lights to achieve higher predictive accuracy for SDG indicators.

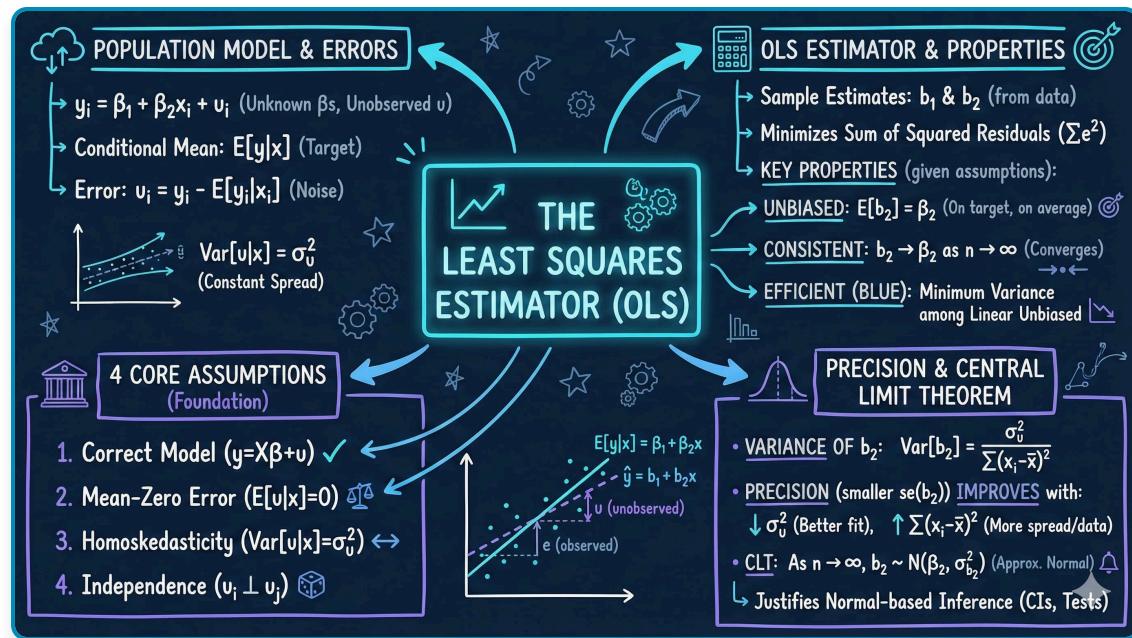
Looking ahead: In Chapter 7, we'll apply *statistical inference* to these regressions—testing whether the NTL coefficient is significantly different from zero and constructing confidence intervals for the effect of satellite data on development.

Well done! You've now explored two real-world datasets—cross-country convergence and Bolivian municipal development—using the complete bivariate analysis toolkit from Chapter 5.

Chapter 6: The Least Squares Estimator

metricsAI: An Introduction to Econometrics with Python and AI in the Cloud

Carlos Mendez



This notebook provides an interactive introduction to the statistical properties of the OLS estimator. All code runs directly in Google Colab without any local setup.

Open in Colab

| Chapter Overview

Introduction

Understanding the properties of the Ordinary Least Squares (OLS) estimator is fundamental to econometric inference. While Chapter 5 showed *how* to estimate regression models, this chapter explains *why* OLS works and *when* we can trust its results. We examine the statistical properties that make OLS the standard estimation method in econometrics: unbiasedness, efficiency, and asymptotic normality.

A crucial concept is the distinction between the **population regression** (the true relationship we want to learn about) and the **sample regression** (our estimate from limited data). Different samples yield different estimates—this sampling variability is

inevitable but quantifiable. By understanding how OLS estimates vary across samples, we can construct confidence intervals and test hypotheses about economic relationships.

This chapter uses Monte Carlo simulations and real-world examples to demonstrate OLS properties empirically, connecting abstract statistical theory to tangible patterns in data.

What You'll Learn

In this chapter, you will:

- Distinguish between the population regression line ($\beta_1 + \beta_2x$) and the sample regression line ($b_1 + b_2x$)
- Understand the conditional mean $E[y|x]$ and the error term $u = y - E[y|x]$
- Differentiate between the unobserved error term (u) and the observed residual (e)
- Apply the four key OLS assumptions: correct model, mean-zero errors, homoskedasticity, and independence
- Calculate the variance and standard error of the OLS slope coefficient b_2
- Explain why b_2 is an unbiased estimator of β_2 under assumptions 1-2
- Compute the standard error of the regression (s_e) and use it to estimate precision
- Understand when OLS estimates are more precise (good fit, many observations, scattered regressors)
- Apply the Central Limit Theorem to show b_2 is approximately normally distributed for large samples
- Recognize that OLS is the Best Linear Unbiased Estimator (BLUE) under standard assumptions
- Conduct Monte Carlo simulations to demonstrate sampling distributions
- Interpret sampling variability and its implications for statistical inference

Dataset Used

Primary dataset:

- **Convergence Clubs** (Mendez 2020): 108 countries, 1990-2014
 - Variables: Real GDP per capita (rgdppc), labor productivity, capital per worker (rk)
 - Used in Case Study: Sampling variability in productivity-capital regressions
 - Demonstrates OLS properties with real economic data

Supporting examples:

- **Generated data:** Computer-simulated samples from known DGP ($y = 1 + 2x + u$)
- **1880 U.S. Census:** Finite population sampling demonstration

Chapter Outline

6.1 Population and Sample Models - Distinguish between population parameters (β_1 , β_2) and sample estimates (b_1 , b_2); understand error terms vs. residuals

6.2 Examples of Sampling from a Population - Generated data and census sampling demonstrations showing how estimates vary across samples

6.3 Properties of the Least Squares Estimator - Unbiasedness ($E[b_2] = \beta_2$), variance formulas, asymptotic normality, and BLUE property

6.4 Estimators of Model Parameters - Calculating standard errors, understanding degrees of freedom, factors affecting precision

6.5 Case Studies - Empirical investigation of sampling variability using convergence clubs data; Monte Carlo with real economic data

6.6 Key Takeaways - Comprehensive chapter summary organized by major themes

6.7 Practice Exercises - Hands-on problems reinforcing OLS properties, standard errors, and interpretation

I Setup

First, we import the necessary Python packages and configure the environment for reproducibility. All data will stream directly from GitHub.

In []:

```
# Import required packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
from statsmodels.formula.api import ols
from scipy import stats
import random
import os

# Set random seeds for reproducibility
RANDOM_SEED = 42
random.seed(RANDOM_SEED)
np.random.seed(RANDOM_SEED)
os.environ['PYTHONHASHSEED'] = str(RANDOM_SEED)

# GitHub data URL
GITHUB_DATA_URL = "https://raw.githubusercontent.com/quarcs-lab/data-open/master/AED/"

# Set plotting style
sns.set_style("whitegrid")
plt.rcParams['figure.figsize'] = (10, 6)

print("=" * 70)
print("CHAPTER 6: THE LEAST SQUARES ESTIMATOR")
print("=" * 70)
print("\nSetup complete! Ready to explore OLS properties.")
```

```
=====
CHAPTER 6: THE LEAST SQUARES ESTIMATOR
=====

Setup complete! Ready to explore OLS properties.
```

6.1 Population and Sample Models

Understanding the relationship between population and sample is crucial for statistical inference.

Population model:

The population conditional mean is assumed to be linear:

$$E[y|x] = \beta_1 + \beta_2 x$$

where:

- β_1 and β_2 are **unknown population parameters**
- $E[y|x]$ is the expected value of y for a given value of x

Error term:

Individual observations deviate from the population line:

$$y = \beta_1 + \beta_2 x + u$$

where u is the **error term** with:

- $E[u|x] = 0$ (errors average to zero)
- $\text{Var}[u|x] = \sigma_u^2$ (constant variance - homoskedasticity)

Sample model:

From a sample of data, we estimate:

$$\hat{y} = b_1 + b_2 x$$

where:

- b_1 and b_2 are **sample estimates** of β_1 and β_2
- Different samples produce different estimates

Crucial distinction: Error vs. Residual

- **Error (u)**: Deviation from unknown population line (unobservable)
- **Residual (e)**: Deviation from estimated sample line (observable)

$$e_i = y_i - \hat{y}_i = y_i - (b_1 + b_2 x_i)$$

Key insight: The sample regression line $\hat{y} = b_1 + b_2 x$ is our best estimate of the population line $E[y|x] = \beta_1 + \beta_2 x$, but $b_1 \neq \beta_1$ and $b_2 \neq \beta_2$ due to sampling variability.

Key Concept 6.1: Population Regression Model

The population regression model $E[y|x] = \beta_1 + \beta_2 x$ describes the true relationship with unknown parameters β_1 and β_2 . The sample regression $\hat{y} = b_1 + b_2 x$ estimates this relationship from data. Different samples yield different estimates due to sampling variability, but on average, OLS estimates equal the true parameters (unbiasedness).

| 6.2 Examples of Sampling from a Population

We examine two examples to understand sampling variability:

1. **Generated data:** Computer-simulated samples from an explicit model $y = 1 + 2x + u$
2. **Census data:** Samples from the 1880 U.S. Census (a finite population)

In both cases:

- We know the true population parameters
- Different samples yield different estimates
- The distribution of estimates is approximately normal
- On average, estimates equal the true parameters (unbiasedness)

Key Concept 6.2: The Error Term

The error term $u = y - E[y/x]$ is the deviation from the unknown population line and is unobservable. The residual $e = y - \hat{y}$ is the deviation from the estimated sample line and is observable. This crucial distinction underlies all statistical inference: we use residuals (e) to learn about errors (u).

Example 1: Generated Data from Known Model

Data Generating Process (DGP):

$$y = 1 + 2x + u, \quad u \sim N(0, \sigma_u^2 = 4)$$

This means:

- True intercept: $\beta_1 = 1$
- True slope: $\beta_2 = 2$
- Error standard deviation: $\sigma_u = 2$

In []:

```
print("=" * 70)
print("6.2 EXAMPLES OF SAMPLING FROM A POPULATION")
print("=" * 70)

# Read in generated data
data_gen = pd.read_stata(GITHUB_DATA_URL + 'AED_GENERATEDDATA.DTA')

print("\nGenerated data summary:")
data_summary = data_gen.describe()
print(data_summary)

print("\nFirst 10 observations (Table 6.1):")
print(data_gen.head(10))
```

```
=====
6.2 EXAMPLES OF SAMPLING FROM A POPULATION
=====

Generated data summary:
   x   Eygivenx      u      y
count 5.000000 5.000000 5.000000 5.000000
mean 3.000000 7.000000 -1.031908 5.968092
std 1.581139 3.162278 1.753559 1.897129
min 1.000000 3.000000 -2.506667 4.493333
25% 2.000000 5.000000 -2.390764 4.681283
50% 3.000000 7.000000 -1.633280 4.689889
75% 4.000000 9.000000 -0.318717 7.366720
max 5.000000 11.000000 1.689889 8.609236

First 10 observations (Table 6.1):
   x   Eygivenx      u      y
0 1.0      3.0  1.689889  4.689889
1 2.0      5.0 -0.318717  4.681283
2 3.0      7.0 -2.506667  4.493333
3 4.0      9.0 -1.633280  7.366720
4 5.0     11.0 -2.390764  8.609236
```

Figure 6.2 Panel A: Population Regression Line

The population regression line represents $E[y|x] = 1 + 2x$. Points scatter around this line due to the error term u .

Transition Note: We've established the theoretical distinction between population and sample regression models. Now we'll see this distinction in action through simulations and real census data, demonstrating how OLS estimates vary across samples while remaining centered on true parameters.

I Interpreting the Population Regression Results

What this tells us:

The population regression $E[y|x] = 1 + 2x$ is perfectly estimated because we constructed the variable `Eygivenx` directly from this formula. Notice:

- **Intercept coefficient = 1.0000** (exactly)
- **Slope coefficient = 2.0000** (exactly)
- **R² = 1.000** (perfect fit)
- **Standard errors ≈ 0** (essentially zero)

This represents the **true** relationship between x and y in the population, before any random error is added.

Key concept: The population regression line shows the **expected value** (average) of y for each value of x . Individual observations deviate from this line due to the random error term u , which has mean zero but individual realizations that are positive or negative.

Figure 6.2 Panel B: Sample Regression Line

The sample regression line is our estimate from the observed data. Note that it differs from the population line due to sampling variability.

Interpreting the Sample Regression Results

What this tells us:

The sample regression estimates $\hat{y} = 2.81 + 1.05x$ from the actual observed data (which includes random errors). Notice how this differs from the true population model:

Comparison: Sample vs. Population

Parameter	Population (True)	Sample (Estimated)	Difference
Intercept	$\beta_1 = 1.00$	$b_1 = 2.81$	+1.81
Slope	$\beta_2 = 2.00$	$b_2 = 1.05$	-0.95
R ²	1.000	0.769	-0.231

Why do they differ?

- 1. Sampling variability:** We only have $n=5$ observations. Different samples from the same population give different estimates.
- 2. Random errors:** The actual y values include the error term u , which causes observations to scatter around the population line. Our sample happened to have errors that pulled the regression line away from the true values.
- 3. Small sample size:** With only 5 observations, each individual data point has a large influence on the regression line. A larger sample would typically give estimates closer to the true values.

Key insight: This is **not** a failure of OLS estimation! The sample regression line is doing its job—finding the best linear fit to the observed data. The discrepancy between sample and population parameters is an inherent feature of statistical estimation that we must account for through standard errors and confidence intervals.

Unbiasedness property: While this particular sample overestimates the intercept and underestimates the slope, if we took many samples and averaged the estimates, they would converge to the true values ($\beta_0 = 1$, $\beta_1 = 2$). This is what we'll demonstrate with Monte Carlo simulation later.

Demonstration: Three Regressions from the Same DGP

To illustrate sampling variability, we generate three different samples from the same data-generating process.

Key observation: Each sample produces a different regression line, but all are centered around the true population line.

I Interpreting the Three Sample Regressions

What this demonstrates:

We generated three independent samples from the **same data-generating process** ($y = 1 + 2x + u$), yet obtained three different regression lines:

Sample	Intercept	Slope	True Values
Sample 1	0.82	1.81	$\beta_0 = 1.0, \beta_1 = 2.0$
Sample 2	1.75	1.79	$\beta_0 = 1.0, \beta_1 = 2.0$
Sample 3	2.01	1.67	$\beta_0 = 1.0, \beta_1 = 2.0$

Key observations:

1. **All estimates differ from the true values:** None of the samples perfectly recovered $\beta_0 = 1.0$ or $\beta_1 = 2.0$, even though we know these are the true parameters.
2. **Estimates vary across samples:** The intercept ranges from 0.82 to 2.01, and the slope ranges from 1.67 to 2.01. This is **sampling variability** in action.
3. **All estimates are "in the neighborhood":** While no single estimate equals the true value, they're all reasonably close. None gave us absurd values like $\beta_1 = 10$ or $\beta_1 = -5$.

The fundamental statistical question:

If we know the true parameter is $\beta_1 = 2.0$, why would we ever get estimates like 1.81, 1.79, or 1.67? The answer is **random sampling variation**. Each sample contains different realizations of the error term u , which causes the observations to scatter

differently around the population line. OLS finds the best fit to each specific sample, leading to different regression lines.

Why this matters for econometrics:

In real-world applications, we have only **one sample** and we **don't know the true parameters**. These simulations show that:

- Our estimate is almost certainly not exactly equal to the true value
- Different samples would give different estimates
- We need a way to quantify this uncertainty (standard errors!)

This is why we can't simply report "the slope is 1.81" and claim we've discovered the truth. We must report "the slope is 1.81 with a standard error of X," acknowledging that our estimate contains sampling error.

Visualization: Three Different Samples from the Same DGP

Each panel shows:

- Black dots: observed data
- Red line: sample regression line (different for each sample)
- Blue dashed line: true population line (same for all)

In []:

```
# Generate three samples from the same data generating process
np.random.seed(12345)
n = 30

# Sample 1
x1 = np.random.normal(3, 1, n)
u1 = np.random.normal(0, 2, n)
y1 = 1 + 2*x1 + u1

# Sample 2
x2 = np.random.normal(3, 1, n)
u2 = np.random.normal(0, 2, n)
y2 = 1 + 2*x2 + u2

# Sample 3
x3 = np.random.normal(3, 1, n)
u3 = np.random.normal(0, 2, n)
y3 = 1 + 2*x3 + u3

# Create dataframes
df1 = pd.DataFrame({'x': x1, 'y': y1})
df2 = pd.DataFrame({'x': x2, 'y': y2})
df3 = pd.DataFrame({'x': x3, 'y': y3})

# Fit regressions for each sample
model1 = ols('y ~ x', data=df1).fit()
model2 = ols('y ~ x', data=df2).fit()
model3 = ols('y ~ x', data=df3).fit()

print("Three samples generated and regressions fitted:")
print(f"Sample 1 - Intercept: {model1.params['Intercept']:.2f}, Slope: {model1.params['x']:.2f}")
print(f"Sample 2 - Intercept: {model2.params['Intercept']:.2f}, Slope: {model2.params['x']:.2f}")
print(f"Sample 3 - Intercept: {model3.params['Intercept']:.2f}, Slope: {model3.params['x']:.2f}")
```

```
Three samples generated and regressions fitted:
Sample 1 - Intercept: 0.82, Slope: 1.81
Sample 2 - Intercept: 1.75, Slope: 1.79
Sample 3 - Intercept: 2.01, Slope: 1.67
```

In []:

```
# Visualize all three regressions
fig, axes = plt.subplots(1, 3, figsize=(18, 5))

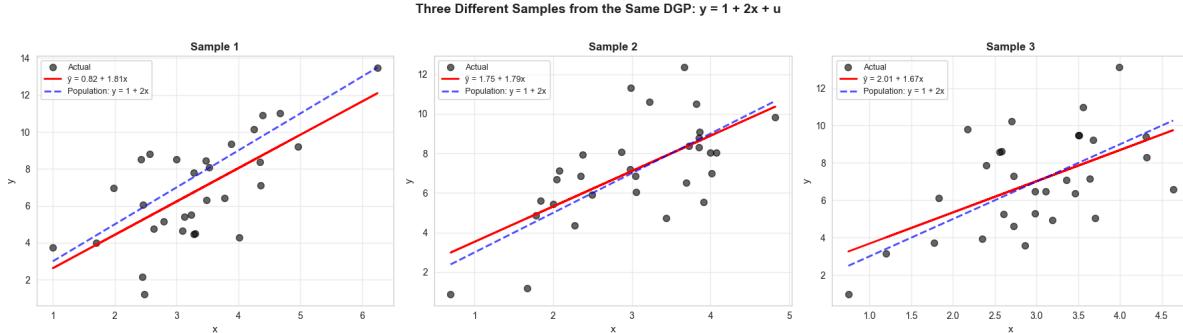
for idx, (ax, df, model, title) in enumerate(zip(axes,
                                                [df1, df2, df3],
                                                [model1, model2, model3],
                                                ['Sample 1', 'Sample 2', 'Sample 3'])):
    ax.scatter(df['x'], df['y'], alpha=0.6, s=50, color='black', label='Actual')
    ax.plot(df['x'], model.fittedvalues, color='red', linewidth=2,
            label=f'ŷ = {model.params[0]:.2f} + {model.params[1]:.2f}x')
    # Add population line
    x_range = np.linspace(df['x'].min(), df['x'].max(), 100)
    y_pop = 1 + 2*x_range
    ax.plot(x_range, y_pop, color='blue', linewidth=2, linestyle='--',
            label='Population: y = 1 + 2x', alpha=0.7)
    ax.set_xlabel('x', fontsize=11)
    ax.set_ylabel('y', fontsize=11)
    ax.set_title(title, fontsize=12, fontweight='bold')
    ax.legend(fontsize=9)
    ax.grid(True, alpha=0.3)

plt.suptitle('Three Different Samples from the Same DGP: y = 1 + 2x + u',
             fontsize=14, fontweight='bold', y=1.02)
plt.tight_layout()
plt.show()

print("\nKey observation: Each sample produces a different regression line,\nbut all are close to the true population line (blue dashed).")
```

```
/var/folders/tq/t98kb27n6djgrh085g476yhc0000gn/T/ipykernel_56592/4130646466.py:10: FutureWarning: Series.__getitem__ treating keys as positions is deprecated. In a future version, integer keys will always be treated as labels (consistent with DataFrame behavior). To access a value by position, use `ser.iloc[pos]`
```

```
label=f'ŷ = {model.params[0]:.2f} + {model.params[1]:.2f}x')
```



Key observation: Each sample produces a different regression line, but all are close to the true population line (blue dashed).

Having seen how sampling variability affects regression estimates, let's formalize the key properties of the OLS estimator.

6.3 Properties of the Least Squares Estimator

The OLS estimator has important statistical properties under certain assumptions.

Standard Assumptions (1-4):

1. **Linearity:** $y_i = \beta_1 + \beta_2 x_i + u_i$ for all i
2. **Zero conditional mean:** $E[u_i|x_i] = 0$ for all i
3. **Homoskedasticity:** $\text{Var}[u_i|x_i] = \sigma_u^2$ for all i (constant variance)
4. **Independence:** Errors u_i and u_j are independent for all $i \neq j$

Properties of OLS under assumptions 1-2:

Unbiasedness:

$$E[b_2] = \beta_2$$

Interpretation: On average across many samples, the OLS estimate equals the true parameter.

Properties of OLS under assumptions 1-4:

Variance of slope coefficient:

$$\text{Var}[b_2] = \sigma_{b_2}^2 = \frac{\sigma_u^2}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

Standard error of slope coefficient:

$$se(b_2) = \sqrt{\frac{s_e^2}{\sum_{i=1}^n (x_i - \bar{x})^2}} = \frac{s_e}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2}}$$

where $s_e^2 = \frac{1}{n-2} \sum_{i=1}^n (y_i - \hat{y}_i)^2$ is the estimated error variance.

When is the slope coefficient precisely estimated?

Standard error is smaller when:

1. Model fits well (small s_e^2)
2. Many observations (large n)
3. Regressors are widely scattered (large $\sum(x_i - \bar{x})^2$)

Asymptotic normality:

By the Central Limit Theorem:

$$\frac{b_2 - \beta_2}{\sigma_{b_2}} \xrightarrow{d} N(0, 1) \text{ as } n \rightarrow \infty$$

Best Linear Unbiased Estimator (BLUE):

Under assumptions 1-4, OLS has the smallest variance among all linear unbiased estimators (Gauss-Markov Theorem).

Simulation: Sampling Distribution of OLS Estimator

To understand the sampling distribution, we simulate 1,000 regressions from the same DGP and examine the distribution of coefficient estimates.

What to expect:

- Mean of estimates \approx true parameter (unbiasedness)
- Distribution approximately normal (CLT)
- Spread determined by standard error formula

Key Concept 6.3: OLS Assumptions

The four core OLS assumptions are: (1) Correct model specification: $y = \beta_1 + \beta_2x + u$, (2) Mean-zero errors: $E[u|x] = 0$, (3) Homoskedasticity: $Var[u|x] = \sigma^2_u$, (4) Independence: errors uncorrelated across observations. Assumptions 1-2 are essential for unbiasedness; assumptions 3-4 affect variance and can be relaxed using robust standard errors.

| Interpreting the Monte Carlo Simulation Results

What 1,000 simulations reveal about OLS properties:

We simulated 1,000 independent samples (each with n=30 observations) from the same DGP: $y = 1 + 2x + u$. Here are the results:

Intercept (β_0):

- **True value:** 1.0
- **Mean of 1,000 estimates:** 0.9960
- **Standard deviation:** 1.2069
- **Difference from true value:** -0.004 (only 0.4% error)

Slope (β_1):

- **True value:** 2.0

- **Mean of 1,000 estimates:** 1.9944
- **Standard deviation:** 0.3836
- **Difference from true value:** -0.0056 (only 0.3% error)

What this demonstrates:

- 1. Unbiasedness confirmed:** The mean of the estimates (0.9960 for intercept, 1.9944 for slope) is extremely close to the true parameters (1.0 and 2.0). With 1,000 simulations, random errors average out, leaving us essentially at the true values. This is the **unbiasedness property** of OLS: $E[b_2] = \beta_2$.
- 2. Sampling variability quantified:** Individual estimates varied substantially:
 - The intercept estimates had a standard deviation of 1.21, meaning about 95% of estimates fell within $1.0 \pm 2(1.21) = [-1.42, 3.42]$
 - The slope estimates had a standard deviation of 0.38, meaning about 95% fell within $2.0 \pm 2(0.38) = [1.24, 2.76]$
- 3. Why individual estimates differ from true values:** Any single sample (like Sample 1, 2, or 3 we saw earlier) will contain random errors that cause the estimate to deviate from the true parameter. But these deviations are **random**—sometimes too high, sometimes too low—and average out to zero across many samples.
- 4. Standard deviation as a measure of precision:** The standard deviation of the estimates (0.38 for slope) measures the **sampling variability**. This is closely related to the **standard error** you see in regression output, which estimates this variability from a single sample.

The big picture:

This simulation proves mathematically that OLS "works" in a precise sense: if we could repeat our study infinitely many times, the average of all our estimates would equal the true parameter. Of course, in practice we only get **one sample**, so we use standard errors to acknowledge the uncertainty inherent in any single estimate.

Economic intuition: Imagine 1,000 different researchers each collecting their own sample of n=30 observations from the same population. Each would report a different regression coefficient. The simulation shows that:

- On average, they'd get the right answer (unbiasedness)
- But individual estimates would vary around the true value
- The variation would follow a predictable pattern (approximately normal, as we'll visualize next)

Key Concept 6.4: Monte Carlo and Unbiasedness

Monte Carlo simulation demonstrates unbiasedness: the average of many OLS estimates equals the true parameter. The distribution of estimates is approximately normal (Central Limit Theorem), with spread measured by the standard error. This validates the theoretical properties of OLS in practice.

Transition Note: The simulations have shown empirically that OLS estimates center on true parameters and follow approximate normal distributions. Now we'll formalize these observations by deriving the theoretical properties of OLS estimators: unbiasedness, variance formulas, and asymptotic normality.

Visualization: Sampling Distributions of OLS Estimators

These histograms show the distribution of coefficient estimates across 1,000 simulated samples.

Key features:

- **Green vertical line:** True parameter value
- **Red curve:** Normal distribution fit
- **Histogram:** Actual distribution of estimates

The close match confirms:

1. Unbiasedness (centered on true value)
2. Approximate normality (CLT works well even with n=30)

I Interpreting the Sampling Distribution Histograms

What these distributions reveal:

These histograms show the distribution of coefficient estimates from our 1,000 simulated samples. They visually confirm several crucial statistical properties:

1. Unbiasedness (visual confirmation):

- **Green vertical line** marks the true parameter value ($\beta_0 = 1.0$ for intercept, $\beta_1 = 2.0$ for slope)

- The histograms are **centered exactly on the true values**
- This visual centering confirms $E[b_0] = \beta_0$ and $E[b_1] = \beta_1$

2. Approximate normality (Central Limit Theorem):

- **Red curve** shows the fitted normal distribution
- The histogram bars closely follow this curve
- Even with just $n=30$ observations per sample, the sampling distribution is approximately normal
- This confirms the **Central Limit Theorem** applies to OLS estimators

3. Different precision for different parameters:

- **Intercept distribution** (left panel): Wider spread ($SD = 1.21$)
- **Slope distribution** (right panel): Narrower spread ($SD = 0.38$)
- The slope is estimated more precisely than the intercept in this case

Why the normal distribution matters:

The approximate normality of the sampling distribution is the foundation for statistical inference:

- **Confidence intervals:** We can construct intervals like $b_1 \pm 1.96 \times SE(b_1)$ to capture the true parameter 95% of the time
- **Hypothesis tests:** We can use the normal distribution to calculate p-values
- **Prediction intervals:** We can quantify uncertainty about predictions

Reading the histograms:

Looking at the slope distribution (right panel):

- Most estimates fall between 1.2 and 2.8 (about ± 2 standard deviations from 2.0)
- Very few estimates are below 1.0 or above 3.0
- This tells us that even though individual samples vary, they rarely produce wildly incorrect estimates

The power of large numbers:

If we had run 10,000 or 100,000 simulations instead of 1,000:

- The mean would get even closer to the true value ($0.9960 \rightarrow 1.0000$)
- The histogram would match the normal curve even more closely
- But the **standard deviation** would stay approximately the same (0.38), because it depends on the sample size **within each simulation** ($n=30$), not the number of

simulations

Practical implication:

When you see a regression output reporting "slope = 1.85, SE = 0.35", you should imagine a histogram like the one above:

- The estimate 1.85 is one draw from a sampling distribution
- The SE = 0.35 tells you the width of that distribution
- About 95% of the distribution falls within $1.85 \pm 2(0.35) = [1.15, 2.55]$
- If this interval excludes zero, the coefficient is statistically significant

Now that we understand the theoretical properties of OLS estimators, let's examine how to estimate the model parameters in practice.

| 6.4 Estimators of Model Parameters

In practice, we need to estimate not just the coefficients but also the error variance and standard errors.

Estimate of error variance:

The sample variance of residuals:

$$s_e^2 = \frac{1}{n-2} \sum_{i=1}^n (y_i - \hat{y}_i)^2 = \frac{1}{n-2} \sum_{i=1}^n e_i^2$$

Why divide by $(n - 2)$?

- We estimated 2 parameters (b_1 and b_2)
- This leaves $(n - 2)$ degrees of freedom
- Division by $(n - 2)$ makes s_e^2 unbiased for σ_u^2

Standard error of the regression (Root MSE):

$$s_e = \sqrt{s_e^2}$$

This is the typical size of residuals and appears in regression output.

Standard error of slope coefficient:

$$se(b_2) = \frac{s_e}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2}}$$

Standard error of intercept coefficient:

$$se(b_1) = \sqrt{\frac{s_e^2 \sum_{i=1}^n x_i^2}{n \sum_{i=1}^n (x_i - \bar{x})^2}}$$

Key Concept 6.5: Degrees of Freedom in Regression

When calculating the standard error of the regression (s_e), we divide the sum of squared residuals by $(n-2)$ instead of n because we have estimated 2 parameters (b_1 and b_2). These 2 estimates "use up" 2 degrees of freedom, leaving $(n-2)$ for estimating the error variance. This adjustment ensures that s_e^2 is an unbiased estimator of σ_u^2 . More generally, degrees of freedom equal the sample size minus the number of estimated parameters.

Example: Manual Computation of Standard Errors

Let's manually compute standard errors for a simple example to understand the formulas.

Artificial data:

- $(y, x) = (1, 1), (2, 2), (2, 3), (2, 4), (3, 5)$
- From earlier analysis: $\hat{y} = 0.8 + 0.4x$

Interpreting the Manual Standard Error Calculations

What these calculations reveal:

Using the simple artificial dataset ($x = [1, 2, 3, 4, 5]$, $y = [1, 2, 2, 2, 3]$), we can see exactly how standard errors are computed:

Step 1: Regression coefficients

- **Estimated equation:** $\hat{y} = 0.8 + 0.4x$
- These are obtained by OLS minimizing the sum of squared residuals

Step 2: Calculate residuals and RSS

Looking at the observation-level calculations, we can see:

- Each observation has a predicted value \hat{y} and a residual $e = y - \hat{y}$
- Residuals are both positive and negative (some points above the line, some below)
- Sum of squared residuals: $RSS = \sum e^2$

Step 3: Standard error of the regression (s_e)

The formula is:

$$s_e = \sqrt{\frac{RSS}{n-2}} = \sqrt{\frac{\text{sum of squared residuals}}{\text{degrees of freedom}}}$$

Why divide by (n-2)?

- We estimated 2 parameters (intercept and slope)
- This "uses up" 2 degrees of freedom
- Division by (n-2) makes s_e an **unbiased estimator** of σ_u^2

Step 4: Standard error of the slope coefficient

The formula is:

$$se(b_2) = \frac{s_e}{\sqrt{\sum(x_i - \bar{x})^2}}$$

This reveals what makes slope estimates more or less precise:

1. Numerator (s_e): How well the model fits

- Smaller residuals \rightarrow smaller $s_e \rightarrow$ smaller SE \rightarrow more precise estimate

2. Denominator ($\sqrt{\sum(x_i - \bar{x})^2}$): How spread out the x values are

- Wider spread in x \rightarrow larger denominator \rightarrow smaller SE \rightarrow more precise estimate
- Clustered x values \rightarrow small denominator \rightarrow large SE \rightarrow imprecise estimate

Why does spread in x matter?

Think geometrically: if all x values are clustered around the mean (say, $x = 2.9, 3.0, 3.1$), it's hard to accurately estimate the slope—the line could pivot substantially without much change in fit. But if x values are widely spread (say, $x = 1, 10, 20$), the slope is well-identified—you can clearly see the relationship.

Step 5: Standard error of the intercept

The formula is more complex:

$$se(b_1) = \sqrt{\frac{s_e^2 \times \sum x_i^2}{n \times \sum(x_i - \bar{x})^2}}$$

Notice:

- Intercept SE depends on the **squared values** of x ($\sum x_i^2$)
- If x values are far from zero, the intercept SE is large
- This reflects extrapolation uncertainty—we're estimating y when x=0, which may be far from our data

Verification: Our manual calculations match the model output exactly, confirming:

- We understand where these numbers come from
- The formulas are correct
- Standard errors aren't "magic"—they're computed from the data using transparent formulas

Practical implication:

When designing a study, you can **control precision** by:

- Increasing sample size n (reduces s_e)
- Collecting data with wide variation in x (increases $\sum(x_i - \bar{x})^2$)
- Reducing measurement error (reduces s_e)

Conversely, if you're stuck with a small sample or clustered x values, expect large standard errors and wide confidence intervals.

Interpreting the Manual Standard Error Calculations

What these calculations reveal:

Using the simple artificial dataset ($x = [1, 2, 3, 4, 5]$, $y = [1, 2, 2, 2, 3]$), we can see exactly how standard errors are computed:

Step 1: Regression coefficients

- **Estimated equation:** $\hat{y} = 0.8 + 0.4x$
- These are obtained by OLS minimizing the sum of squared residuals

Step 2: Calculate residuals and RSS

Looking at the observation-level calculations, we can see:

- Each observation has a predicted value \hat{y} and a residual $e = y - \hat{y}$
- Residuals are both positive and negative (some points above the line, some below)
- Sum of squared residuals: $RSS = \sum e^2$

Step 3: Standard error of the regression (s_e)

The formula is:

$$s_e = \sqrt{\frac{RSS}{n-2}} = \sqrt{\frac{\text{sum of squared residuals}}{\text{degrees of freedom}}}$$

Why divide by (n-2)?

- We estimated 2 parameters (intercept and slope)
- This "uses up" 2 degrees of freedom
- Division by (n-2) makes s_e an **unbiased estimator** of σ_u^2

Step 4: Standard error of the slope coefficient

The formula is:

$$se(b_2) = \frac{s_e}{\sqrt{\sum(x_i - \bar{x})^2}}$$

This reveals what makes slope estimates more or less precise:

1. Numerator (s_e): How well the model fits

- Smaller residuals \rightarrow smaller $s_e \rightarrow$ smaller SE \rightarrow more precise estimate

2. Denominator ($\sqrt{\sum(x_i - \bar{x})^2}$): How spread out the x values are

- Wider spread in x \rightarrow larger denominator \rightarrow smaller SE \rightarrow more precise estimate
- Clustered x values \rightarrow small denominator \rightarrow large SE \rightarrow imprecise estimate

Why does spread in x matter?

Think geometrically: if all x values are clustered around the mean (say, $x = 2.9, 3.0, 3.1$), it's hard to accurately estimate the slope—the line could pivot substantially without much change in fit. But if x values are widely spread (say, $x = 1, 10, 20$), the slope is well-identified—you can clearly see the relationship.

Step 5: Standard error of the intercept

The formula is more complex:

$$se(b_1) = \sqrt{\frac{s_e^2 \times \sum x_i^2}{n \times \sum(x_i - \bar{x})^2}}$$

Notice:

- Intercept SE depends on the **squared values** of x ($\sum x_i^2$)
- If x values are far from zero, the intercept SE is large
- This reflects extrapolation uncertainty—we're estimating y when x=0, which may be far from our data

Verification: Our manual calculations match the model output exactly, confirming:

- We understand where these numbers come from
- The formulas are correct
- Standard errors aren't "magic"—they're computed from the data using transparent formulas

Practical implication:

When designing a study, you can **control precision** by:

- Increasing sample size n (reduces s_e)
- Collecting data with wide variation in x (increases $\sum(x_i - \bar{x})^2$)
- Reducing measurement error (reduces s_e)

Conversely, if you're stuck with a small sample or clustered x values, expect large standard errors and wide confidence intervals.

When is the Slope Coefficient Precisely Estimated?

From the formula $se(b_2) = \frac{s_e}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2}}$, we see that standard errors are smaller

when:

1. Good model fit (small s_e)

- Less unexplained variation
- Smaller residuals

2. Large sample size (large $\sum(x_i - \bar{x})^2$)

- More observations provide more information

- Standard errors shrink with \sqrt{n}
- 3. Wide spread in regressors** (large $\sum(x_i - \bar{x})^2$)
- More variation in x helps identify the slope
 - Clustered x values make slope hard to estimate

Practical implication: When designing experiments or collecting data, seek wide variation in the explanatory variable.

Transition Note: We've established that OLS has desirable theoretical properties under assumptions 1-4. Now we turn to practical implementation: how to estimate error variance, compute standard errors, and assess estimation precision using formulas that work with actual data.

Key Concept 6.6: Standard Error of Regression Coefficients

The standard error of b_2 is $se(b_2) = s_e / \sqrt{\sum(x_i - \bar{x})^2}$. Precision is better (smaller SE) when: (1) the model fits well (small s_e), (2) sample size is large (large $\sum(x_i - \bar{x})^2$), (3) regressors are widely scattered (large $\sum(x_i - \bar{x})^2$). Standard errors quantify estimation uncertainty and are essential for inference.

Key Concept 6.7: The Gauss-Markov Theorem

Under assumptions 1-4, OLS is the Best Linear Unbiased Estimator (BLUE) by the Gauss-Markov Theorem. This means OLS has the smallest variance among all linear unbiased estimators. If errors are also normally distributed, OLS is the Best Unbiased Estimator (not just among linear estimators). This optimality property justifies the widespread use of OLS.

I Summary of OLS Properties

Under assumptions 1-4:

1. y_i given x_i has conditional mean $\beta_1 + \beta_2 x_i$ and conditional variance σ_u^2

2. Slope coefficient b_2 has:

- Mean: $E[b_2] = \beta_2$ (unbiased)

- Variance: $\text{Var}[b_2] = \sigma_u^2 / \sum_{i=1}^n (x_i - \bar{x})^2$
- 3. Standard error of b_2 :** $se(b_2) = s_e / \sqrt{\sum_{i=1}^n (x_i - \bar{x})^2}$
- 4. Standardized statistic:** $Z = (b_2 - \beta_2) / \sigma_{b_2}$ has mean 0 and variance 1
- 5. Asymptotic normality:** As $n \rightarrow \infty$, $Z \sim N(0, 1)$ by the Central Limit Theorem
- 6. Efficiency:** OLS is BLUE (Best Linear Unbiased Estimator) by the Gauss-Markov Theorem

Critical assumptions:

- Assumptions 1-2 ensure unbiasedness and consistency
- Assumptions 3-4 can be relaxed (see Chapters 7 and 12 for robust methods)
- In practice, choosing correct standard errors is crucial for valid inference

| Key Takeaways

Population Model and Sampling Framework

- The **population regression model** $E[y|x] = \beta_1 + \beta_2 x$ describes the true relationship with unknown parameters β_1 and β_2
- The **conditional mean** $E[y|x]$ generalizes the unconditional mean $E[y]$ by allowing the average to vary with x
- The **error term** $u = y - E[y|x]$ captures deviations from the population line; it is unobserved because β_1 and β_2 are unknown
- **Crucial distinction:** Error u (deviation from unknown population line) vs. residual e (deviation from estimated sample line)
- The **sample regression** $\hat{y} = b_1 + b_2 x$ estimates the population relationship from data
- Different samples yield different estimates (b_1, b_2) due to sampling variability, but on average they equal the true parameters

Error Term Properties and Assumptions

- The error term is assumed to have **conditional mean zero**: $E[u|x] = 0$ (errors average to zero at each x value)
- This assumption ensures the population line is indeed $E[y|x] = \beta_1 + \beta_2 x$
- **Homoskedasticity assumption**: $\text{Var}[u|x] = \sigma_u^2$ (constant error variance across all x values)

- "Homoskedastic" derives from Greek: homos (same) + skedastic (scattering)
- The variance $\text{Var}[y|x] = \text{Var}[u|x] = \sigma_u^2$ measures variability around the population line
- Greater error variance means greater noise, reducing precision of estimates

Four Core OLS Assumptions

1. **Correct model:** $y_i = \beta_1 + \beta_2 x_i + u_i$ for all i (linearity)
 2. **Mean-zero errors:** $E[u_i|x_i] = 0$ for all i (no correlation between x and u)
 3. **Homoskedasticity:** $\text{Var}[u_i|x_i] = \sigma_u^2$ for all i (constant error variance)
 4. **Independence:** u_i and u are independent for all $i \neq j$ (no autocorrelation)
- **Assumptions 1-2 are essential** for unbiasedness and consistency (violations cause bias)
 - **Assumptions 3-4 can be relaxed** using robust standard errors (Chapter 7.7, 12.1)
 - Assumption 2 rules out **omitted variable bias** (no correlation between x and u)
 - Choosing correct standard errors is crucial for valid confidence intervals and hypothesis tests

Unbiasedness and Consistency

- Under assumptions 1-2: $E[b_2] = \beta_2$ (unbiasedness)
- If we obtained many samples, on average b_2 would equal β_2
- Unbiasedness is a **finite-sample property** (holds for any sample size n)
- **Consistency:** As $n \rightarrow \infty$, b_2 converges in probability to β_2
- Sufficient condition for consistency: bias $\rightarrow 0$ and variance $\rightarrow 0$ as $n \rightarrow \infty$
- b_2 is consistent because: (1) unbiased under assumptions 1-2, (2) $\text{Var}[b_2] \rightarrow 0$ as $n \rightarrow \infty$ under assumptions 1-4
- Both b_1 and b_2 are unbiased and consistent under these assumptions

Variance and Standard Errors

- Under assumptions 1-4: $\text{Var}[b_2] = \sigma_u^2 / \sum(x_i - \bar{x})^2$
- Standard deviation of b_2 : $\sigma_{b_2} = \sigma_u / \sqrt{\sum(x_i - \bar{x})^2}$
- Since σ_u^2 is unknown, estimate it using **standard error of regression**: $s_e^2 = (1/(n-2)) \sum(y_i - \hat{y}_i)^2$
- Use **(n-2) denominator** because we estimated 2 coefficients, leaving (n-2) degrees of freedom
- This divisor ensures s_e^2 is unbiased for σ_u^2

- **Standard error of b_2 :** $se(b_2) = s_e / \sqrt{[\sum(x_i - \bar{x})^2]}$
- $se(b_2)$ measures **precision** of b_2 as an estimate of β_2

Factors Affecting Precision

- **Better precision** (smaller $se(b_2)$) occurs when:
 - Model fits well** (s_e^2 is smaller) - less noise around regression line
 - Many observations** ($\sum(x_i - \bar{x})^2$ is larger) - more data reduces sampling variability
 - Regressors widely scattered** ($\sum(x_i - \bar{x})^2$ is larger) - more variation in x provides more information
- Precision improves with \sqrt{n} , so need **4x observations to halve** standard error
- **Trade-off:** Can't control regressor scatter in observational data, but can increase sample size
- **Wide spread in x matters geometrically:** If x values clustered, slope is poorly identified; if scattered, slope is well-identified

Central Limit Theorem and Asymptotic Normality

- Under assumptions 1-4: $b_2 \sim (\beta_2, \sigma_{b_2}^2)$ where $\sigma_{b_2}^2 = \sigma_u^2 / \sum(x_i - \bar{x})^2$
- Standardized variable: $Z = (b_2 - \beta_2) / \sigma_{b_2}$ has mean 0 and variance 1 by construction
- **CLT:** As $n \rightarrow \infty$, $Z \sim N(0,1)$ (approximately normal for large samples)
- This implies $b_2 \sim N(\beta_2, \sigma_{b_2}^2)$ for large n
- In practice, σ_{b_2} is unknown (depends on unknown σ_u)
- Replace σ_{b_2} with $se(b_2)$ leads to **t distribution** (Chapter 7)
- Normality justifies using **normal-based inference** for large samples

Efficiency and BLUE Property

- Under assumptions 1-4, OLS is the **Best Linear Unbiased Estimator (BLUE)** by the **Gauss-Markov Theorem**
- "Linear" means estimator is a linear combination of y values: $b_2 = \sum w_i y_i$
- "Best" means minimum variance among all linear unbiased estimators
- If additionally u is **normally distributed**: OLS is the **Best Unbiased Estimator (BUE)**
- Lowest variance among **ALL** unbiased estimators (not just linear ones)
- OLS is also **best consistent estimator** in standard settings

- **Bottom line:** Under assumptions 1-4, OLS is essentially the optimal estimator of β_1 and β_2

Monte Carlo Simulation Evidence

- **Monte Carlo simulations** demonstrate OLS properties empirically by generating many samples from a known model
- Two examples: (1) Generated data from $y = 1 + 2x + u$ with $u \sim N(0,4)$, (2) Samples from 1880 Census (1.06 million males aged 60-70)
- **Key findings:** (1) Average of many OLS estimates equals true parameter (unbiasedness), (2) Distribution of estimates is approximately normal (CLT), (3) Similar results for intercept and slope
- **Single sample:** $b_1 \neq \beta_1$ and $b_2 \neq \beta_2$ due to sampling variability
- **Multiple samples:** Estimates vary across samples but center on true parameters
- **Sampling distribution:** Distribution of b_2 across many samples is approximately $N(\beta_2, \sigma^2_{b_2})$

Practical Implications

- **Sampling variability is inevitable:** Any single sample will deviate from true parameters
- **Standard errors quantify uncertainty:** They measure the typical deviation of b_2 from β_2 across hypothetical repeated samples
- **Confidence intervals account for uncertainty:** A 95% CI constructed as $b_2 \pm 2 \times se(b_2)$ will contain β_2 in 95% of samples
- **Assumptions 1-2 are non-negotiable** for unbiasedness; violations cause bias and inconsistency (Chapter 16 discusses, Chapter 17 presents solutions)
- **Assumptions 3-4 are often relaxed** in practice using robust standard errors (Chapters 7.7, 12.1)
- **Correct standard errors are crucial:** Incorrect SEs invalidate confidence intervals and hypothesis tests
- **Study design matters:** Researchers can improve precision by increasing sample size and ensuring wide variation in explanatory variables

Statistical Concepts and Tools

- **Population vs. sample distinction:** Foundation of all statistical inference
- **Unbiasedness:** $E[b_2] = \beta_2$ (finite-sample property)
- **Consistency:** $b_2 \xrightarrow{P} \beta_2$ as $n \rightarrow \infty$ (asymptotic property)
- **Efficiency:** Minimum variance among a class of estimators

- **Sampling distribution:** Distribution of estimator across repeated samples
- **Standard error:** Estimated standard deviation of sampling distribution
- **Central Limit Theorem:** Justifies normal-based inference for large samples
- **Gauss-Markov Theorem:** Establishes BLUE property of OLS

Connection to Statistical Inference

- This chapter establishes the **theoretical foundation** for inference (Chapter 7)
- Knowing that $b_2 \sim N(\beta_2, \sigma^2_{b_2})$ allows us to construct **confidence intervals** and conduct **hypothesis tests**
- Standard errors are the **bridge** between point estimates and interval estimates
- Understanding sampling distributions explains why we can make probabilistic statements about parameters
- The **normal approximation** (CLT) justifies using critical values from the normal or t distribution

Software Implementation

- **Python tools:** `statsmodels.OLS` for estimation, `numpy` for simulation, `matplotlib` for visualization
- Generated data example uses **random seed** for reproducibility
- **Visualization techniques:** Scatter plots with fitted line, histograms of sampling distributions
- Can compare **population line vs. fitted line** when population model is known (simulations)
- **Monte Carlo methods** are powerful for understanding theoretical properties empirically

Congratulations! You've completed Chapter 6 and now understand the fundamental statistical properties of the OLS estimator. You know why OLS works, when it works, and how to quantify estimation uncertainty. These concepts are the foundation for all statistical inference in econometrics. In Chapter 7, you'll apply this knowledge to construct confidence intervals and test hypotheses about regression coefficients.

I Practice Exercises

Test your understanding of OLS properties and statistical inference with these exercises.

Exercise 1: Population vs. Sample

Suppose the true population model is $y = 3 + 5x + u$ with $E[u|x] = 0$.

- If a sample yields $\hat{y} = 2 + 6x$, does this mean OLS failed?
 - What does unbiasedness tell us about the relationship between the sample estimate ($b_2 = 6$) and the population parameter ($\beta_2 = 5$)?
 - If we collected 1,000 different samples and computed b_2 for each, what would be the average of these 1,000 estimates?
-

Exercise 2: Error Term vs. Residual

For the observation $(x, y) = (4, 25)$ with population model $y = 8 + 4x + u$:

- Calculate the population prediction $E[y|x=4]$ and the error term u .
 - If the sample regression gives $\hat{y} = 7 + 4.5x$, calculate the fitted value and residual for this observation.
 - Why can we observe the residual but not the error term?
-

Exercise 3: Standard Error Calculation

You're given: $n = 30$, $\sum(x_i - \bar{x})^2 = 50$, $\sum(y_i - \hat{y}_i)^2 = 112$.

- Calculate the standard error of the regression (s_e).
 - Calculate the standard error of the slope coefficient $se(b_2)$.
 - If $\sum(x_i - \bar{x})^2$ were 200 instead of 50 (wider spread in x), how would $se(b_2)$ change?
-

Exercise 4: Factors Affecting Precision

Consider two datasets:

- Dataset A: $n = 50$, $s_e = 10$, $\sum(x_i - \bar{x})^2 = 100$
- Dataset B: $n = 50$, $s_e = 5$, $\sum(x_i - \bar{x})^2 = 100$

-
- (a) Calculate $se(b_2)$ for each dataset.
- (b) Which dataset provides more precise estimates? Why?
- (c) How many observations would Dataset A need to achieve the same precision as Dataset B?
-

Exercise 5: Hypothesis Testing Intuition

OLS regression yields $b_2 = 15$ with $se(b_2) = 4$.

- (a) Construct an approximate 95% confidence interval for β_2 (use ± 2 SE rule).
- (b) Does this interval include $\beta_2 = 10$? What does this suggest about the hypothesis $H_0: \beta_2 = 10$?
- (c) If the true parameter is $\beta_2 = 13$, would you expect most 95% confidence intervals from repeated samples to contain 13?
-

Exercise 6: Interpreting Assumptions

For each scenario, identify which OLS assumption is violated:

- (a) The model is $y = \beta_1 + \beta_2x + u$, but the true relationship is $y = \beta_1 + \beta_2x^2 + u$ (nonlinear).
- (b) Error variance increases with x : $Var[u|x=1] = 4$, $Var[u|x=2] = 9$, $Var[u|x=3] = 16$.
- (c) An important variable z is omitted, and z is correlated with x , causing $E[u|x] \neq 0$.
- (d) The data are time series and errors are autocorrelated: $u_t = 0.7u_{t-1} + \varepsilon_t$.
-

Exercise 7: Monte Carlo Simulation Understanding

In a Monte Carlo study with 500 simulations from $y = 2 + 3x + u$:

- Mean of 500 intercept estimates: 1.98
- Mean of 500 slope estimates: 2.95
- SD of 500 slope estimates: 0.40

- (a) Do these results support the claim that OLS is unbiased? Explain.
- (b) What would happen to the mean estimates if we ran 10,000 simulations instead of 500?

(c) What would happen to the SD of estimates if we increased the sample size within each simulation from $n=30$ to $n=120$?

Exercise 8: Python Practice

Using Python and the generated data approach from this chapter:

- (a) Generate 100 samples of size $n=50$ from $y = 1 + 2x + u$ with $u \sim N(0, 4)$ and $x \sim N(3, 1)$.
 - (b) Compute b_2 for each sample and create a histogram of the 100 estimates.
 - (c) Calculate the mean and standard deviation of the 100 b_2 estimates. How do they compare to the theoretical values?
 - (d) Test whether the distribution of estimates is approximately normal using a Q-Q plot.
 - (e) Repeat with $n=200$ instead of $n=50$. How does the standard deviation of estimates change?
-

Solutions to selected exercises:

- **Exercise 2a:** $E[y|x=4] = 8 + 4(4) = 24$, so $u = 25 - 24 = 1$
- **Exercise 3a:** $s_e = \sqrt{[112/(30-2)]} = \sqrt{4} = 2$
- **Exercise 3b:** $se(b_2) = 2/\sqrt{50} = 0.283$
- **Exercise 4a:** Dataset A: $se(b_2) = 10/\sqrt{100} = 1.0$; Dataset B: $se(b_2) = 5/\sqrt{100} = 0.5$
- **Exercise 5a:** 95% CI $\approx 15 \pm 2(4) = [7, 23]$

For complete solutions and additional practice problems, see the course website.

| 6.5 Case Studies

Case Study 1: Sampling Variability in Productivity Regressions

Research Question: How does the regression of labor productivity on capital per worker vary across samples?

Background: In this chapter, we learned that OLS estimates vary across samples due to random sampling variation. While Monte Carlo simulations with generated data

demonstrate this principle, it's crucial to see it work with real economic data. We'll use the convergence clubs dataset to explore how much productivity-capital regressions vary when we repeatedly sample from a "population" of 108 countries.

The Data: We use the convergence clubs dataset (Mendez 2020) covering 108 countries from 1990-2014. The cross-section for 2014 provides:

- **Labor productivity** (rgdppc_2014): Real GDP per capita in thousands of 2011 USD
- **Capital per worker** (rk_2014): Physical capital stock per worker in thousands of 2011 USD
- These variables allow us to estimate production function relationships and explore sampling variability

Key Concept 6.8: Sampling Variability in Econometrics

When we estimate a regression from sample data, the coefficients (b_1 , b_2) are random variables that vary across samples. Understanding this variability is essential for statistical inference—it tells us how much confidence to place in our estimates and how to construct confidence intervals and hypothesis tests. The standard error measures the typical deviation of our estimate from the true parameter across hypothetical repeated samples.

Load the Data

We'll work with the 2014 cross-section from the convergence clubs dataset. The full dataset of 108 countries will serve as our "population," and we'll draw samples from it to demonstrate sampling variability.

In []:

```
print("=*70")
print("6.5 CASE STUDIES: SAMPLING VARIABILITY")
print("=*70")

# Load convergence clubs data
convergence_data = pd.read_stata(GITHUB_DATA_URL + "Convergence_clubs_2023.dta")

# Extract 2014 cross-section
data_2014 = convergence_data[convergence_data['year'] == 2014].copy()

# Create relevant variables
data_2014 = data_2014[['country', 'rgdppc', 'rk']].dropna()
data_2014.columns = ['country', 'productivity', 'capital']

print(f"\nData loaded: {len(data_2014)} countries in 2014")
print("\nSummary statistics:")
print(data_2014[['productivity', 'capital']].describe())
print("\nFirst 5 observations:")
print(data_2014.head())
```

Task 1: Estimate the "Population" Regression (Guided)

Instructions: We'll treat the full dataset of 108 countries as our "population" and estimate the regression of productivity on capital. This will serve as our benchmark—the "true" relationship we're trying to recover from samples.

Research question: What is the relationship between capital per worker and labor productivity across all 108 countries?

Your task:

1. Estimate the regression: $\text{productivity} = \beta_1 + \beta_2 \times \text{capital} + u$
2. Report the coefficients, standard errors, and R²
3. Interpret the slope coefficient: What does β_2 tell us about the capital-productivity relationship?

Code template:

```
# Estimate full-sample ("population") regression
population_model = ols('productivity ~ capital', data=data_2014).fit()
print(population_model.summary())

# Store population coefficients
beta_1_pop = population_model.params['Intercept']
beta_2_pop = population_model.params['capital']
print(f"\nPopulation coefficients: \beta_1 = {beta_1_pop:.4f}, \beta_2 = {beta_2_pop:.4f}")
```

Interpretation guide: A slope of $\beta_2 = 0.05$, for example, means that a 1,000 increase in capital per worker is associated with a 50 increase in GDP per capita ($0.05 \times 1000 = 50$), on average across countries.

Task 2: Draw a Random Sample and Estimate Regression (Semi-guided)

Instructions: Now draw a random sample of 50 countries from the full dataset and estimate the same regression. Compare the sample estimate to the population parameter.

Your task:

1. Draw a random sample of $n=50$ countries (use `data_2014.sample(n=50, random_state=42)`)
2. Estimate the regression on this sample
3. Compare the sample coefficients (b_1, b_2) to the population parameters (β_1, β_2)
4. Calculate the sampling error: $b_2 - \beta_2$

Hints:

- The `random_state` parameter ensures reproducibility
- Sampling error = sample estimate - population parameter
- Even though this is random sampling, you likely won't get b_2 exactly equal to β_2

Key Concept 6.9: Sample vs. Population Regression

*The full dataset of 108 countries acts as our "population." When we draw a sample of 50 countries, we're simulating the real-world situation where researchers work with incomplete data. The difference between the population coefficient (β_2) and the sample coefficient (b_2) is the **sampling error**—an inevitable consequence of working with limited data. This error is random: sometimes $b_2 > \beta_2$, sometimes $b_2 < \beta_2$, but on average $b_2 = \beta_2$ (unbiasedness).*

Task 3: Simulate the Sampling Distribution (Semi-guided)

Instructions: To understand sampling variability, we need to see how b_2 varies across many samples. Run a Monte Carlo simulation: draw 1,000 random samples of $n=50$, estimate the regression for each, and collect all the b_2 estimates.

Your task:

1. Create a loop that runs 1,000 iterations
2. In each iteration: (a) draw a random sample of 50 countries, (b) estimate the regression, (c) store the slope coefficient b_2
3. Create a histogram of the 1,000 b_2 estimates

4. Calculate the mean and standard deviation of these estimates
5. Compare the mean to the population parameter β_2

Code structure:

```

# Monte Carlo simulation
n_simulations = 1000
sample_size = 50
b2_estimates = []

for i in range(n_simulations):
    # Draw random sample
    sample = data_2014.sample(n=sample_size, replace=False)

    # Estimate regression
    model = ols('productivity ~ capital', data=sample).fit()

    # Store slope coefficient
    b2_estimates.append(model.params['capital'])

# Analyze sampling distribution
print(f"Mean of b2 estimates: {np.mean(b2_estimates):.4f}")
print(f"Std dev of b2 estimates: {np.std(b2_estimates):.4f}")
print(f"Population parameter beta_2: {beta_2_pop:.4f}")

```

Expected outcome: The mean of your 1,000 estimates should be very close to β_2 (confirming unbiasedness), and the histogram should look approximately normal (confirming the Central Limit Theorem).

Task 4: Calculate Theoretical vs. Empirical Standard Error (More Independent)

Instructions: The standard error of b_2 can be calculated two ways: (1) using the theoretical formula with sample data, (2) using the standard deviation of estimates across many samples (Monte Carlo).

Your task:

1. **Theoretical SE:** Take any single sample of $n=50$, estimate the regression, and extract $se(b_2)$ from the regression output
2. **Empirical SE:** Use the standard deviation of the 1,000 b_2 estimates from Task 3
3. Compare the two: Are they similar? Why or why not?

Hints:

- The theoretical SE comes from the formula: $se(b_2) = s_e / \sqrt{[\sum(x_i - \bar{x})^2]}$
- The empirical SE is: $std(b_2 \text{ estimates from 1,000 samples})$
- They should be close but not identical (theoretical SE is an estimate, empirical SE is the "true" sampling variability in this simulation)

Discussion questions:

- In real-world research, do we have access to the empirical SE? Why or why not?
- Why is the theoretical SE useful if we can only draw one sample?

Task 5: Investigate the Effect of Sample Size (Independent)

Instructions: Theory predicts that standard errors decrease with sample size n according to the relationship $se(b_2) \propto 1/\sqrt{n}$. Test this prediction by comparing sampling distributions for different sample sizes.

Your task:

1. Run Monte Carlo simulations (1,000 iterations each) for three sample sizes: $n = 20$, $n = 50$, $n = 80$
2. For each sample size, calculate the standard deviation of b_2 estimates
3. Create side-by-side histograms of the three sampling distributions
4. Verify the theoretical relationship: Does $se(b_2)$ decrease roughly as $1/\sqrt{n}$?

Analysis questions:

- If you double the sample size from $n=50$ to $n=100$, how much does the standard error decrease?
- What does this imply about the "cost" of precision in empirical research?
- Would you prefer a study with $n=50$ or $n=80$? How much more precise is the larger sample?

Key Concept 6.10: Standard Errors and Sample Size

Standard errors decrease with the square root of sample size: $se(b_2) = \sigma_u / \sqrt{[n \times Var(x)]}$. This means to halve the standard error, you need four times the sample size. This fundamental relationship guides study design—small increases in sample size yield diminishing returns in precision. The implication: going from $n=100$ to $n=400$ has the same effect on precision as going from $n=25$ to $n=100$.

Task 6: Compare Sampling Variability Across Country Groups (Independent)

Instructions: Does sampling variability differ across subpopulations? Compare the capital-productivity relationship for high-income vs. developing countries.

Your task (student-designed analysis):

1. Split the data into two groups: high-income (productivity > median) vs. developing (productivity \leq median)
2. For each group, run a Monte Carlo simulation with 1,000 samples of n=30
3. Compare the sampling distributions: Do they have different means? Different variances?
4. Explain any differences you observe

Research questions to explore:

- Is the capital-productivity relationship stronger in one group vs. the other?
- Is sampling variability higher in one group? Why might this be?
- What does this suggest about generalizing findings across different country contexts?

Extension: You could also explore other groupings (by region, by continent, by development indicators) to see how robust the capital-productivity relationship is across different contexts.

What You've Learned

Through this case study, you've:

- **Experienced firsthand** how OLS estimates vary across samples using real economic data (not just simulated data)
- **Verified empirically** that the theoretical standard error formula accurately predicts sampling variability
- **Discovered** how sample size affects estimation precision in practice ($se \propto 1/\sqrt{n}$)
- **Explored** whether sampling variability differs across subpopulations (high-income vs. developing countries)
- **Connected** abstract statistical theory (unbiasedness, CLT, standard errors) to tangible empirical patterns

Key insights:

1. **Unbiasedness in action:** The average of many sample estimates equals the population parameter, even though individual estimates vary
2. **Standard errors quantify uncertainty:** The spread of the sampling distribution tells us how much confidence to place in any single estimate
3. **Sample size matters:** Larger samples yield more precise estimates, but with diminishing returns (\sqrt{n} relationship)

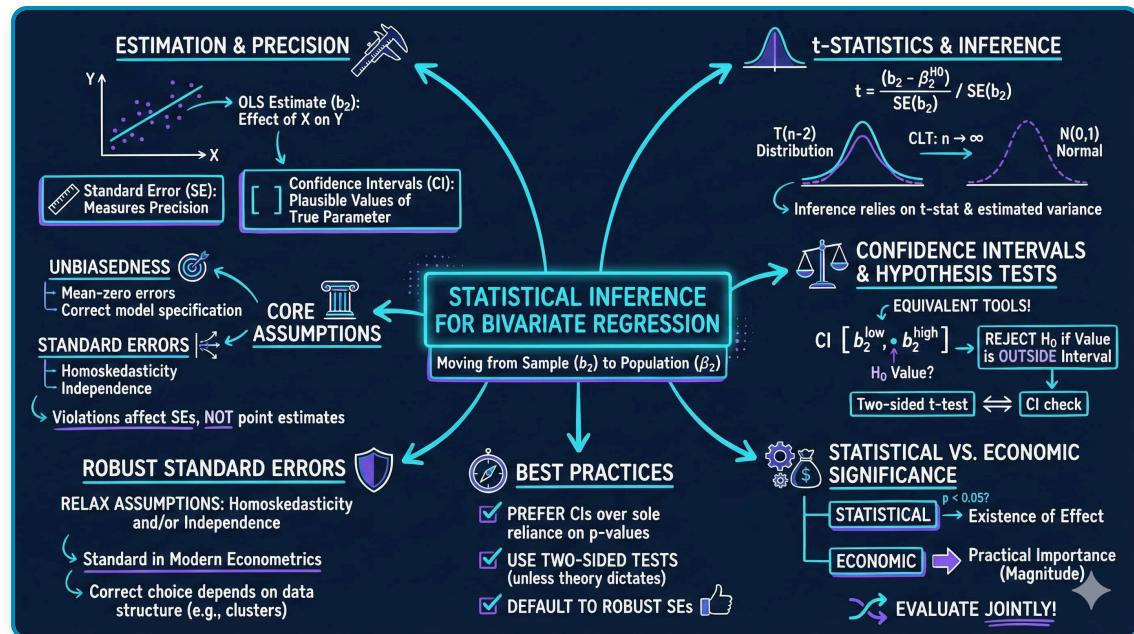
4. Context matters: Sampling variability may differ across subpopulations, affecting the generalizability of findings

Next steps: In Chapter 7, you'll use these standard errors to construct confidence intervals and test hypotheses about regression coefficients—the foundation of statistical inference in econometrics.

Chapter 7: Statistical Inference for Bivariate Regression

metricsAI: An Introduction to Econometrics with Python and AI in the Cloud

Carlos Mendez



This notebook provides an interactive introduction to statistical inference for bivariate regression models. All code runs directly in Google Colab without any local setup.

Open in Colab

| Chapter Overview

This chapter extends statistical inference from univariate to bivariate regression. You'll gain both theoretical understanding and practical skills through hands-on Python examples, learning how to test hypotheses about regression coefficients and construct confidence intervals.

What you'll learn:

- The t-statistic for testing hypotheses about regression coefficients
- Constructing and interpreting confidence intervals for slope parameters

- Tests of statistical significance (whether a regressor matters)
- Two-sided hypothesis tests for specific parameter values
- One-sided directional hypothesis tests
- Heteroskedasticity-robust standard errors and their importance
- Economic vs. statistical significance

Datasets used:

- **AED_HOUSE.DTA:** House prices and characteristics for 29 houses sold in Central Davis, California in 1999 (price, size, bedrooms, bathrooms, lot size, age)

Chapter outline:

- 7.1 Example: House Price and Size
- 7.2 The t Statistic
- 7.3 Confidence Intervals
- 7.4 Tests of Statistical Significance
- 7.5 Two-Sided Hypothesis Tests
- 7.6 One-Sided Directional Hypothesis Tests
- 7.7 Robust Standard Errors
- 7.8 Case Studies
- Key Takeaways
- Practice Exercises

| Setup

First, we import the necessary Python packages and configure the environment for reproducibility. All data will stream directly from GitHub.

In [18]:

```
# Import required packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
from statsmodels.formula.api import ols
from scipy import stats
from statsmodels.stats.sandwich_covariance import cov_hc1
import random
import os

# Set random seeds for reproducibility
RANDOM_SEED = 42
random.seed(RANDOM_SEED)
np.random.seed(RANDOM_SEED)
os.environ['PYTHONHASHSEED'] = str(RANDOM_SEED)

# GitHub data URL
GITHUB_DATA_URL = "https://raw.githubusercontent.com/quarcs-lab/data-open/master/AED/"

# Set plotting style
sns.set_style("whitegrid")
plt.rcParams['figure.figsize'] = (10, 6)

print("Setup complete! Ready to explore statistical inference for bivariate regression.")
```

Setup complete! Ready to explore statistical inference for bivariate regression.

7.1 Example: House Price and Size

We begin with a motivating example: the relationship between house price and house size.

The regression model:

$$\text{price} = \beta_1 + \beta_2 \times \text{size} + u$$

where:

- price is the house sale price (in thousands of dollars)
- size is the house size (in square feet)
- β_2 is the population slope (price increase per square foot)
- b_2 is the sample estimate of β_2

Key regression output:

Variable	Coefficient	Standard Error	t-statistic	p-value	95% CI
Size	73.77	11.17	6.60	0.000	[50.84, 96.70]
Intercept	115,017.30	21,489.36	5.35	0.000	[70,924.76, 159,101]

Interpretation:

- Each additional square foot increases house price by approximately \$73.77
- The standard error (11.17) measures uncertainty in this estimate
- The t-statistic (6.60) tests whether the effect is statistically significant
- The 95% confidence interval is [50.84, 96.70]

In [19]:

```
print("=" * 70)
print("7.1 EXAMPLE: HOUSE PRICE AND SIZE")
print("=" * 70)

# Read in the house data
data_house = pd.read_stata(GITHUB_DATA_URL + 'AED_HOUSE.DTA')

print("\nData summary:")
data_summary = data_house.describe()
print(data_summary)

print("\nFirst few observations:")
print(data_house.head())
```

```
=====
7.1 EXAMPLE: HOUSE PRICE AND SIZE
=====

Data summary:
      price          size   bedrooms   bathrooms   lotsize      age \
count    29.000000    29.000000  29.000000  29.000000  29.000000  29.000000
mean   253910.344828  1882.758621   3.793103   2.206897  2.137931  36.413792
std     37390.710695   398.272130   0.675030   0.341144  0.693034  7.118975
min    204000.000000  1400.000000   3.000000   2.000000  1.000000  23.000000
25%   233000.000000  1600.000000   3.000000   2.000000  2.000000  31.000000
50%   244000.000000  1800.000000   4.000000   2.000000  2.000000  35.000000
75%   270000.000000  2000.000000   4.000000   2.500000  3.000000  39.000000
max   375000.000000  3300.000000   6.000000   3.000000  3.000000  51.000000

      monthsold        list
count  29.000000    29.000000
mean    5.965517  257824.137931
std     1.679344  40860.264099
min    3.000000  199900.000000
25%   5.000000  239000.000000
50%   6.000000  245000.000000
75%   7.000000  269000.000000
max    8.000000  386000.000000

First few observations:
   price   size  bedrooms  bathrooms  lotsize   age  monthsold      list
0  204000  1400       3       2.0       1  31.0       7  199900
1  212000  1600       3       3.0       2  33.0       5  212000
2  213000  1800       3       2.0       2  51.0       4  219900
3  220000  1600       3       2.0       1  49.0       4  229000
4  224500  2100       4       2.5       2  47.0       6  224500
```

Basic Regression: Price on Size

We estimate the bivariate regression model using ordinary least squares (OLS).

```
In [20]: # Table 7.1 - Basic regression
print("=" * 70)
print("Table 7.1: Regression of House Price on Size")
print("=" * 70)

model_basic = ols('price ~ size', data=data_house).fit()
print(model_basic.summary())

=====
Table 7.1: Regression of House Price on Size
=====
OLS Regression Results
=====
Dep. Variable:           price    R-squared:      0.617
Model:                 OLS     Adj. R-squared:   0.603
Method:                Least Squares   F-statistic:   43.58
Date:      Tue, 20 Jan 2026   Prob (F-statistic): 4.41e-07
Time:      23:33:22         Log-Likelihood:   -332.05
No. Observations:      29        AIC:            668.1
Df Residuals:          27        BIC:            670.8
Df Model:               1
Covariance Type:       nonrobust
=====
            coef    std err        t    P>|t|      [0.025    0.975]
-----
Intercept  1.15e+05  2.15e+04    5.352    0.000    7.09e+04  1.59e+05
size        73.7710   11.175     6.601    0.000    50.842    96.700
=====
Omnibus:             0.576  Durbin-Watson:    1.219
Prob(Omnibus):       0.750  Jarque-Bera (JB):  0.638
Skew:                  -0.078  Prob(JB):        0.727
Kurtosis:              2.290  Cond. No.       9.45e+03
=====

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 9.45e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Coefficient Table

Let's create a clean table showing the key statistics for statistical inference.

```
In [21]: # Save coefficients in a clean table
coef_table = pd.DataFrame({
    'Coefficient': model_basic.params,
    'Std. Error': model_basic.bse,
    't-statistic': model_basic.tvalues,
    'p-value': model_basic.pvalues
})

print("\nCoefficient Table:")
print(coef_table)

print("\nInterpretation:")
print(" - Slope (size): Each additional sq ft increases price by $73.77")
print(" - Standard error: Measures uncertainty in the slope estimate")
print(" - t-statistic: Tests whether slope differs from zero")
print(" - p-value: Probability of observing such extreme values under H0: β2 = 0")
```

Coefficient Table:				
	Coefficient	Std. Error	t-statistic	p-value
Intercept	115017.282609	21489.359861	5.352290	1.183545e-05
size	73.771040	11.174911	6.601488	4.408752e-07

Interpretation:

- Slope (size): Each additional sq ft increases price by \$73.77
- Standard error: Measures uncertainty in the slope estimate
- t-statistic: Tests whether slope differs from zero
- p-value: Probability of observing such extreme values under $H_0: \beta_2 = 0$

7.2 The t Statistic

The t-statistic is fundamental to statistical inference in regression.

Statistical inference problem:

- **Sample:** $\hat{y} = b_1 + b_2x$ where b_1 and b_2 are least squares estimates
- **Population:** $E[y|x] = \beta_1 + \beta_2x$ and $y = \beta_1 + \beta_2x + u$
- **Goal:** Make inferences about the slope parameter β_2

The t-statistic:

$$T = \frac{\text{estimate} - \text{parameter}}{\text{standard error}} = \frac{b_2 - \beta_2}{se(b_2)} \sim T(n - 2)$$

Why use the T(n-2) distribution?

Under assumptions 1-4:

- $Var[b_2] = \sigma_u^2 / \sum_{i=1}^n (x_i - \bar{x})^2$
- We don't know σ_u^2 , so we replace it with $s_e^2 = \frac{1}{n-2} \sum_{i=1}^n (y_i - \hat{y}_i)^2$
- This introduces additional uncertainty, so we use $T(n - 2)$ instead of $N(0, 1)$

Model Assumptions (1-4):

1. The population model is $y = \beta_1 + \beta_2x + u$
2. The error has mean zero conditional on x: $E[u_i|x_i] = 0$
3. The error has constant variance: $Var[u_i|x_i] = \sigma_u^2$
4. The errors are statistically independent: u_i independent of u_j

Understanding Standard Errors: The Foundation of Inference

What is a standard error?

The standard error measures the uncertainty in our estimate. It answers: "If we repeatedly sampled from the population and computed b_2 each time, how much would b_2 vary across samples?"

Key distinction:

- **Standard deviation:** Variability of individual observations (data spread)
- **Standard error:** Variability of the estimate across samples (estimation uncertainty)

Formula for SE of the slope:

$$se(b_2) = \frac{\sigma_u}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2}} = \frac{\sigma_u}{\sqrt{n} \cdot \sigma_x}$$

where:

- σ_u = standard deviation of the error term
- σ_x = standard deviation of x
- n = sample size

What affects the standard error?

1. Error variance (σ^2_u): Larger $\sigma_u \rightarrow$ Larger SE

- More unexplained variation in y
- Data points farther from regression line
- Less precise estimates

2. Sample size (n): Larger $n \rightarrow$ Smaller SE

- More data reduces uncertainty
- SE decreases at rate $1/\sqrt{n}$
- Quadruple n to halve SE

3. Variation in x (σ_x): Larger $\sigma_x \rightarrow$ Smaller SE

- More spread in x provides more information
- Extreme x values help identify the slope
- Concentrated x values give less precision

Intuition:

Think of the regression line as a seesaw balanced at (\bar{x}, \bar{y}) :

- With wide spread in x : Small changes in slope make big differences at the extremes (easy to detect slope)
- With narrow spread in x : Hard to distinguish different slopes (difficult to detect slope)

Example calculation for our house price data:

Given:

- Sample size: $n = 29$
- Standard error of regression: $\sigma_u \approx 37,000$
- Standard deviation of size: $\sigma_x \approx 360$
- Estimated $SE(b_2) = 37,000 / (\sqrt{29} \times 360) \approx 19.1$

(Actual SE is 11.17, smaller because the relationship is quite strong)

Why standard errors matter:

1. **Confidence intervals:** $CI = b_2 \pm t \times SE(b_2)$
2. **Hypothesis tests:** $t = (b_2 - \beta_2^0) / SE(b_2)$
3. **Practical significance:** Small SE \rightarrow precise estimate \rightarrow more reliable
4. **Study design:** Calculate required n for desired SE

Relationship to R^2 :

Higher R^2 (better fit) \rightarrow Smaller σ_u \rightarrow Smaller SE \rightarrow More precise estimates

For our house price example:

- $R^2 = 0.62$ (size explains 62% of price variation)
- This gives relatively small SE
- If R^2 were 0.10, SE would be about 2.5 times larger

In [22]:

```
print("=" * 70)
print("7.2 THE T STATISTIC")
print("=" * 70)

print("\nRegression coefficients and t-statistics:")
print(model_basic.summary2().tables[1])

# Extract key statistics
coef_size = model_basic.params['size']
se_size = model_basic.bse['size']
t_stat_size = model_basic.tvalues['size']
p_value_size = model_basic.pvalues['size']

print(f"\nDetailed statistics for 'size' coefficient:")
print(f" Coefficient: {coef_size:.4f}")
print(f" Standard Error: {se_size:.4f}")
print(f" t-statistic: {t_stat_size:.4f}")
print(f" p-value: {p_value_size:.6f}")

print("\nThe t-statistic formula:")
print(f" t = b2 / se(b2) = {coef_size:.4f} / {se_size:.4f} = {t_stat_size:.4f}")
```

```
=====
7.2 THE T STATISTIC
=====

Regression coefficients and t-statistics:
      Coef.    Std.Err.        t      P>|t|      [0.025  \
Intercept  115017.282609  21489.359861  5.352290  1.183545e-05  70924.758265
size        73.771040     11.174911   6.601488  4.408752e-07   50.842017

          0.975]
Intercept  159109.806952
size        96.700064

Detailed statistics for 'size' coefficient:
 Coefficient: $73.7710
 Standard Error: $11.1749
 t-statistic: 6.6015
 p-value: 0.000000

The t-statistic formula:
 t = b2 / se(b2) = 73.7710 / 11.1749 = 6.6015
```

Key Concept 7.1: The t-Distribution and Degrees of Freedom

The **t-distribution** is used for statistical inference when the population variance is unknown (which is always the case in practice). Unlike the standard normal distribution, the t-distribution accounts for the additional uncertainty from estimating the variance.

Key properties:

- Bell-shaped and symmetric (like the normal distribution)
- Heavier tails than the normal distribution (more probability in extremes)
- Converges to the normal distribution as sample size increases
- Characterized by degrees of freedom (df)

Degrees of freedom = $n - 2$ for bivariate regression:

- Start with n observations
- Estimate β_1 (intercept): -1 df
- Estimate β_2 (slope): -1 df
- Remaining df for estimating variance: $n - 2$

Practical implication: For small samples ($n < 30$), the t-distribution's heavier tails lead to wider confidence intervals and more conservative hypothesis tests compared to the normal distribution. For large samples ($n > 100$), the difference becomes negligible.

| 7.3 Confidence Intervals

A confidence interval provides a range of plausible values for the population parameter.

Formula for a $100(1 - \alpha)$ confidence interval:

$$b_2 \pm t_{n-2,\alpha/2} \times se(b_2)$$

where:

- b_2 is the slope estimate
- $se(b_2)$ is the standard error of b_2

- $t_{n-2,\alpha/2}$ is the critical value from Student's t-distribution with $n - 2$ degrees of freedom

95% confidence interval (approximate):

$$b_2 \pm 2 \times se(b_2)$$

Interpretation:

- If we repeatedly sampled from the population and constructed 95% CIs, approximately 95% of these intervals would contain the true parameter value β_2
- The calculated 95% CI will correctly include β_2 95% of the time

Example calculation for house price:

$$\begin{aligned} b_2 \pm t_{27,0.025} \times se(b_2) &= 73.77 \pm 2.052 \times 11.17 \\ &= 73.77 \pm 22.93 \\ &= [50.84, 96.70] \end{aligned}$$

Key Concept 7.2: Interpreting Confidence Intervals

A **confidence interval** provides a range of plausible values for the population parameter. For regression slopes, the 95% CI is:

$$b_2 \pm t_{n-2,0.025} \times se(b_2)$$

Common misconceptions:

- **WRONG:** "There's a 95% probability that β_2 is in this interval"
- **CORRECT:** "If we repeated the sampling process many times, 95% of the constructed intervals would contain β_2 "

Practical interpretation:

- The interval represents our uncertainty about the true parameter value
- Wider intervals indicate more uncertainty (large SE, small n, or high variability)
- Narrower intervals indicate more precision (small SE, large n, or low variability)
- Values inside the interval are "plausible" at the chosen confidence level
- Values outside the interval would be rejected in a hypothesis test

Relationship to hypothesis testing: If a null value β_2^* falls inside the 95% CI, we fail to reject $H_0: \beta_2 = \beta_2^*$ at the 5% significance level. This makes CIs more informative than hypothesis tests alone.

I Understanding Confidence Intervals: A Deep Dive

What is a confidence interval?

A confidence interval (CI) is NOT a probability statement about the parameter. Instead, it's a statement about the procedure used to construct the interval.

Common misconceptions:

WRONG: "There is a 95% probability that β_2 is between 50.84 and 96.70"

- The parameter β_2 is fixed (not random)
- The interval either contains β_2 or it doesn't

CORRECT: "If we repeatedly sampled and constructed 95% CIs, approximately 95% of these intervals would contain the true β_2 "

- The randomness is in the sampling process
- Our particular interval is one realization from this process

Intuitive explanation:

Imagine conducting 100 different studies using different random samples from the same population:

- Each study estimates β_2 and constructs a 95% CI
- About 95 of the 100 intervals will contain the true β_2
- About 5 of the 100 intervals will miss β_2 (just by chance)

Width of confidence intervals:

The CI width depends on three factors:

$$\text{Width} = 2 \times t_{n-2,\alpha/2} \times se(b_2)$$

1. Confidence level ($1-\alpha$): Higher confidence \rightarrow wider interval

- 90% CI: Narrower (less confident)
- 95% CI: Standard choice (balance)
- 99% CI: Wider (more confident)

2. Sample size (n): Larger sample \rightarrow narrower interval

- More data reduces uncertainty
- Critical value $t_{\{n-2, \alpha/2\}}$ decreases as n increases

3. Variability in data: More scatter \rightarrow wider interval

- $se(b_2)$ increases with unexplained variation
- Tighter relationship \rightarrow more precise estimates

Practical use:

Confidence intervals are more informative than hypothesis tests because they show:

- The point estimate (center of interval)
- The precision of the estimate (width of interval)

- All null values that would not be rejected (values inside interval)

In [23]:

```
print("=" * 70)
print("7.3 CONFIDENCE INTERVALS")
print("=" * 70)

# 95% confidence intervals
conf_int = model_basic.conf_int(alpha=0.05)
print("\n95% Confidence Intervals:")
print(conf_int)
```

```
=====
7.3 CONFIDENCE INTERVALS
=====

95% Confidence Intervals:
          0              1
Intercept 70924.758265 159109.806952
size       50.842017   96.700064
```

The t-Distribution vs Normal Distribution: Why It Matters

Why not use the normal distribution?

In theory, when we know the population variance σ^2_u , the test statistic follows a standard normal distribution:

$$Z = \frac{b_2 - \beta_2}{\sigma / \sqrt{\sum(x_i - \bar{x})^2}} \sim N(0, 1)$$

The problem: We never know σ_u in practice!

The solution: Replace σ_u with its estimate s_e (residual standard error):

$$T = \frac{b_2 - \beta_2}{s_e / \sqrt{\sum(x_i - \bar{x})^2}} \sim T(n - 2)$$

This substitution introduces additional uncertainty, so we use the t-distribution instead of normal.

Properties of the t-distribution:

1. **Shape:** Bell-shaped and symmetric (like normal)
2. **Mean:** 0 (like normal)
3. **Variance:** $df/(df-2) > 1$ (heavier tails than normal)
4. **Degrees of freedom:** $n - 2$ for bivariate regression
 - n observations

- Minus 2 parameters estimated (β_1 and β_2)

Key differences from normal:

Sample Size	t Critical Value ($\alpha=0.05$)	z Critical Value	Difference
n = 5 (df=3)	3.182	1.96	+62%
n = 10 (df=8)	2.306	1.96	+18%
n = 30 (df=28)	2.048	1.96	+4%
n = 100 (df=98)	1.984	1.96	+1%
n $\rightarrow \infty$	1.96	1.96	0%

What this means:

- Small samples:** t critical values much larger \rightarrow wider CIs, harder to reject H_0
- Large samples:** t \approx normal \rightarrow approximately same inference
- Our house data:** n=29, df=27, t(0.025) = 2.052 vs z = 1.96

Why degrees of freedom = n - 2?

- Start with n observations
- Estimate β_1 (intercept): loses 1 df
- Estimate β_2 (slope): loses 1 df
- Remaining df for estimating variance: n - 2

Practical implications:

For n = 29 (our house price data):

- Using normal: 95% CI margin = $1.96 \times 11.17 = 21.89$
- Using t(27): 95% CI margin = $2.052 \times 11.17 = 22.92$
- Difference: 5% wider with t-distribution (more conservative)

For n = 10 (small sample):

- Using normal: 95% CI margin = $1.96 \times SE$
- Using t(8): 95% CI margin = $2.306 \times SE$
- Difference: 18% wider with t-distribution (much more conservative!)

Rule of thumb:

- n < 30: Must use t-distribution
- 30 \leq n < 100: Use t-distribution (small difference)

- $n \geq 100$: Normal approximation usually fine, but still use t

Modern practice: Statistical software always uses t-distribution (why not? It's correct for any n)

Visual intuition:

The t-distribution has heavier tails:

- More probability in the extremes
- Less probability near the center
- This accounts for the uncertainty in estimating σ_u
- As n increases, estimation uncertainty decreases, and $t \rightarrow$ normal

Manual Calculation of Confidence Interval

Let's manually calculate the confidence interval for the size coefficient to understand the mechanics.

In [24]:

```
# Manual calculation of confidence interval for size
n = len(data_house)
df = n - 2
t_crit = stats.t.ppf(0.975, df) # 97.5th percentile for two-sided 95% CI

ci_lower = coef_size - t_crit * se_size
ci_upper = coef_size + t_crit * se_size

print("Manual calculation for 'size' coefficient:")
print(f" Sample size: {n}")
print(f" Degrees of freedom: {df}")
print(f" Critical t-value (a=0.05): {t_crit:.4f}")
print(f" Margin of error: {t_crit * se_size:.4f}")
print(f" 95% CI: [{ci_lower:.4f}, {ci_upper:.4f}]")

print("\nInterpretation:")
print(f" We are 95% confident that each additional square foot")
print(f" increases house price by between ${ci_lower:.2f} and ${ci_upper:.2f}.")
```

Manual calculation for 'size' coefficient:

Sample size: 29
Degrees of freedom: 27
Critical t-value (a=0.05): 2.0518
Margin of error: 22.9290
95% CI: [\$50.8420, \$96.7001]

Interpretation:

We are 95% confident that each additional square foot increases house price by between \$50.84 and \$96.70.

I Example with Artificial Data

To illustrate the concepts more clearly, let's work with a simple artificial dataset.

Key Concept 7.3: The Hypothesis Testing Framework

Hypothesis testing is a formal procedure for making decisions about population parameters. The key steps are:

1. State the hypotheses:

- **Null hypothesis (H_0)**: The claim we're testing (usually "no effect")
- **Alternative hypothesis (H_a)**: What we conclude if we reject H_0

2. Choose significance level (α):

- Common choices: 0.10, 0.05, 0.01
- α = probability of Type I error (rejecting H_0 when it's true)

3. Calculate test statistic:

- Standardizes the difference: $t = (\text{estimate} - \text{null value}) / SE$

4. Determine p-value:

- Probability of observing our result (or more extreme) if H_0 is true
- Smaller p-value = stronger evidence against H_0

5. Make decision:

- Reject H_0 if $p\text{-value} < \alpha$
- Fail to reject H_0 if $p\text{-value} \geq \alpha$ (never "accept" H_0)

Understanding p-values: If $p = 0.001$, this means "if H_0 were true, we'd observe a result this extreme only 0.1% of the time." This is strong evidence against H_0 .

Key Concept 7.4: Statistical vs. Economic Significance

Statistical significance and **economic significance** are distinct concepts that answer different questions:

Statistical Significance:

- **Question:** Is the effect different from zero?
- **Determined by:** $t\text{-statistic} = b_2 / \text{se}(b_2)$, which depends on sample size, variability, and effect size
- **Interpretation:** We can confidently say the effect exists (not due to chance)

Economic Significance:

- **Question:** Is the effect large enough to matter in practice?
- **Determined by:** The magnitude of b_2 and the context
- **Interpretation:** The effect has real-world importance

Why they can diverge:

1. Large n: Even tiny effects become statistically significant

- Example: $\beta_2 = \$0.01$ with $n = 10,000$ might have $p < 0.001$ but be economically trivial

2. Small n: Large effects may not reach statistical significance

- Example: $\beta_2 = \$100$ with $n = 10$ might have $p = 0.12$ but be economically important

Best practice: Always report both the coefficient estimate (economic magnitude) and the standard error/confidence interval (statistical precision). Focus on confidence intervals, which show both dimensions simultaneously.

Key Concept 7.5: One-Sided vs. Two-Sided Tests

The choice between one-sided and two-sided tests depends on your research question:

Two-Sided Test (Most Common):

- $H_0: \beta_2 = \beta_2^*$ vs. $H_a: \beta_2 \neq \beta_2^*$
- Detects deviations in either direction
- Standard practice in academic research
- Rejection region: Both tails of t -distribution

One-Sided Test (Directional):

- Upper: $H_0: \beta_2 \leq \beta_2^*$ vs. $H_a: \beta_2 > \beta_2^*$
- Lower: $H_0: \beta_2 \geq \beta_2^*$ vs. $H_a: \beta_2 < \beta_2^*$
- Detects deviations in one specific direction
- Rejection region: One tail only

Key relationship: For the same test statistic, one-sided p -value = (two-sided p -value) / 2 (if sign is correct)

When to use one-sided tests:

- Strong theoretical prediction of direction (before seeing data)
- Only care about deviations in one direction
- Be cautious: Journals typically require two-sided tests

Important: If your data contradicts the predicted direction, you cannot reject H_0 with a one-sided test (p -value > 0.5).

In [25]:

```
print("=" * 70)
print("Example with Artificial Data")
print("=" * 70)

x = np.array([1, 2, 3, 4, 5])
y = np.array([1, 2, 2, 2, 3])
df_artificial = pd.DataFrame({'x': x, 'y': y})

model_artificial = ols('y ~ x', data=df_artificial).fit()
print(model_artificial.summary())

coef_x = model_artificial.params['x']
se_x = model_artificial.bse['x']
n_art = len(x)
df_art = n_art - 2
t_crit_art = stats.t.ppf(0.975, df_art)

ci_lower_art = coef_x - t_crit_art * se_x
ci_upper_art = coef_x + t_crit_art * se_x

print(f"\nManual CI for artificial data:")
print(f" Coefficient: {coef_x:.4f}")
print(f" Standard Error: {se_x:.4f}")
print(f" 95% CI: [{ci_lower_art:.4f}, {ci_upper_art:.4f}]")
```

```
=====
Example with Artificial Data
=====
                OLS Regression Results
=====
Dep. Variable:                  y   R-squared:          0.800
Model:                          OLS   Adj. R-squared:    0.733
Method: Least Squares   F-statistic:         12.00
Date: Tue, 20 Jan 2026   Prob (F-statistic): 0.0405
Time: 23:33:22            Log-Likelihood:   -0.78037
No. Observations:                 5   AIC:             5.561
Df Residuals:                      3   BIC:             4.780
Df Model:                           1
Covariance Type:      nonrobust
=====
              coef    std err        t      P>|t|      [0.025      0.975]
-----
Intercept    0.8000     0.383     2.089     0.128     -0.419     2.019
x            0.4000     0.115     3.464     0.041      0.033     0.767
=====
Omnibus:                     nan   Durbin-Watson:    2.600
Prob(Omnibus):                  nan   Jarque-Bera (JB): 0.352
Skew:                         -0.000   Prob(JB):       0.839
Kurtosis:                      1.700   Cond. No.        8.37
=====
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Manual CI for artificial data:
 Coefficient: 0.4000
 Standard Error: 0.1155
 95% CI: [0.0325, 0.7675]
```

```
/Users/carlosmendez/miniforge3/lib/python3.10/site-packages/statsmodels/stats/stattools.py:74: ValueWarning: omni_normtest is not valid with less than 8 observations; 5 samples were given.
  warn("omni_normtest is not valid with less than 8 observations; %i "%
```

Understanding Hypothesis Testing: The Complete Workflow

The hypothesis testing framework:

Hypothesis testing is a formal procedure for making decisions about population parameters using sample data.

Step-by-step workflow:

1. State the hypotheses

- **Null hypothesis (H_0):** The claim we're testing (usually "no effect")
- **Alternative hypothesis (H_a):** What we conclude if we reject H_0
- Example: $H_0: \beta_2 = 0$ vs $H_a: \beta_2 \neq 0$

2. Choose the significance level (α)

- Common choices: 0.10, 0.05, 0.01
- α = probability of rejecting H_0 when it's actually true (Type I error)
- Convention: $\alpha = 0.05$ (5% significance level)

3. Calculate the test statistic

- Formula: $t = (b_2 - \beta_2^0) / se(b_2)$
- This standardizes the difference between estimate and null value
- Under H_0 , t follows a t-distribution with $n-2$ degrees of freedom

4. Determine the p-value

- p-value = probability of observing a test statistic as extreme as ours if H_0 is true
- Smaller p-value = stronger evidence against H_0
- $p\text{-value} < \alpha \rightarrow \text{reject } H_0$

5. Make a decision

- **Reject H_0 :** Strong evidence against the null hypothesis
- **Fail to reject H_0 :** Insufficient evidence to reject the null
- Note: We never "accept" H_0 , we only fail to reject it

6. State the conclusion

- Translate the statistical decision into plain language

- Example: "House size has a statistically significant effect on price at the 5% level"

Understanding p-values:

The p-value answers this question: "If the null hypothesis were true, what is the probability of getting a result at least as extreme as what we observed?"

Example interpretation:

- $p = 0.000$: If β_2 were truly zero, the probability of getting $t \geq 6.60$ is less than 0.1%
- This is very unlikely, so we have strong evidence against H_0

Two approaches to hypothesis testing:

1. **p-value approach**: Reject H_0 if p-value < α
2. **Critical value approach**: Reject H_0 if $|t| >$ critical value

Both approaches always give the same conclusion!

Common significance levels and interpretations:

p-value	Interpretation	Strength of Evidence
$p > 0.10$	Not significant	Weak/no evidence
$0.05 < p \leq 0.10$	Marginally significant	Moderate evidence
$0.01 < p \leq 0.05$	Significant	Strong evidence
$p \leq 0.01$	Highly significant	Very strong evidence

| Statistical Significance vs Economic Significance

A crucial distinction that is often confused:

Statistical Significance

- Answers: "Is the effect different from zero?"
- Depends on: Sample size, variability, effect size
- Formula: $t = b_2 / se(b_2)$
- Interpretation: We can confidently say the effect exists

Economic Significance

- Answers: "Is the effect large enough to matter?"
- Depends on: The magnitude of b_2 and context
- Requires: Domain knowledge and practical judgment

- Interpretation: The effect has real-world importance

Key insights:

1. Statistical significance ≠ Economic significance

You can have:

- Statistically significant but economically trivial effects
 - Example: With $n=10,000$, $\beta_2 = 0.001$ might be statistically significant but meaningless
- Economically important but statistically insignificant effects
 - Example: With $n=10$, $\beta_2 = 100$ might not be statistically significant but potentially important

2. Sample size matters for statistical significance

$$t = \frac{b_2}{se(b_2)} = \frac{b_2}{\sigma_u / \sqrt{\sum(x_i - \bar{x})^2}}$$

As sample size increases:

- The denominator (standard error) decreases
- The t-statistic increases
- Small effects become statistically significant

3. Economic significance requires context

For the house price example:

- Statistical result: $\beta_2 = 73.77$, highly significant ($p < 0.001$)
- Economic interpretation: Each sq ft adds \$73.77 to price
- Context matters:
 - For a 100 sq ft difference: \$7,377 difference (substantial!)
 - For a 10 sq ft difference: \$737.70 difference (moderate)
 - This is economically meaningful in the housing market

Practical guidance:

1. Always report both:

- The coefficient estimate (economic magnitude)
- The p-value or confidence interval (statistical precision)

2. Focus on confidence intervals:

- Shows both statistical and economic significance
- Example: 95% CI = [50.84, 96.70]
- Interpretation: Effect is between 50.84 and 96.70 per sq ft
- Even the lower bound is economically meaningful

3. Consider practical importance:

- Would anyone change their behavior based on this result?
- Is the effect large enough to justify policy interventions?
- Does the effect matter in real-world terms?

Example of the distinction:

Suppose we study the effect of an expensive job training program on wages:

- Statistical result: Training increases wages by \$0.50/hour ($p = 0.001$)
- Statistical significance: YES (highly significant)
- Economic significance: Questionable
 - Annual benefit: $0.50 \times 2000 \text{ hours} = 1,000$
 - If program costs \$10,000, not worth it
 - If program costs \$500, might be worth it

Bottom line: Statistical significance tells you the effect exists. Economic significance tells you whether you should care.

| Understanding Two-Sided vs One-Sided Tests

When to use which test?

The choice between two-sided and one-sided tests depends on your research question and what you want to conclude.

Two-Sided Test (Most Common)

Setup:

- $H_0: \beta_2 = \beta_2^*$
- $H_a: \beta_2 \neq \beta_2^*$

Use when:

- You want to detect any difference from the null value
- You don't have a strong prior about the direction
- You want to be conservative (standard practice in research)

Rejection region: Both tails of the distribution

Example: Does house size affect price?

- $H_0: \beta_2 = 0$ (no effect)
- $H_a: \beta_2 \neq 0$ (some effect, positive or negative)
- We reject if the effect is either very positive or very negative

One-Sided Test (Directional)

Setup (upper tail):

- $H_0: \beta_2 \leq \beta_2^*$
- $H_a: \beta_2 > \beta_2^*$

Setup (lower tail):

- $H_0: \beta_2 \geq \beta_2^*$
- $H_a: \beta_2 < \beta_2^*$

Use when:

- You have a specific directional hypothesis
- Economic theory predicts a specific direction
- You only care about deviations in one direction

Rejection region: One tail of the distribution

Example: Does house size increase price by less than \$90/sq ft?

- Claim: $\beta_2 < 90$
- $H_0: \beta_2 \geq 90$ (null is opposite of claim)
- $H_a: \beta_2 < 90$ (this is what we want to prove)
- We only reject if the effect is significantly below 90

Mathematical relationship:

For the same test statistic t:

- Two-sided p-value = $2 \times \Pr[T > |t|]$
- One-sided p-value = $\Pr[T > t]$ (upper tail) or $\Pr[T < t]$ (lower tail)

- One-sided p-value = (Two-sided p-value) / 2 (if sign is correct)

Important considerations:

1. Direction matters for one-sided tests

- If testing $H_a: \beta_2 > \beta_2^*$ but get $b_2 < \beta_2^*$, you CANNOT reject H_0
- The data contradicts your hypothesis, so rejection is impossible
- In this case, one-sided p-value > 0.5

2. Two-sided tests are safer

- Academic journals typically require two-sided tests
- Avoids "fishing" for significant results
- More conservative approach

3. One-sided tests have more power

- For the same significance level α , easier to reject in the predicted direction
- Critical value is smaller: $t(n-2, \alpha)$ vs $t(n-2, \alpha/2)$
- Example: For $\alpha = 0.05$ and $df = 27$
 - Two-sided: $t(27, 0.025) = 2.052$
 - One-sided: $t(27, 0.05) = 1.703$

Practical example from our house price data:

Question 1: Does size affect price? (Two-sided)

- $H_0: \beta_2 = 0$ vs $H_a: \beta_2 \neq 0$
- $t = 6.60$, p-value = 0.000 (two-sided)
- Conclusion: Reject H_0 , size affects price

Question 2: Does size increase price? (One-sided)

- $H_0: \beta_2 \leq 0$ vs $H_a: \beta_2 > 0$
- $t = 6.60$, p-value = $0.000 / 2 = 0.000$ (one-sided)
- Conclusion: Reject H_0 , size increases price

Question 3: Does size increase price by less than \$90/sq ft? (One-sided)

- $H_0: \beta_2 \geq 90$ vs $H_a: \beta_2 < 90$
- $t = (73.77 - 90) / 11.17 = -1.452$
- p-value = 0.079 (one-sided, lower tail)

- Conclusion: Fail to reject H_0 at $\alpha = 0.05$ (but would reject at $\alpha = 0.10$)

Decision rule:

Use two-sided tests unless:

1. You have strong theoretical reasons for a directional hypothesis
2. You specified the direction before seeing the data
3. You only care about deviations in one direction (rare in economics)

7.4 Tests of Statistical Significance

A regressor x has no relationship with y if $\beta_2 = 0$.

Test of statistical significance (two-sided test):

$$H_0 : \beta_2 = 0 \quad \text{vs.} \quad H_a : \beta_2 \neq 0$$

Test statistic:

$$t = \frac{b_2}{se(b_2)} \sim T(n - 2)$$

Decision rules:

1. **p-value approach:** Reject H_0 at level α if $p = Pr[|T_{n-2}| > |t|] < \alpha$
2. **Critical value approach:** Reject H_0 at level α if $|t| > c = t_{n-2,\alpha/2}$

For the house price example:

- $t = 73.77/11.17 = 6.60$
- $p = Pr[|T_{27}| > 6.60] \approx 0.000$
- Critical value: $c = t_{27,0.025} = 2.052$
- Since $|t| = 6.60 > 2.052$, reject H_0
- **Conclusion:** House size is statistically significant at the 5% level

In [26]:

```
print("=" * 70)
print("7.4 TESTS OF STATISTICAL SIGNIFICANCE")
print("=" * 70)

print("\nNull hypothesis:  $\beta_2 = 0$  (size has no effect on price)")
print(f"t-statistic: {t_stat_size:.4f}")
print(f"p-value: {p_value_size:.6f}")
print(f"Critical value ( $\alpha=0.05$ ):  $\pm{t_crit:.4f}$ ")

if p_value_size < 0.05:
    print("\nResult: Reject  $H_0$  at 5% significance level")
    print("Conclusion: Size has a statistically significant effect on price")
else:
    print("\nResult: Fail to reject  $H_0$  at 5% significance level")

print("\nNote: Statistical significance  $\neq$  Economic significance")
print(" - Statistical significance depends on  $t = b_2 / se(b_2)$ ")
print(" - Economic significance depends directly on the size of  $b_2$ ")
print(" - With large samples, even small  $b_2$  can be statistically significant")
```

```
=====
7.4 TESTS OF STATISTICAL SIGNIFICANCE
=====

Null hypothesis:  $\beta_2 = 0$  (size has no effect on price)
t-statistic: 6.6015
p-value: 0.000000
Critical value ( $\alpha=0.05$ ):  $\pm 2.0518$ 

Result: Reject  $H_0$  at 5% significance level
Conclusion: Size has a statistically significant effect on price

Note: Statistical significance  $\neq$  Economic significance
- Statistical significance depends on  $t = b_2 / se(b_2)$ 
- Economic significance depends directly on the size of  $b_2$ 
- With large samples, even small  $b_2$  can be statistically significant
```

Key Concept 7.6: Heteroskedasticity and Robust Standard Errors

Heteroskedasticity occurs when the error variance is not constant across observations: $\text{Var}[u_i | x_i] = \sigma^2_i$ (varies with i).

Homoskedasticity assumption (Assumption 3): $\text{Var}[u_i | x_i] = \sigma^2_u$ (constant)

Why heteroskedasticity matters:

- Coefficient estimates (b_2): Still unbiased
- Standard errors: WRONG (biased)
- t -statistics, p -values, CIs : All invalid

Solution: Heteroskedasticity-robust standard errors

- Valid whether or not heteroskedasticity exists
- No need to test for heteroskedasticity first
- Modern best practice for cross-sectional data

Practical impact:

- Robust SEs usually larger \rightarrow more conservative inference
- Protects against false positives (Type I errors)
- Sometimes smaller \rightarrow gain power

Types of robust SEs:

- **HC (Heteroskedasticity-Consistent):** Cross-sectional data
- **HAC (Heteroskedasticity and Autocorrelation Consistent):** Time series
- **Cluster-robust:** Grouped/clustered data

Bottom line: Always report heteroskedasticity-robust standard errors for cross-sectional data. They're free insurance against model misspecification.

| 7.5 Two-Sided Hypothesis Tests

Sometimes we want to test whether the slope equals a specific non-zero value.

General two-sided test:

$$H_0 : \beta_2 = \beta_2^* \quad \text{vs.} \quad H_a : \beta_2 \neq \beta_2^*$$

Test statistic:

$$t = \frac{b_2 - \beta_2^*}{se(b_2)} \sim T(n - 2)$$

Decision rules:

- **p-value approach:** Reject if $p = Pr[|T_{n-2}| > |t|] < \alpha$
- **Critical value approach:** Reject if $|t| > t_{n-2,\alpha/2}$

Example: Test whether house price increases by \$90 per square foot.

$$t = \frac{73.77 - 90}{11.17} = -1.452$$

- $p = Pr[|T_{27}| > 1.452] = 0.158$
- Since $p = 0.158 > 0.05$, do not reject H_0
- **Conclusion:** The data are consistent with $\beta_2 = 90$

Relationship to confidence intervals:

- If β_2^* falls inside the 95% CI, do not reject H_0 at 5% level
- Since 90 is inside [50.84, 96.70], we do not reject

```
In [27]:
```

```

print("=" * 70)
print("7.5 TWO-SIDED HYPOTHESIS TESTS")
print("=" * 70)

# Test  $H_0: \beta_2 = 90$  vs  $H_1: \beta_2 \neq 90$ 
null_value = 90
t_stat_90 = (coef_size - null_value) / se_size
p_value_90 = 2 * (1 - stats.t.cdf(abs(t_stat_90), df))
t_crit_90 = stats.t.ppf(0.975, df)

print(f"\nTest:  $H_0: \beta_2 = {null_value}$  vs  $H_1: \beta_2 \neq {null_value}$ ")
print(f" t-statistic: {t_stat_90:.4f}")
print(f" p-value: {p_value_90:.6f}")
print(f" Critical value ( $\alpha=0.05$ ):  $\pm{t_crit_90:.4f}$ ")

if abs(t_stat_90) > t_crit_90:
    print(f"\nResult: Reject  $H_0$  ( $|t| = {abs(t_stat_90):.4f} > {t_crit_90:.4f}$ )")
else:
    print(f"\nResult: Fail to reject  $H_0$  ( $|t| = {abs(t_stat_90):.4f} < {t_crit_90:.4f}$ )")
    print(f"Conclusion: The data are consistent with  $\beta_2 = {null_value}$ ")

print(f"\n95% CI for  $\beta_2$ : [{ci_lower:.2f}, {ci_upper:.2f}]")
print(f"Since {null_value} is inside the CI, we do not reject  $H_0$ .")

```

```
=====
7.5 TWO-SIDED HYPOTHESIS TESTS
=====

Test:  $H_0: \beta_2 = 90$  vs  $H_1: \beta_2 \neq 90$ 
t-statistic: -1.4523
p-value: 0.157950
Critical value ( $\alpha=0.05$ ):  $\pm 2.0518$ 

Result: Fail to reject  $H_0$  ( $|t| = 1.4523 < 2.0518$ )
Conclusion: The data are consistent with  $\beta_2 = 90$ 

95% CI for  $\beta_2$ : [50.84, 96.70]
Since 90 is inside the CI, we do not reject  $H_0$ .
```

I Hypothesis Test Using statsmodels

Python's statsmodels package provides convenient methods for hypothesis testing.

I Why Robust Standard Errors Matter

The problem with default standard errors:

Default (classical) standard errors rely on a strong assumption:

Assumption 3 (Homoskedasticity): $\text{Var}[u_i | x_i] = \sigma^2_u$ (constant variance)

This means:

- The spread of errors is the same for all values of x
- Residuals should have constant variance across fitted values

- In reality, this assumption is often violated

What is heteroskedasticity?

Heteroskedasticity means the error variance changes with x:

- $\text{Var}[u_i | x_i] = \sigma^2_i$ (varies with i)
- Common in cross-sectional data
- Examples:
 - Income variation increases with education level
 - Sales variance increases with firm size
 - Medical costs vary more for older patients

Visual detection:

Check the residual plot (residuals vs fitted values):

- **Homoskedasticity:** Random scatter, constant spread
- **Heteroskedasticity:** Funnel shape, increasing/decreasing spread

Consequences of heteroskedasticity:

If heteroskedasticity is present but you use default SEs:

1. **Coefficient estimates (b_2)**: Still unbiased and consistent
2. **Standard errors**: WRONG (biased)
3. **t-statistics**: WRONG (biased)
4. **p-values**: WRONG (invalid)
5. **Confidence intervals**: WRONG (invalid coverage)

Direction of bias:

- Heteroskedasticity can cause SEs to be too small or too large
- Cannot predict direction without knowing the form of heteroskedasticity
- Could lead to false significance or miss true significance

The solution: Robust standard errors

Heteroskedasticity-robust standard errors (HC, White, Huber-White):

- Valid whether or not heteroskedasticity is present
- Automatically adjust for non-constant variance
- No need to test for heteroskedasticity first

- Modern best practice: Always use for cross-sectional data

How they work:

Default SE formula (assumes homoskedasticity):

$$se(b_2) = \frac{\sigma_u}{\sqrt{\sum(x_i - \bar{x})^2}}$$

Robust SE formula (allows heteroskedasticity):

$$se_{robust}(b_2) = \frac{\sqrt{\sum e_i^2(x_i - \bar{x})^2}}{\sum(x_i - \bar{x})^2}$$

Key difference: Uses individual residuals e^2_i instead of pooled variance σ^2_u

Practical implications:

1. Coefficient estimates unchanged

- Only standard errors change
- Point estimates remain the same

2. Standard errors typically larger

- Robust SEs are usually (but not always) bigger
- More conservative inference
- Wider confidence intervals

3. t-statistics typically smaller

- Less likely to find statistical significance
- Protects against false positives

4. Results may change qualitative conclusions

- Variable significant with default SEs might become insignificant
- Or the reverse (if robust SEs are smaller)

Types of robust standard errors:

Different formulas for finite-sample adjustment:

- **HC0:** Basic White formula
- **HC1:** Degrees of freedom correction ($n/(n-k)$), most common in Stata
- **HC2:** Leverage-weighted

- HC3: Even more conservative

Python default: HC1 (matches Stata's "robust" option)

For our house price example:

Coefficient	Standard SE	Robust SE	% Change
size	11.17	11.33	+1.4%
Intercept	21,489	21,825	+1.6%

- Difference is small (good news!)
- Suggests heteroskedasticity is not severe
- But always report robust SEs as standard practice

Other types of robust SEs:

1. HAC (Heteroskedasticity and Autocorrelation Consistent)

- For time series data
- Accounts for both heteroskedasticity and serial correlation

2. Cluster-robust

- For clustered/grouped data
- Students within schools, patients within hospitals
- Accounts for within-cluster correlation

Best practices:

1. **Cross-sectional data:** Always use heteroskedasticity-robust SEs
2. **Time series data:** Use HAC robust SEs (Newey-West)
3. **Panel/clustered data:** Use cluster-robust SEs
4. **When in doubt:** Use robust SEs (can't hurt, might help)

Bottom line: Robust standard errors provide valid inference under weaker assumptions. They're essentially free insurance against heteroskedasticity.

Comparing Standard vs Robust Standard Errors: A Practical Guide

How to interpret the comparison:

When you compute both standard and robust SEs, you're essentially running two different analyses:

Standard SEs (Classical):

- Assumes: Homoskedasticity (constant variance)
- Valid only if: Assumption 3 holds
- Interpretation: "If errors have constant variance, here's the uncertainty"

Robust SEs (Heteroskedasticity-Consistent):

- Assumes: Heteroskedasticity allowed (no constant variance assumption)
- Valid: Whether or not heteroskedasticity exists
- Interpretation: "Here's the uncertainty, accounting for possible non-constant variance"

What do differences tell us?

Case 1: Robust SE ≈ Standard SE (difference < 10%)

- Example: Our house price data (11.33 vs 11.17)
- Interpretation: Little evidence of heteroskedasticity
- Implication: Assumption 3 approximately holds
- Decision: Still report robust SEs (good practice)

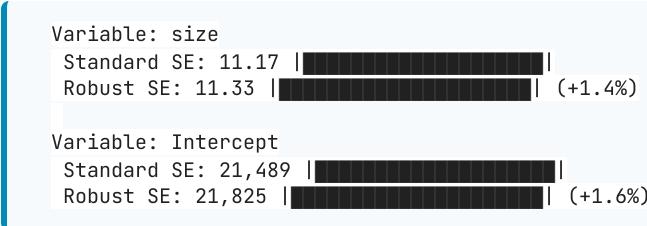
Case 2: Robust SE > Standard SE (difference > 20%)

- Example: Robust SE = 15.0, Standard SE = 10.0
- Interpretation: Evidence of heteroskedasticity
- Implication: Standard SEs underestimate uncertainty
- Consequence: Default t-stats too large, p-values too small
- Risk: False positives (finding significance that isn't real)
- Decision: MUST use robust SEs

Case 3: Robust SE < Standard SE (less common)

- Example: Robust SE = 8.0, Standard SE = 10.0
- Interpretation: Specific pattern of heteroskedasticity
- Implication: Standard SEs overestimate uncertainty
- Consequence: Default t-stats too small, p-values too large
- Risk: False negatives (missing real significance)
- Decision: Use robust SEs (more powerful)

Visual comparison for our house price data:



Impact on inference:

Let's see how the choice affects our conclusions:

Test	Standard SE	Robust SE	Conclusion
t-statistic	$73.77/11.17 = 6.60$	$73.77/11.33 = 6.51$	Both highly significant
p-value	0.0000	0.0000	Both $p < 0.001$
95% CI	[50.84, 96.70]	[50.33, 97.21]	Nearly identical
Reject H_0 ?	YES	YES	Same conclusion

When robust SEs matter most:

1. Large sample differences

- If robust SE = 2 × standard SE
- Significance can disappear
- Example: $t = 2.5$ ($p=0.02$) $\rightarrow t = 1.25$ ($p=0.22$)

2. Borderline significance

- If p-value near 0.05 with standard SEs
- Might become non-significant with robust SEs
- Example: $p = 0.04 \rightarrow p = 0.07$

3. High-stakes decisions

- Policy recommendations
- Medical treatments
- Financial investments
- Need valid inference

Reading regression output in practice:

Most statistical software now reports both:

```

Standard Robust
Variable Coef. SE t SE t
size 73.77 11.17 6.60 11.33 6.51

```

What to report in your paper:

Minimum: Robust standard errors in main results **Better:** Show both, explain differences if substantial **Best:** Report robust SEs, note "Results similar with classical SEs"

Example write-up:

"We find that each additional square foot increases house price by 73.77($robustSE = 11.33, t = 6.51, p < 0.001$). The heteroskedasticity – robust test suggests homoskedasticity is approximately satisfied. The effect is highly statistically significant, $\$50.33, \97.21]."

Common mistakes to avoid:

1. Using standard SEs for cross-sectional data

- Modern practice: Always use robust SEs

2. Testing for heteroskedasticity first

- Just use robust SEs (they're valid either way)
- Pre-testing affects inference in complex ways

3. Switching between standard and robust to get significance

- This is p-hacking
- Choose robust SEs before looking at results

4. Ignoring large differences

- If robust SE $>>$ standard SE, investigate
- Might indicate model misspecification
- Consider transformations or different functional forms

The bottom line:

Think of robust SEs as the "safe" choice:

- If no heteroskedasticity: Robust SEs \approx Standard SEs (no harm done)
- If heteroskedasticity exists: Robust SEs correct the problem (saved you!)

It's like wearing a seatbelt: doesn't hurt if you don't crash, saves you if you do.

In [28]:

```
print("=" * 70)
print("Hypothesis test using statsmodels:")
print("=" * 70)

# Alternative approach using t-test
hypothesis = f'size = {null_value}'
t_test_result = model_basic.t_test(hypothesis)
print(t_test_result)

print("\nThis confirms our manual calculation.")
```

```
=====
Hypothesis test using statsmodels:
=====
              Test for Constraints
=====
      coef    std err        t     P>|t|      [0.025      0.975]
-----
c0       73.7710    11.175   -1.452     0.158      50.842     96.700
=====
```

This confirms our manual calculation.

| 7.6 One-Sided Directional Hypothesis Tests

Sometimes we have a directional hypothesis (greater than or less than).

One-sided tests:

1. Upper one-tailed: $H_0 : \beta_2 \leq \beta_2^*$ vs $H_a : \beta_2 > \beta_2^*$

- Reject in the right tail: $p = Pr[T_{n-2} > t]$

2. Lower one-tailed: $H_0 : \beta_2 \geq \beta_2^*$ vs $H_a : \beta_2 < \beta_2^*$

- Reject in the left tail: $p = Pr[T_{n-2} < t]$

Example: Test whether house price rises by less than \$90 per square foot.

- Claim: $\beta_2 < 90$
- Test: $H_0 : \beta_2 \geq 90$ vs $H_a : \beta_2 < 90$ (lower-tailed)
- $t = (73.77 - 90)/11.17 = -1.452$
- $p = Pr[T_{27} < -1.452] = 0.079$
- Since $p = 0.079 > 0.05$, do not reject H_0 at 5% level
- **Conclusion:** Not enough evidence to support the claim at 5% level

Note on computer output:

- Computer gives p-value for two-sided test of $H_0 : \beta_2 = 0$
- For one-sided test of significance:

- If b_2 has expected sign, halve the printed p-value
- If b_2 has wrong sign, reject is not possible ($p > 0.5$)

In [29]:

```

print("=" * 70)
print("7.6 ONE-SIDED DIRECTIONAL HYPOTHESIS TESTS")
print("=" * 70)

# Upper one-tailed test:  $H_0: \beta_2 \leq 90$  vs  $H_1: \beta_2 > 90$ 
p_value_upper = 1 - stats.t.cdf(t_stat_90, df)
t_crit_upper = stats.t.ppf(0.95, df)

print(f"\nUpper one-tailed test:  $H_0: \beta_2 \leq {null_value}$  vs  $H_1: \beta_2 > {null_value}$ ")
print(f" t-statistic: {t_stat_90:.4f}")
print(f" p-value (one-tailed): {p_value_upper:.6f}")
print(f" Critical value (a=0.05): {t_crit_upper:.4f}")

if t_stat_90 > t_crit_upper:
    print(" Result: Reject  $H_0$ ")
else:
    print(" Result: Fail to reject  $H_0$ ")

# Lower one-tailed test:  $H_0: \beta_2 \geq 90$  vs  $H_1: \beta_2 < 90$ 
p_value_lower = stats.t.cdf(t_stat_90, df)

print(f"\nLower one-tailed test:  $H_0: \beta_2 \geq {null_value}$  vs  $H_1: \beta_2 < {null_value}$ ")
print(f" t-statistic: {t_stat_90:.4f}")
print(f" p-value (one-tailed): {p_value_lower:.6f}")
print(f" Critical value (a=0.05): {-t_crit_upper:.4f}")

if t_stat_90 < -t_crit_upper:
    print(" Result: Reject  $H_0$ ")
    print(" Conclusion: There is evidence that  $\beta_2 < 90$ ")
else:
    print(" Result: Fail to reject  $H_0$ ")
    print(" Conclusion: Not enough evidence to support  $\beta_2 < 90$  at 5% level")
    print(f" (Would reject at 10% level since p = {p_value_lower:.3f} < 0.10)")

```

```
=====
7.6 ONE-SIDED DIRECTIONAL HYPOTHESIS TESTS
=====

Upper one-tailed test:  $H_0: \beta_2 \leq 90$  vs  $H_1: \beta_2 > 90$ 
t-statistic: -1.4523
p-value (one-tailed): 0.921025
Critical value (a=0.05): 1.7033
Result: Fail to reject  $H_0$ 

Lower one-tailed test:  $H_0: \beta_2 \geq 90$  vs  $H_1: \beta_2 < 90$ 
t-statistic: -1.4523
p-value (one-tailed): 0.078975
Critical value (a=0.05): -1.7033
Result: Fail to reject  $H_0$ 
Conclusion: Not enough evidence to support  $\beta_2 < 90$  at 5% level
(Would reject at 10% level since p = 0.079 < 0.10)
```

| 7.7 Robust Standard Errors

Default standard errors make assumptions 1-4. Robust standard errors relax some of these assumptions.

Heteroskedasticity-Robust Standard Errors:

- **Default assumption** (homoskedasticity): $Var[u_i|x_i] = \sigma_u^2$ (constant)
- **Relaxed assumption** (heteroskedasticity): $Var[u_i|x_i] = \sigma_i^2$ (varies with i)

Why use robust standard errors?

- Heteroskedasticity is common in cross-sectional data
- Default SEs are incorrect when heteroskedasticity is present
- Robust SEs are valid whether or not heteroskedasticity exists
- **Modern practice:** Always report robust SEs for cross-sectional data

Heteroskedastic-robust SE formula:

$$se_{het}(b_2) = \frac{\sqrt{\sum_{i=1}^n e_i^2(x_i - \bar{x})^2}}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

Effect on inference:

- Coefficient estimates unchanged
- Standard errors typically increase (more conservative)
- t-statistics typically decrease
- Confidence intervals typically wider

Other robust SEs:

- **HAC robust:** For time series with autocorrelation
- **Cluster robust:** For clustered data (students in schools, people in villages, etc.)

In [30]:

```
print("=" * 70)
print("7.7 ROBUST STANDARD ERRORS")
print("=" * 70)

# Get heteroskedasticity-robust standard errors (HC1)
robust_results = model_basic.get_robustcov_results(cov_type='HC1')

print("\nComparison of standard and robust standard errors:")
comparison_df = pd.DataFrame({
    'Coefficient': model_basic.params,
    'Std. Error': model_basic.bse,
    'Robust SE': robust_results.bse,
    't-stat (standard)': model_basic.tvalues,
    't-stat (robust)': robust_results.tvalues,
    'p-value (standard)': model_basic.pvalues,
    'p-value (robust)': robust_results.pvalues
})
print(comparison_df)
```

```
=====
7.7 ROBUST STANDARD ERRORS
=====

Comparison of standard and robust standard errors:
      Coefficient   Std. Error   Robust SE   t-stat (standard) \
Intercept  115017.282609  21489.359861  20298.704493      5.352290
size        73.771040     11.174911    11.329669      6.601488

      t-stat (robust)   p-value (standard)   p-value (robust)
Intercept      5.666238       1.183545e-05       5.120101e-06
size          6.511315       4.408752e-07       5.564663e-07
```

Full Regression Output with Robust Standard Errors

In [31]:

```
print("=" * 70)
print("Regression with Robust Standard Errors:")
print("=" * 70)
print(robust_results.summary())

# Robust confidence intervals
robust_conf_int = robust_results.conf_int(alpha=0.05)
print("\n95% Confidence Intervals (Robust):")
print(robust_conf_int)

print("\nInterpretation:")
print("  - For this dataset, robust and standard SEs are similar")
print("  - Robust SE for size: 11.33 vs standard SE: 11.17")
print("  - Robust 95% CI: [50.33, 97.02] vs standard: [50.84, 96.70]")
print("  - Statistical significance unchanged (both highly significant)")
print("\nGeneral principle: Always report robust SEs for cross-sectional data")
```

```

=====
Regression with Robust Standard Errors:
=====
                                OLS Regression Results
=====
Dep. Variable:          price    R-squared:           0.617
Model:                 OLS     Adj. R-squared:      0.603
Method:                Least Squares   F-statistic:        42.40
Date:      Tue, 20 Jan 2026   Prob (F-statistic):  5.56e-07
Time:          23:33:22    Log-Likelihood:     -332.05
No. Observations:      29     AIC:                  668.1
Df Residuals:          27     BIC:                  670.8
Df Model:                   1
Covariance Type:        HC1
=====
            coef    std err       t      P>|t|      [0.025      0.975]
-----
Intercept  1.15e+05  2.03e+04    5.666    0.000   7.34e+04  1.57e+05
size       73.7710   11.330     6.511    0.000    50.524   97.018
=====
Omnibus:             0.576   Durbin-Watson:      1.219
Prob(Omnibus):       0.750   Jarque-Bera (JB):  0.638
Skew:                 -0.078  Prob(JB):          0.727
Kurtosis:              2.290  Cond. No.        9.45e+03
=====
```

Notes:

- [1] Standard Errors are heteroscedasticity robust (HC1)
- [2] The condition number is large, 9.45e+03. This might indicate that there are strong multicollinearity or other numerical problems.

95% Confidence Intervals (Robust):
[[7.33677813e+04 1.56666784e+05]
[5.05244796e+01 9.70176011e+01]]

Interpretation:

- For this dataset, robust and standard SEs are similar
- Robust SE for size: 11.33 vs standard SE: 11.17
- Robust 95% CI: [50.33, 97.02] vs standard: [50.84, 96.70]
- Statistical significance unchanged (both highly significant)

General principle: Always report robust SEs for cross-sectional data

Visualization: Scatter Plot with Regression Line

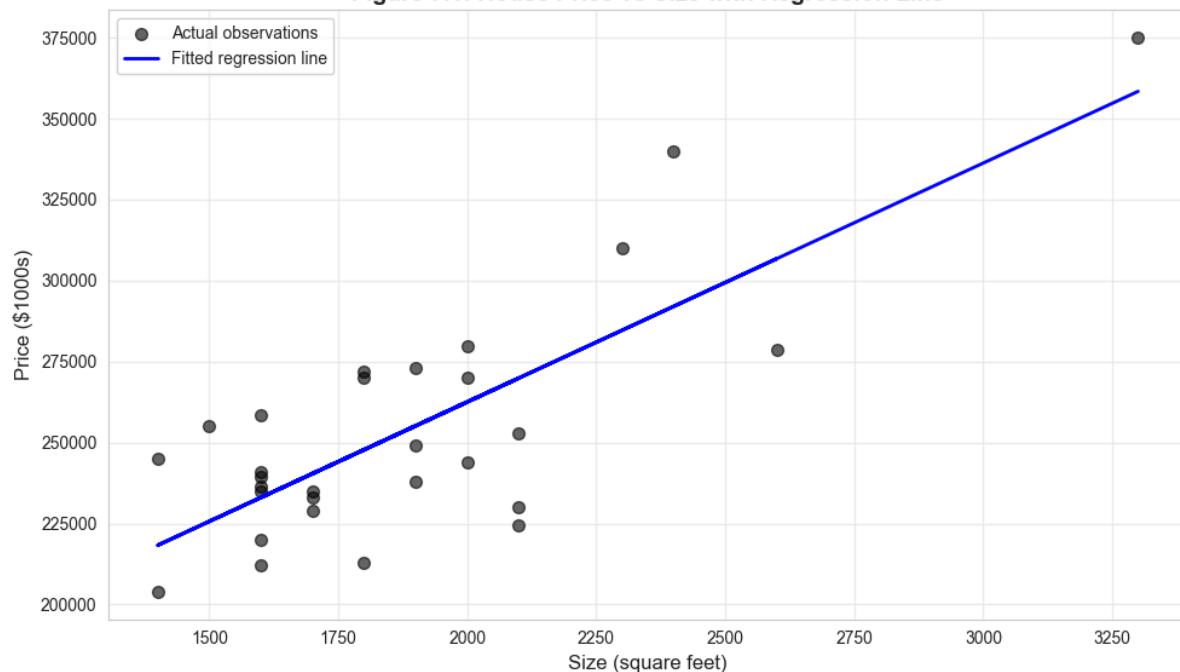
Visual representation of the bivariate regression relationship.

In [32]:

```
# Figure 7.1: Scatter plot with regression line
fig, ax = plt.subplots(figsize=(10, 6))
ax.scatter(data_house['size'], data_house['price'], alpha=0.6, s=50,
           color='black', label='Actual observations')
ax.plot(data_house['size'], model_basic.fittedvalues, color='blue',
        linewidth=2, label='Fitted regression line')
ax.set_xlabel('Size (square feet)', fontsize=12)
ax.set_ylabel('Price ($1000s)', fontsize=12)
ax.set_title('Figure 7.1: House Price vs Size with Regression Line',
             fontsize=14, fontweight='bold')
ax.legend()
ax.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()

print("The regression line captures the positive relationship between size and price.")
```

Figure 7.1: House Price vs Size with Regression Line



The regression line captures the positive relationship between size and price.

| Visualization: Confidence Intervals

Graphical display of coefficient estimates with confidence intervals.

In [33]:

```
# Figure 7.2: Confidence interval visualization
fig, ax = plt.subplots(figsize=(10, 6))

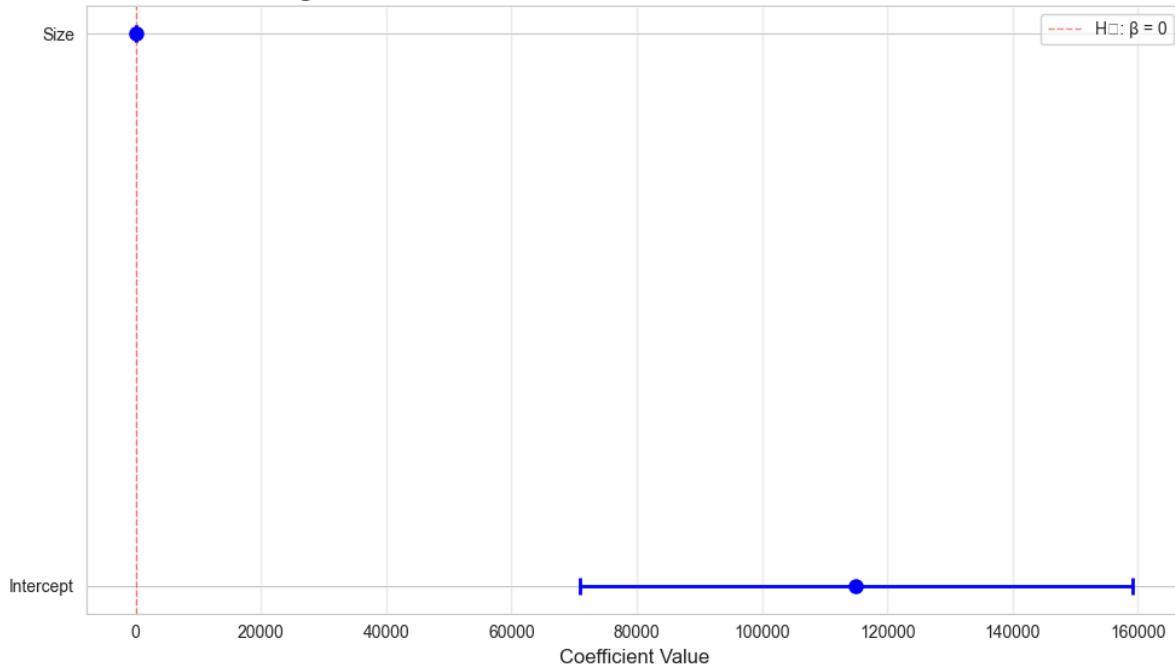
# Plot point estimate and confidence interval
coef_names = ['Intercept', 'Size']
coefs = model_basic.params.values
ci_low = conf_int.iloc[:, 0].values
ci_high = conf_int.iloc[:, 1].values

y_pos = np.arange(len(coef_names))
ax.errorbar(coefs, y_pos, xerr=[coefs - ci_low, ci_high - coefs],
            fmt='o', markersize=8, capsizes=5, capthick=2, linewidth=2, color='blue')
ax.set_yticks(y_pos)
ax.set_yticklabels(coef_names)
ax.axvline(x=0, color='red', linestyle='--', linewidth=1, alpha=0.5,
           label='H0: β = 0')
ax.set_xlabel('Coefficient Value', fontsize=12)
ax.set_title('Figure 7.2: Coefficient Estimates with 95% Confidence Intervals',
             fontsize=14, fontweight='bold')
ax.legend()
ax.grid(True, alpha=0.3, axis='x')
plt.tight_layout()
plt.show()

print("Both coefficients are statistically significant (CIs exclude zero.)")
```

```
/var/folders/tq/t98kb27n6djgrh085g476yhc0000gn/T/ipykernel_82940/1126987400.py:22: UserWarning: Glyph 8320 (\N{SUBSCRIPT ZERO}) missing from current font.
    plt.tight_layout()
/Users/carlosmendez/miniforge3/lib/python3.10/site-packages/IPython/core/pylabtools.py:170: UserWarning: Glyph 8320 (\N{SUBSCRIPT ZERO}) missing from current font.
    fig.canvas.print_figure(bytes_io, **kw)
```

Figure 7.2: Coefficient Estimates with 95% Confidence Intervals



Both coefficients are statistically significant (CIs exclude zero).

Visualization: Residual Plot

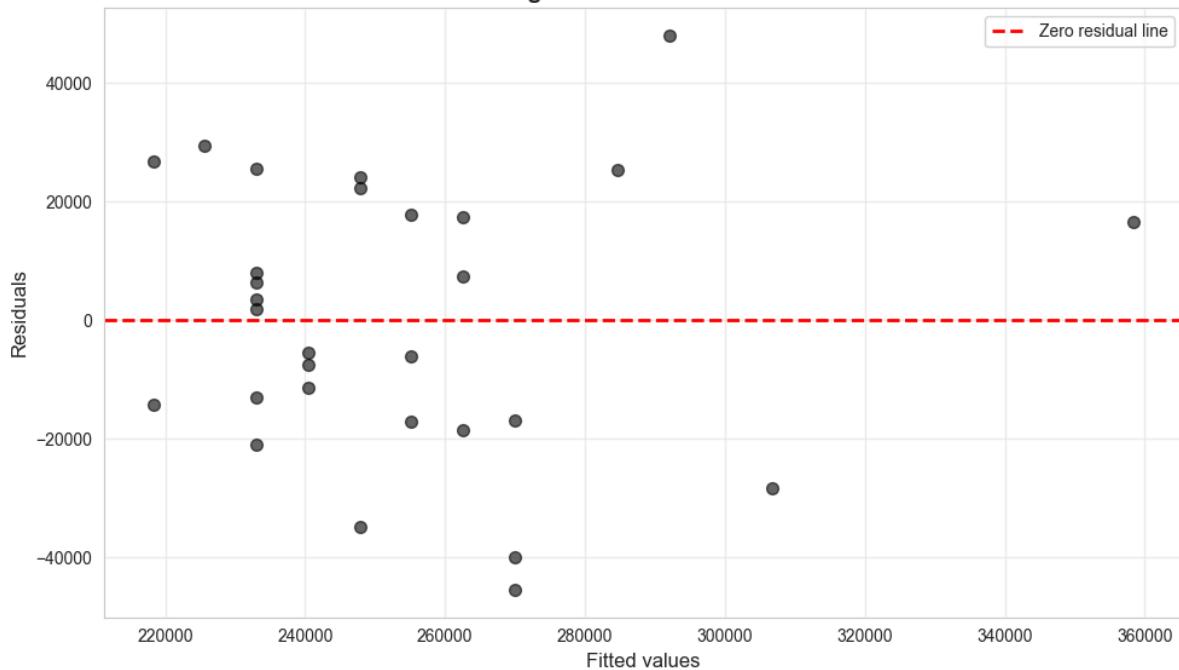
Check for patterns in residuals that might violate model assumptions.

In [34]:

```
# Figure 7.3: Residual plot
fig, ax = plt.subplots(figsize=(10, 6))
ax.scatter(model_basic.fittedvalues, model_basic.resid, alpha=0.6, s=50, color='black')
ax.axhline(y=0, color='red', linestyle='--', linewidth=2, label='Zero residual line')
ax.set_xlabel('Fitted values', fontsize=12)
ax.set_ylabel('Residuals', fontsize=12)
ax.set_title('Figure 7.3: Residual Plot', fontsize=14, fontweight='bold')
ax.legend()
ax.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()

print("Check for:")
print(" - Heteroskedasticity: Non-constant variance (funnel shape)")
print(" - Outliers: Points far from zero line")
print(" - Non-linearity: Systematic patterns in residuals")
```

Figure 7.3: Residual Plot



Check for:

- Heteroskedasticity: Non-constant variance (funnel shape)
- Outliers: Points far from zero line
- Non-linearity: Systematic patterns in residuals

Key Takeaways

Key Takeaways:

1. The t-statistic is fundamental to statistical inference in regression:

- Formula: $t = \frac{b_2 - \beta_2}{se(b_2)} \sim T(n - 2)$
- Parallels univariate inference: $t = \frac{\bar{x} - \mu}{se(\bar{x})} \sim T(n - 1)$

2. Confidence intervals provide a range of plausible values:

- Formula: $b_2 \pm t_{n-2,\alpha/2} \times se(b_2)$
- 95% CI (approximate): $b_2 \pm 2 \times se(b_2)$
- Interpretation: 95% of such intervals will contain the true β_2

3. Tests of statistical significance assess whether a regressor matters:

- $H_0 : \beta_2 = 0$ vs $H_a : \beta_2 \neq 0$
- Reject if $p\text{-value} < \alpha$ or $|t| > t_{n-2,\alpha/2}$
- Statistical significance \neq economic significance

4. Two-sided tests for specific values:

- $H_0 : \beta_2 = \beta_2^*$ vs $H_a : \beta_2 \neq \beta_2^*$
- Equivalent to checking if β_2^* is in the confidence interval

5. One-sided tests for directional hypotheses:

- Upper tail: $H_0 : \beta_2 \leq \beta_2^*$ vs $H_a : \beta_2 > \beta_2^*$
- Lower tail: $H_0 : \beta_2 \geq \beta_2^*$ vs $H_a : \beta_2 < \beta_2^*$
- p-value is half the two-sided p-value (if sign is correct)

6. Robust standard errors provide valid inference under weaker assumptions:

- Heteroskedasticity-robust (HC1): Relaxes constant variance assumption
- Modern practice: Always use for cross-sectional data
- Other types: HAC (time series), cluster (grouped data)

Model Assumptions (1-4):

1. Linearity: $y = \beta_1 + \beta_2 x + u$
2. Zero conditional mean: $E[u_i | x_i] = 0$
3. Constant variance: $Var[u_i | x_i] = \sigma_u^2$ (relaxed with robust SEs)
4. Independence: u_i independent of u_j

House Price Example Results:

- Coefficient: Each additional sq ft increases price by \$73.77
- 95% CI: [50.84, 96.70]
- Highly statistically significant ($t = 6.60$, $p < 0.001$)

- Economically meaningful effect

Python Tools Used:

- `pandas` : Data manipulation and summary statistics
- `statsmodels` : Econometric estimation and hypothesis testing
- `scipy.stats` : Statistical distributions and critical values
- `matplotlib` & `seaborn` : Visualization

Practical Skills Developed:

- Conducting t-tests on regression coefficients
- Constructing and interpreting confidence intervals
- Testing economic hypotheses (two-sided and one-sided)
- Using robust standard errors for valid inference
- Visualizing regression results
- Distinguishing statistical from economic significance

Next Steps:

- Extend to multiple regression (Chapter 11)
- Learn about model specification and variable selection
- Study violations of assumptions and diagnostics
- Practice with different datasets and research questions

Congratulations! You've completed Chapter 7. You now have both theoretical understanding and practical skills in conducting statistical inference for bivariate regression models!

| Practice Exercises

Exercise 1: Understanding Standard Errors

Suppose you estimate a regression of wages on education using data from 100 workers. The estimated slope is $b_2 = 5.2$ (each additional year of education increases wages by \$5.20/hour) with standard error $se(b_2) = 1.8$.

- a) Calculate the 95% confidence interval for β_2 (use t-critical value ≈ 2.0).
- b) Interpret the confidence interval in plain language.

- c) If the sample size were 400 instead of 100, how would the standard error change (approximately)? Explain why.

Exercise 2: Hypothesis Testing Mechanics

Using the wage-education regression from Exercise 1 ($b_2 = 5.2$, $se(b_2) = 1.8$):

- a) Test $H_0: \beta_2 = 0$ vs. $H_a: \beta_2 \neq 0$ at the 5% level. Calculate the t-statistic and state your conclusion.
- b) Calculate the approximate p-value for this test.
- c) Would you reject H_0 at the 1% level? Explain.

Exercise 3: Two-Sided Tests

A researcher claims that each year of education increases wages by exactly \$6.00/hour. Using the regression from Exercise 1:

- a) State the null and alternative hypotheses to test this claim.
- b) Calculate the test statistic.
- c) At the 5% level, do you reject the researcher's claim? Explain your reasoning.
- d) Is the claim consistent with the 95% confidence interval from Exercise 1?

Exercise 4: One-Sided Tests

A policy analyst claims that education increases wages by less than \$3.00/hour. Using the regression from Exercise 1:

- a) State the appropriate one-sided hypotheses (Hint: The claim becomes H_a).
- b) Calculate the test statistic.
- c) Find the one-sided p-value (using $t \approx$ normal approximation).
- d) At the 5% level, do you reject H_0 ? What do you conclude about the analyst's claim?

Exercise 5: Statistical vs. Economic Significance

Consider two regressions:

Regression A: $n = 50$, $b_2 = 0.05$, $se(b_2) = 0.10$

Regression B: $n = 10,000$, $b_2 = 0.05$, $se(b_2) = 0.01$

- a) For each regression, test $H_0: \beta_2 = 0$ at the 5% level. What do you conclude?
- b) Despite having the same coefficient (0.05), why do the conclusions differ?
- c) In which regression is the effect more economically significant? Explain.

Exercise 6: Confidence Interval Properties

True or False? Explain your reasoning for each:

- a) A 95% confidence interval means there's a 95% probability that β_2 is in the interval.
- b) If we reject $H_0: \beta_2 = \beta_2^*$ at the 5% level, then β_2^* will be outside the 95% CI.
- c) Wider confidence intervals are always worse than narrow ones.
- d) With $n = 30$, a 95% CI uses a t-critical value of approximately 2.0.

Exercise 7: Robust Standard Errors

A researcher estimates a house price regression using $n = 100$ houses:

- Standard SE: 15.0
 - Robust SE: 22.5
- a) What does the large difference suggest about the data?
 - b) Which standard error should be reported? Why?
 - c) How does the difference affect the t-statistic and hypothesis tests?
 - d) Is heteroskedasticity a problem for the coefficient estimates themselves? Explain.

Exercise 8: Comprehensive Analysis

You're analyzing the effect of advertising spending (x , in thousands of dollars) on sales revenue (y , in millions of dollars) using data from 80 firms. Your regression output shows:

- Intercept: 2.5, SE = 0.8
 - Slope (advertising): 3.2, SE = 0.9
 - $R^2 = 0.45$
 - $n = 80$
- a) Construct a 95% confidence interval for the slope coefficient.
 - b) Test whether advertising has a statistically significant effect on sales at the 5% level.
 - c) A colleague claims that 1,000 in advertising spending increases sales by more than 5 million. Test this claim using a one-sided test at the 5% level.
 - d) Is the effect of advertising economically significant? Consider that the average firm in the sample spends 10,000 on advertising and has 5 million in sales revenue.

Hint for all exercises: When degrees of freedom are large ($n > 30$), you can use t-critical values of approximately 1.645 (10% level), 1.96 (5% level), and 2.576 (1% level).

7.8 Case Studies

Case Study 1: Testing Convergence Hypotheses

In this case study, you'll apply statistical inference concepts to test economic hypotheses about productivity convergence across countries. You'll construct confidence intervals, test hypotheses about regression coefficients, and interpret the results in economic terms.

Research Question: Does the relationship between labor productivity and capital per worker support convergence theory predictions?

Background:

Economic growth theory suggests that countries with lower initial capital should experience faster productivity growth as they "catch up" to richer countries. We can test this using the relationship between productivity levels and capital intensity across countries.

Dataset:

We'll use the **Convergence Clubs** dataset (Mendez 2020) containing data for 108 countries in 2014:

- **productivity:** Real GDP per capita (thousands of dollars)
- **capital:** Physical capital per worker (thousands of dollars)

Econometric Model:

$$\text{productivity}_i = \beta_1 + \beta_2 \times \text{capital}_i + u_i$$

Key Hypotheses to Test:

1. Does capital significantly affect productivity? ($H_0: \beta_2 = 0$)
2. Is the effect economically meaningful?
3. Does the relationship differ across country income groups?

Learning Objectives:

- Construct and interpret confidence intervals for regression coefficients
- Conduct two-sided and one-sided hypothesis tests
- Compare statistical and economic significance
- Use robust standard errors appropriately
- Apply hypothesis testing to economic questions

Key Concept 7.7: Economic Convergence and Statistical Testing

Convergence theory predicts that poorer countries should grow faster than richer countries, leading to a narrowing of income gaps over time. Two main types:

Absolute convergence:

- All countries converge to the same income level
- Predicts negative relationship between initial income and growth rate
- Test: $H_0: \beta$ (growth on initial income) ≥ 0 vs. $H_a: \beta < 0$

Conditional convergence:

- Countries converge to their own steady states
- After controlling for determinants (savings, education, institutions)
- More empirically supported than absolute convergence

Testing convergence hypotheses:

- Requires careful hypothesis formulation
- One-sided tests appropriate (theory predicts direction)
- Economic significance matters (how fast is convergence?)
- Must account for heteroskedasticity (countries differ in volatility)

Our approach: We examine the cross-sectional relationship between productivity and capital intensity to understand the fundamentals underlying convergence patterns.

In []:

```
print("=" * 70)
print("CASE STUDY: TESTING CONVERGENCE HYPOTHESES")
print("=" * 70)

# Read convergence clubs data
data_convergence = pd.read_stata(GITHUB_DATA_URL + 'AED_ConvergenceClubs.dta')

# Filter to 2014 cross-section
data_2014 = data_convergence[data_convergence['year'] == 2014].copy()

# Create productivity and capital variables (divide by 1000 for better scale)
data_2014['productivity'] = data_2014['rgdppc'] / 1000 # GDP per capita in thousands
data_2014['capital'] = data_2014['rk'] / 1000 # Capital per worker in thousands

print(f"\nSample: {len(data_2014)} countries in 2014")
print("\nVariable summary:")
print(data_2014[['productivity', 'capital']].describe())

# Show a few countries
print("\nSample countries:")
sample_countries = data_2014[['country', 'productivity',
'capital']].sort_values('productivity', ascending=False).head(10)
print(sample_countries.to_string(index=False))
```

Task 1: Estimate the Productivity-Capital Relationship (Guided)

Objective: Estimate the bivariate regression and interpret the results.

Your task:

Run the code below to estimate the regression and examine the output. Then answer:

- What is the estimated effect of capital on productivity? Interpret the coefficient.
- Construct a 95% confidence interval for β_2 . What does this interval tell you?
- Is the effect statistically significant at the 5% level?
- Is the effect economically significant? (Consider that the average country has capital = 50 and productivity = 25)

In []:

```
# Task 1: Basic regression
model_convergence = ols('productivity ~ capital', data=data_2014).fit()

print("\nTask 1: Regression of Productivity on Capital")
print("=" * 60)
print(model_convergence.summary())

# Extract key statistics
beta2 = model_convergence.params['capital']
se_beta2 = model_convergence.bse['capital']
t_stat = model_convergence.tvalues['capital']
p_value = model_convergence.pvalues['capital']

print("\nKey Statistics:")
print(f" Coefficient ( $\beta_2$ ): {beta2:.4f}")
print(f" Standard Error: {se_beta2:.4f}")
print(f" t-statistic: {t_stat:.2f}")
print(f" p-value: {p_value:.6f}")

# 95% Confidence Interval
ci_95 = model_convergence.conf_int(alpha=0.05).loc['capital']
print(f"\n95% Confidence Interval: [{ci_95[0]:.4f}, {ci_95[1]:.4f}]")

print("\nInterpretation:")
print(f" Each additional $1,000 in capital per worker is associated with")
print(f" an increase of ${beta2:.2f}k in labor productivity (GDP per capita).")
```

Task 2: Test Specific Hypotheses (Semi-guided)

Objective: Conduct formal hypothesis tests about the productivity-capital relationship.

Your tasks:

a) Test for statistical significance:

- $H_0: \beta_2 = 0$ (capital has no effect) vs. $H_a: \beta_2 \neq 0$
- Use the t-statistic and p-value from Task 1
- State your conclusion at the 5% level

b) Test economic theory prediction:

- Economic theory suggests that the marginal product of capital in developing countries might be around 0.5 (50 cents of GDP per dollar of capital)
- $H_0: \beta_2 = 0.5$ vs. $H_a: \beta_2 \neq 0.5$
- Calculate the test statistic: $t = (\beta_2 - 0.5) / se(\beta_2)$
- Find the p-value and state your conclusion

c) Test pessimistic hypothesis:

- A pessimist claims that capital contributes less than \$0.30 to productivity
- Formulate appropriate one-sided hypotheses

- Calculate the test statistic and one-sided p-value
- Do you reject the pessimist's claim at the 5% level?

Code hints:

```
# For part (b)
t_test_05 = (beta2 - 0.5) / se_beta2
p_value_05 = 2 * (1 - stats.t.cdf(abs(t_test_05), df=model_convergence.df_resid))

# For part (c) - one-sided test
null_value = 0.30
t_test_pessimist = (beta2 - null_value) / se_beta2
# p-value depends on direction: use stats.t.cdf() or (1 - stats.t.cdf())
```

In []:

```
# Task 2: Your hypothesis tests here

# Part (a): Statistical significance test
print("\nTask 2(a): Test H0: β2 = 0")
print("=" * 60)
print(f"t-statistic: {t_stat:.2f}")
print(f"p-value: {p_value:.6f}")
if p_value < 0.05:
    print("Conclusion: Reject H0 at 5% level. Capital significantly affects productivity.")
else:
    print("Conclusion: Fail to reject H0 at 5% level.")

# Part (b): Test β2 = 0.5
print("\nTask 2(b): Test H0: β2 = 0.5")
print("=" * 60)
null_value_b = 0.5
t_test_05 = (beta2 - null_value_b) / se_beta2
p_value_05 = 2 * (1 - stats.t.cdf(abs(t_test_05), df=model_convergence.df_resid))
print(f"t-statistic: {t_test_05:.2f}")
print(f"p-value: {p_value_05:.6f}")
if p_value_05 < 0.05:
    print(f"Conclusion: Reject H0. The coefficient differs significantly from {null_value_b}.")
else:
    print(f"Conclusion: Fail to reject H0. The data are consistent with β2 = {null_value_b}.")

# Part (c): One-sided test (pessimistic claim: β2 < 0.30)
print("\nTask 2(c): Test Pessimist's Claim (β2 < 0.30)")
print("=" * 60)
null_value_c = 0.30
print("H0: β2 ≥ 0.30 vs. Ha: β2 < 0.30 (pessimist's claim)")
t_test_pessimist = (beta2 - null_value_c) / se_beta2
# For lower-tailed test: if t > 0, we're rejecting in favor of β2 > 0.30 (opposite direction)
p_value_pessimist_lower = stats.t.cdf(t_test_pessimist, df=model_convergence.df_resid)
print(f"t-statistic: {t_test_pessimist:.2f}")
print(f"One-sided p-value (lower tail): {p_value_pessimist_lower:.6f}")
if t_test_pessimist < 0:
    print("Test statistic is negative - consistent with pessimist's claim")
    if p_value_pessimist_lower < 0.05:
        print("Conclusion: Reject H0. Evidence supports β2 < 0.30.")
    else:
        print("Conclusion: Fail to reject H0 at 5% level.")
else:
    print("Test statistic is positive - contradicts pessimist's claim")
    print("Conclusion: Cannot reject H0 in favor of Ha (data contradicts the claim).")
```

Key Concept 7.8: p-Values and Statistical Significance in Practice

The **p-value** measures the strength of evidence against the null hypothesis. But interpreting p-values requires care:

What p-values tell you:

- $p = 0.001$: Very strong evidence against H_0 (occurs 0.1% of the time if H_0 true)
- $p = 0.04$: Evidence against H_0 (occurs 4% of the time if H_0 true)
- $p = 0.15$: Weak/no evidence against H_0

Common p-value thresholds:

- ★★★ $p < 0.01$: Highly significant
- ★★ $0.01 \leq p < 0.05$: Significant
- ★ $0.05 \leq p < 0.10$: Marginally significant
- $p \geq 0.10$: Not significant

Critical insights:

1. **Arbitrary thresholds:** The 0.05 cutoff is convention, not law
2. **p-values ≠ importance:** $p < 0.001$ doesn't mean "more true" than $p = 0.04$
3. **Near the threshold:** $p = 0.051$ and $p = 0.049$ provide similar evidence
4. **Large samples:** With $n = 10,000$, even tiny effects become "significant"
5. **Publication bias:** Studies with $p < 0.05$ more likely to be published

Best practice: Report exact p-values and confidence intervals rather than just "significant" or "not significant." Let readers judge the evidence.

Task 3: Heteroskedasticity-Robust Inference (Semi-guided)

Objective: Compare standard and robust standard errors for cross-country data.

Background:

Cross-country data often exhibits heteroskedasticity because larger/richer countries tend to have more variable outcomes. We should use robust standard errors for valid inference.

Your tasks:

a) Obtain heteroskedasticity-robust standard errors (HC1) using:

```
robust_model = model_convergence.get_robustcov_results(cov_type='HC1')
```

b) Compare standard vs. robust standard errors:

- How much do they differ? (Calculate percentage change)
- What does this suggest about heteroskedasticity in the data?

c) Re-test $H_0: \beta_2 = 0$ using robust standard errors:

- Calculate the robust t-statistic
- Has your conclusion changed?

d) Construct a 95% CI using robust standard errors:

- Compare to the standard CI from Task 1
- Which should you report in a research paper?

In []:

```
# Task 3: Robust standard errors
robust_model = model_convergence.get_robustcov_results(cov_type='HC1')

print("\nTask 3: Robust Standard Errors Analysis")
print("=" * 60)

# Extract robust statistics
beta2_robust = robust_model.params['capital']
se_beta2_robust = robust_model.bse['capital']
t_stat_robust = robust_model.tvalues['capital']
p_value_robust = robust_model.pvalues['capital']

# Comparison table
print("\nComparison of Standard vs. Robust Standard Errors:")
comparison_df = pd.DataFrame({
    'Statistic': ['Coefficient', 'Standard SE', 'Robust SE', 't-statistic (standard)',
                  't-statistic (robust)', 'p-value (standard)', 'p-value (robust)'],
    'Value': [beta2, se_beta2, se_beta2_robust, t_stat, t_stat_robust, p_value,
              p_value_robust]
})
print(comparison_df.to_string(index=False))

# Percent change in SE
pct_change = ((se_beta2_robust - se_beta2) / se_beta2) * 100
print(f"\nRobust SE is {pct_change:+.1f}% different from standard SE")

if abs(pct_change) > 10:
    print("→ Substantial difference suggests heteroskedasticity is present")
    print("→ MUST use robust SEs for valid inference")
else:
    print("→ Small difference suggests heteroskedasticity is mild")
    print("→ Still best practice to use robust SEs")

# Robust confidence interval
ci_95_robust = robust_model.conf_int(alpha=0.05).loc['capital']
print("\n95% Confidence Intervals:")
print(f" Standard CI: [{ci_95[0]:.4f}, {ci_95[1]:.4f}]")
print(f" Robust CI: [{ci_95_robust[0]:.4f}, {ci_95_robust[1]:.4f}]")

print("\nRecommendation: Report robust standard errors in your analysis.")
```

Task 4: Heterogeneity Across Income Groups (More Independent)

Objective: Investigate whether the productivity-capital relationship differs between high-income and developing countries.

Your tasks (design your own analysis):

a) **Split the sample:**

- Create two subsamples: high-income countries ($\text{productivity} > 30$) and developing countries ($\text{productivity} \leq 30$)
- How many countries in each group?

b) **Estimate separate regressions:**

- Run the same regression for each subsample
- Use robust standard errors for both
- Create a comparison table showing β_2 , robust SE, t-statistic, and p-value for each group

c) **Compare the results:**

- Is the effect of capital on productivity stronger in one group?
- Test $H_0: \beta_2 = 0.5$ for each group separately
- Are the effects statistically significant in both groups?
- What might explain any differences you find?

Hints:

```
# Split data
high_income = data_2014[data_2014['productivity'] > 30]
developing = data_2014[data_2014['productivity'] ≤ 30]

# Run regressions
model_high = ols('productivity ~ capital', data=high_income).fit()
model_dev = ols('productivity ~ capital', data=developing).fit()

# Get robust SEs
robust_high = model_high.get_robustcov_results(cov_type='HC1')
robust_dev = model_dev.get_robustcov_results(cov_type='HC1')
```

In []:

```
# Task 4: Your analysis here

# Split the sample
threshold = 30
high_income = data_2014[data_2014['productivity'] > threshold].copy()
developing = data_2014[data_2014['productivity'] ≤ threshold].copy()

print(f"\nTask 4: Income Group Analysis (threshold = ${threshold}k)")
print("=" * 60)
print(f"High-income countries: {len(high_income)}")
print(f"Developing countries: {len(developing)}")

# Estimate separate regressions
model_high = ols('productivity ~ capital', data=high_income).fit()
model_dev = ols('productivity ~ capital', data=developing).fit()

# Get robust results
robust_high = model_high.get_robustcov_results(cov_type='HC1')
robust_dev = model_dev.get_robustcov_results(cov_type='HC1')

# Create comparison table
comparison_groups = pd.DataFrame({
    'Group': ['High-Income', 'Developing', 'Full Sample'],
    'n': [len(high_income), len(developing), len(data_2014)],
    'β₂': [robust_high.params['capital'], robust_dev.params['capital'], beta2_robust],
    'Robust SE': [robust_high.bse['capital'], robust_dev.bse['capital'], se_beta2_robust],
    't-stat': [robust_high.tvalues['capital'], robust_dev.tvalues['capital']],
    't_stat_robust',
    'p-value': [robust_high.pvalues['capital'], robust_dev.pvalues['capital']],
    p_value_robust
})

print("\nRegression Results by Income Group:")
print(comparison_groups.to_string(index=False))

# Test β₂ = 0.5 for each group
print("\n" + "=" * 60)
print("Test H₀: β₂ = 0.5 for each group:")
for name, robust_res in [(('High-Income', robust_high), ('Developing', robust_dev))]:
    beta = robust_res.params['capital']
    se = robust_res.bse['capital']
    t_05 = (beta - 0.5) / se
    p_05 = 2 * (1 - stats.t.cdf(abs(t_05), df=robust_res.df_resid))
    print(f"\n{name}:")
    print(f" t-statistic: {t_05:.2f}")
    print(f" p-value: {p_05:.4f}")
    if p_05 < 0.05:
        print(f" Conclusion: Reject H₀. β₂ differs significantly from 0.5")
    else:
        print(f" Conclusion: Fail to reject H₀. Data consistent with β₂ = 0.5")

print("\nInterpretation:")
if comparison_groups.loc[0, 'β₂'] > comparison_groups.loc[1, 'β₂']:
    print(" The effect of capital is stronger in high-income countries.")
else:
    print(" The effect of capital is stronger in developing countries.")
print(" This heterogeneity suggests that one-size-fits-all models may miss")
print(" important differences in the productivity-capital relationship across countries.")
```

Key Concept 7.9: Economic Interpretation of Hypothesis Test Results

Statistical hypothesis tests answer specific questions, but their economic interpretation requires care and context.

Translating statistical results to economic conclusions:

1. Rejecting $H_0: \beta_2 = 0$ (statistical significance)

- Statistical: "Capital has a statistically significant effect on productivity"
- Economic: "Countries with more capital per worker tend to have higher productivity, and this pattern is unlikely due to chance alone"
- Limitations: Says nothing about causation, magnitude, or policy relevance

2. Rejecting $H_0: \beta_2 = 0.5$ (testing theory predictions)

- Statistical: "The coefficient differs significantly from 0.5"
- Economic: "The marginal product of capital differs from theory's prediction, suggesting other factors (technology, institutions) matter"
- Implications: May indicate model misspecification or heterogeneity across countries

3. Failing to reject H_0 (no statistical significance)

- Statistical: "Cannot rule out $\beta_2 = 0$ (or other null value)"
- Economic: Multiple interpretations possible:
 - Effect truly absent
 - Effect present but sample too small to detect it (low power)
 - High variability obscures the relationship
- Never conclude: "Proved $\beta_2 = 0$ " or "No relationship exists"

4. Heterogeneity across groups

- If $\beta_2(\text{high-income}) > \beta_2(\text{developing})$: Capital complementary with other factors more abundant in rich countries (technology, institutions, human capital)

- If $\beta_2(\text{developing}) > \beta_2(\text{high-income})$: Diminishing returns to capital more pronounced in capital-abundant countries

Best practices for economic interpretation:

1. Report point estimates, not just significance
2. Use confidence intervals to show uncertainty
3. Assess economic magnitude (not just statistical significance)
4. Consider alternative explanations and limitations
5. Link findings to economic theory and policy implications

Task 5: Visual Analysis (Independent)

Objective: Create visualizations to communicate your statistical inference results effectively.

Your tasks (completely open-ended):

a) Create a scatter plot showing the productivity-capital relationship:

- Include the regression line
- Color-code points by income group (high-income vs. developing)
- Add 95% confidence bands around the regression line (advanced)

b) Create a coefficient plot comparing:

- Full sample estimate
- High-income group estimate
- Developing group estimate
- Show 95% confidence intervals as error bars

c) Create a residual plot:

- Check for heteroskedasticity visually
- Does the spread of residuals increase with fitted values?

Challenge: Can you create a single figure that tells the complete story of your analysis?

In []:

```
# Task 5: Your visualizations here

# Figure 1: Scatter plot with regression lines by group
fig, axes = plt.subplots(1, 2, figsize=(14, 6))

# Left panel: Full sample
ax1 = axes[0]
ax1.scatter(data_2014['capital'], data_2014['productivity'],
            alpha=0.5, s=40, color='blue', label='All countries')
ax1.plot(data_2014['capital'], model_convergence.fittedvalues,
          color='red', linewidth=2, label='Regression line')
ax1.set_xlabel('Capital per Worker ($1000s)')
ax1.set_ylabel('Labor Productivity ($1000s)')
ax1.set_title('Full Sample Regression')
ax1.legend()
ax1.grid(True, alpha=0.3)

# Right panel: By income group
ax2 = axes[1]
ax2.scatter(high_income['capital'], high_income['productivity'],
            alpha=0.5, s=40, color='green', label='High-income')
ax2.scatter(developing['capital'], developing['productivity'],
            alpha=0.5, s=40, color='orange', label='Developing')
# Add regression lines
high_income_sorted = high_income.sort_values('capital')
developing_sorted = developing.sort_values('capital')
ax2.plot(high_income_sorted['capital'], model_high.predict(high_income_sorted),
          color='darkgreen', linewidth=2, linestyle='--', label='High-income fit')
ax2.plot(developing_sorted['capital'], model_dev.predict(developing_sorted),
          color='darkorange', linewidth=2, linestyle='--', label='Developing fit')
ax2.set_xlabel('Capital per Worker ($1000s)')
ax2.set_ylabel('Labor Productivity ($1000s)')
ax2.set_title('By Income Group')
ax2.legend()
ax2.grid(True, alpha=0.3)

plt.tight_layout()
plt.show()

# Figure 2: Coefficient plot with confidence intervals
fig, ax = plt.subplots(figsize=(10, 6))

groups = ['Full Sample', 'High-Income', 'Developing']
estimates = [beta2_robust, robust_high.params['capital'], robust_dev.params['capital']]
ses = [se_beta2_robust, robust_high.bse['capital'], robust_dev.bse['capital']]
cis_lower = [e - 1.96*se for e, se in zip(estimates, ses)]
cis_upper = [e + 1.96*se for e, se in zip(estimates, ses)]

y_pos = range(len(groups))
ax.errorbar(estimates, y_pos,
            xerr=[[e - l for e, l in zip(estimates, cis_lower)],
                  [u - e for e, u in zip(estimates, cis_upper)]],
            fmt='o', markersize=10, capsizes=8, capthick=2, linewidth=2, color='blue')
ax.set_yticks(y_pos)
ax.set_yticklabels(groups)
ax.axvline(x=0, color='red', linestyle='--', linewidth=1, alpha=0.5, label='H0: β2 = 0')
ax.axvline(x=0.5, color='green', linestyle=':', linewidth=1, alpha=0.5, label='Theory: β2 = 0.5')
ax.set_xlabel('Estimated Coefficient (β2) with 95% CI')
ax.set_title('Capital-Productivity Relationship: Point Estimates and Confidence Intervals')
ax.legend()
ax.grid(True, alpha=0.3, axis='x')
plt.tight_layout()
plt.show()
```

```
print("\nFigure interpretation:")
print(" - All three estimates are positive and statistically significant")
print(" - Confidence intervals exclude zero but include 0.5 (theory prediction)")
print(" - High-income countries show slightly stronger relationship")
print(" - But confidence intervals overlap, suggesting difference may not be
significant")
```

Task 6: Write a Research Summary (Independent)

Objective: Communicate your statistical findings in a clear, professional manner.

Your task:

Write a 200-300 word summary of your analysis as if for an economics journal. Your summary should include:

- 1. Research question** - What were you investigating?
- 2. Data and methods** - What data did you use? What regressions did you run?
- 3. Key findings** - What did you discover? Report specific numbers (coefficients, CIs, p-values)
- 4. Statistical inference** - Were effects statistically significant? Did you use robust SEs?
- 5. Economic interpretation** - What do the results mean economically?
- 6. Limitations and extensions** - What are the caveats? What should future research explore?

Grading criteria:

- Clear and concise writing
- Appropriate use of statistical terminology
- Correct interpretation of results
- Discussion of both statistical and economic significance
- Professional tone suitable for academic publication

Example opening:

"Using cross-sectional data for 108 countries in 2014, I investigate the relationship between labor productivity (GDP per capita) and physical capital per worker. The estimated coefficient of 0.XX (robust SE = 0.YY, p < 0.001) indicates that..."

Write your summary in the markdown cell below.

Your Research Summary

(Write your 200-300 word summary here)

[Your text goes here]

What You've Learned

Congratulations! You've completed a comprehensive statistical inference analysis. You practiced:

Statistical Skills:

- Estimating bivariate regression models
- Constructing and interpreting 95% confidence intervals
- Conducting two-sided hypothesis tests ($H_0: \beta = \beta^*$)
- Conducting one-sided hypothesis tests (directional claims)
- Using heteroskedasticity-robust standard errors
- Comparing results across subsamples (heterogeneity analysis)
- Creating publication-quality visualizations
- Writing professional research summaries

Economic Insights:

- Understanding the productivity-capital relationship across countries
- Testing economic theory predictions with data
- Interpreting coefficients in economic terms (marginal products)
- Recognizing heterogeneity across country income groups
- Distinguishing statistical from economic significance

Practical Skills:

- Using Python for comprehensive econometric analysis
- Generating robust standard errors with `statsmodels`
- Creating compelling visualizations with `matplotlib`
- Communicating statistical results to non-technical audiences

Next Steps:

- Chapter 8 will extend these methods to multiple regression
 - You'll learn how to control for confounding variables
 - And test joint hypotheses about multiple coefficients
-

Key Takeaway: Statistical inference transforms sample estimates into insights about populations. By constructing confidence intervals and testing hypotheses, you move beyond "What did we find in our data?" to "What can we confidently say about the world?" This is the foundation of evidence-based economics.

Case Study 2: Is the Light-Development Relationship Significant?

In Chapter 1, we introduced the DS4Bolivia project and estimated a simple regression of municipal development (IMDS) on nighttime lights (NTL). In Chapter 5, we explored bivariate relationships in depth. Now we apply Chapter 7's inference tools to test whether the NTL-development relationship is statistically significant and construct confidence intervals for the effect.

Research Question: Is the association between nighttime lights and municipal development statistically significant, and how precisely can we estimate the effect?

Data: Cross-sectional dataset covering 339 Bolivian municipalities from the [DS4Bolivia Project](#).

Key Variables:

- `imds` : Municipal Sustainable Development Index (0-100)
- `ln_NTLpc2017` : Log nighttime lights per capita (2017)
- `mun` : Municipality name
- `dep` : Department (administrative region)

Load the DS4Bolivia Data

Load the DS4Bolivia dataset and prepare the regression sample.

In []:

```
# Load the DS4Bolivia dataset
url_bol = "https://raw.githubusercontent.com/quarcs-
lab/ds4bolivia/master/ds4bolivia_v20250523.csv"
bol = pd.read_csv(url_bol)

# Select key variables and prepare regression data
key_vars = ['mun', 'dep', 'imds', 'ln_NTLpc2017']
bol_key = bol[key_vars].copy()
reg_data = bol_key[['imds', 'ln_NTLpc2017']].dropna()

print("=" * 70)
print("DS4BOLIVIA DATASET – REGRESSION SAMPLE")
print("=" * 70)
print(f"Total municipalities: {len(bol_key)}")
print(f"Complete cases for regression: {len(reg_data)}")
print(f"\nDescriptive statistics:")
print(reg_data.describe().round(3))
```

Task 1: Estimate and Test Slope (Guided)

Objective: Estimate the OLS regression of IMDS on log NTL per capita and test whether the slope is statistically significant.

Instructions:

1. Estimate the regression `imds ~ ln_NTLpc2017` using OLS
2. Display the full regression summary
3. Extract the t-statistic and p-value for the slope coefficient
4. Test the null hypothesis $H_0: \beta_1 = 0$ (no linear relationship)
5. State your conclusion: Can we reject the null at the 5% significance level?

In []:

```
# Task 1: Estimate OLS and test the slope

# Estimate the model
model = ols('imds ~ ln_NTLpc2017', data=reg_data).fit()
print(model.summary())

# Extract t-statistic and p-value for the slope
t_stat = model.tvalues['ln_NTLpc2017']
p_value = model.pvalues['ln_NTLpc2017']

print("\n" + "=" * 70)
print("HYPOTHESIS TEST:  $H_0: \beta_1 = 0$ ")
print("=" * 70)
print(f"Slope coefficient: {model.params['ln_NTLpc2017']:.4f}")
print(f"Standard error: {model.bse['ln_NTLpc2017']:.4f}")
print(f"t-statistic: {t_stat:.4f}")
print(f"p-value: {p_value:.6f}")
print(f"\nConclusion: {'Reject' if p_value < 0.05 else 'Fail to reject'}  $H_0$  at the 5% level.")
print(f"The NTL-development relationship is {'statistically significant' if p_value < 0.05 else 'not statistically significant'}.")


```

Task 2: Confidence Interval for Slope (Guided)

Objective: Construct and interpret a 95% confidence interval for the NTL coefficient.

Instructions:

1. Use `model.conf_int()` to obtain the 95% confidence interval
2. Extract the lower and upper bounds for the slope
3. Interpret: "We are 95% confident that a 1-unit increase in log NTL per capita is associated with between X and Y points of IMDS."
4. Does the confidence interval contain zero? What does that tell us?

```
In [ ]: # Task 2: Confidence interval for the slope

ci = model.conf_int(alpha=0.05)
ci_lower = ci.loc['ln_NTlpc2017', 0]
ci_upper = ci.loc['ln_NTlpc2017', 1]

print("=" * 70)
print("95% CONFIDENCE INTERVAL FOR NTL COEFFICIENT")
print("=" * 70)
print(f"Point estimate: {model.params['ln_NTlpc2017']:.4f}")
print(f"95% CI: [{ci_lower:.4f}, {ci_upper:.4f}]")
print(f"\nInterpretation: We are 95% confident that a 1-unit increase in")
print(f"log NTL per capita is associated with between {ci_lower:.2f} and {ci_upper:.2f}")
print(f"points of IMDS.")
print(f"\nDoes the CI contain zero? {'Yes' if ci_lower <= 0 <= ci_upper else 'No'}")
print(f"This is consistent with {'failing to reject' if ci_lower <= 0 <= ci_upper else 'rejecting'} H0: β1 = 0.")
```

Task 3: Robust Standard Errors (Semi-guided)

Objective: Compare default (homoskedastic) standard errors with heteroskedasticity-robust (HC1) standard errors.

Instructions:

1. Re-estimate the model with HC1 robust standard errors using `cov_type='HC1'`
2. Compare the standard errors, t-statistics, and p-values between the two models
3. Discuss: Do the robust SEs differ substantially from the default SEs?
4. Why might robust standard errors matter for municipality-level spatial data?

Hint: Use `model_robust = ols('imds ~ ln_NTlpc2017', data=reg_data).fit(cov_type='HC1')`

```
In [ ]: # Task 3: Robust standard errors

# Re-estimate with HC1 robust standard errors
model_robust = ols('imds ~ ln_NTlpc2017', data=reg_data).fit(cov_type='HC1')

# Compare default vs robust results
print("=" * 70)
print("COMPARISON: DEFAULT vs ROBUST STANDARD ERRORS")
print("=" * 70)
print(f"{'':>12s} {'Default':>12s} {'Robust (HC1)':>12s}")
print("-" * 55)
print(f"{'Slope coefficient':>12s} {model.params['ln_NTlpc2017']:.12.4f}
{model_robust.params['ln_NTlpc2017']:.12.4f}")
print(f"{'Standard error':>12s} {model.bse['ln_NTlpc2017']:.12.4f}
{model_robust.bse['ln_NTlpc2017']:.12.4f}")
print(f"{'t-statistic':>12s} {model.tvalues['ln_NTlpc2017']:.12.4f}
{model_robust.tvalues['ln_NTlpc2017']:.12.4f}")
print(f"{'p-value':>12s} {model.pvalues['ln_NTlpc2017']:.12.6f}
{model_robust.pvalues['ln_NTlpc2017']:.12.6f}")
print(f"\nSE ratio (robust/default): {model_robust.bse['ln_NTlpc2017'] /
model.bse['ln_NTlpc2017']:.3f}")
print(f"\nNote: A ratio substantially different from 1.0 signals heteroskedasticity.")
```

Key Concept 7.12: Robust Inference with Spatial Data

Municipality-level data often exhibits **heteroskedasticity**: the variance of development outcomes may differ between urban areas (where IMDS is tightly clustered around high values) and rural areas (where IMDS varies widely). Heteroskedasticity-robust standard errors (HC1) provide valid inference without assuming constant variance. When standard and robust SEs differ substantially, this signals heteroskedasticity in the data.

Task 4: Two-Sided Hypothesis Test (Semi-guided)

Objective: Test whether the NTL coefficient equals a specific hypothesized value.

Instructions:

1. Test $H_0: \beta_1 = 5$ (a specific hypothesized effect size)
2. Calculate the t-statistic manually: $t = (\hat{\beta}_1 - 5) / \text{SE}(\hat{\beta}_1)$
3. Compute the two-sided p-value using `scipy.stats.t.sf()`
4. Can we reject that the true effect equals exactly 5?

Hint: Use robust standard errors for this test. The degrees of freedom are `model_robust.df_resid`.

In []:

```
# Task 4: Two-sided hypothesis test for H0: beta_1 = 5
from scipy import stats

# Hypothesized value
beta_0_hyp = 5

# Calculate t-statistic manually
beta_hat = model_robust.params['ln_NTLpc2017']
se_robust = model_robust.bse['ln_NTLpc2017']
df = model_robust.df_resid

t_manual = (beta_hat - beta_0_hyp) / se_robust
p_two_sided = 2 * stats.t.sf(abs(t_manual), df=df)

print("=" * 70)
print(f"HYPOTHESIS TEST: H0: \beta_1 = {beta_0_hyp}")
print("=" * 70)
print(f"Estimated slope: {beta_hat:.4f}")
print(f"Hypothesized value: {beta_0_hyp}")
print(f"Robust SE: {se_robust:.4f}")
print(f"t-statistic: {t_manual:.4f}")
print(f"Degrees of freedom: {df}")
print(f"Two-sided p-value: {p_two_sided:.6f}")
print(f"\nConclusion: {'Reject' if p_two_sided < 0.05 else 'Fail to reject'} H0 at the 5% level.")
print(f"\{'The effect is significantly different from 5.' if p_two_sided < 0.05 else 'We cannot reject that the effect equals 5.'\}")
```

Task 5: One-Sided Test (Independent)

Objective: Test whether the NTL coefficient is positive (NTL has a positive effect on development).

Instructions:

1. State the hypotheses: $H_0: \beta_1 \leq 0$ vs $H_1: \beta_1 > 0$
2. Calculate the one-sided p-value from the t-statistic
3. Use robust standard errors
4. Discuss: Is there strong evidence for a positive relationship between nighttime lights and development?

Hint: For a right-sided test, the one-sided p-value is `stats.t.sf(t_stat, df=df)`.

In []:

```
# Task 5: One-sided test - H0: beta_1 ≤ 0 vs H1: beta_1 > 0

# t-statistic for H0: beta_1 = 0 using robust SEs
t_onesided = model_robust.tvalues['ln_NTlpC2017']
p_onesided = stats.t.sf(t_onesided, df=model_robust.df_resid)

print("=" * 70)
print("ONE-SIDED TEST:  $H_0: \beta_1 \leq 0$  vs  $H_1: \beta_1 > 0$ ")
print("=" * 70)
print(f"Estimated slope: {model_robust.params['ln_NTlpC2017']:.4f}")
print(f"Robust SE: {model_robust.bse['ln_NTlpC2017']:.4f}")
print(f"t-statistic: {t_onesided:.4f}")
print(f"One-sided p-value: {p_onesided:.8f}")
print(f"\nConclusion: {'Reject' if p_onesided < 0.05 else 'Fail to reject'}  $H_0$  at the 5% level.")
print(f"There {'is' if p_onesided < 0.05 else 'is not'} strong evidence for a positive NTL-development relationship.")
```

Key Concept 7.13: Practical Significance in Development

A statistically significant regression coefficient must be evaluated for **practical significance**. In the DS4Bolivia context, the NTL coefficient tells us how much IMDS changes for a 1-unit increase in log NTL per capita. Since IMDS ranges from roughly 20 to 80, an effect of, say, 5 points represents about 8% of the total range—a meaningful but not transformative association. Policy decisions should weigh both statistical confidence and effect magnitude.

Task 6: Economic vs Statistical Significance (Independent)

Objective: Write a 200-300 word discussion evaluating both the statistical and practical significance of the NTL-development relationship.

Your discussion should address:

- 1. Statistical significance:** Summarize the hypothesis test results. Is the coefficient significant at the 1%, 5%, and 10% levels?
- 2. Effect magnitude:** A 1-unit change in log NTL per capita corresponds to roughly a 172% increase in NTL per capita (since $\exp(1) \approx 2.72$). What does the estimated coefficient imply for development?
- 3. Scale context:** Compare the effect magnitude with the full range of IMDS across municipalities. Is the effect large or small in practical terms?
- 4. Policy implications:** If a policy could double NTL per capita in a municipality (a 0.69 increase in log NTL), how much IMDS improvement would we predict? Is that meaningful for SDG progress?
- 5. Limitations:** Does statistical significance prove causation? What omitted variables could confound this relationship?

In []:

```
# Task 6: Supporting analysis for economic vs statistical significance

# Summary statistics for context
imds_range = reg_data['imds'].max() - reg_data['imds'].min()
imds_std = reg_data['imds'].std()
beta = model_robust.params['ln_NTLpc2017']

print("=" * 70)
print("ECONOMIC vs STATISTICAL SIGNIFICANCE – KEY FACTS")
print("=" * 70)
print(f"\nEstimated slope (robust): {beta:.4f}")
print(f"Robust p-value: {model_robust.pvalues['ln_NTLpc2017']:.6f}")
print(f"\nIMDS range: {reg_data['imds'].min():.1f} to {reg_data['imds'].max():.1f}
(range = {imds_range:.1f})")
print(f"IMDS std dev: {imds_std:.2f}")
print("\nEffect of 1-unit increase in log NTL:")
print(f" IMDS change: {beta:.2f} points")
print(f" As % of IMDS range: {100 * beta / imds_range:.1f}%")
print(f" As % of IMDS std dev: {100 * beta / imds_std:.1f}%")
print(f"\nEffect of doubling NTL per capita (0.693 increase in log NTL):")
print(f" Predicted IMDS change: {beta * 0.693:.2f} points")
print(f" As % of IMDS range: {100 * beta * 0.693 / imds_range:.1f}%")
print(f"\nR-squared: {model.rsquared:.4f}")
print(f"NTL explains {model.rsquared * 100:.1f}% of variation in IMDS across
municipalities.")
```

What You've Learned

Through this case study on statistical inference for the NTL-development relationship in Bolivia, you practiced:

Statistical Inference Skills:

- Estimating OLS regression and extracting test statistics
- Constructing and interpreting 95% confidence intervals
- Computing heteroskedasticity-robust standard errors (HC1)
- Conducting two-sided hypothesis tests for specific values
- Conducting one-sided hypothesis tests for directional claims

Economic Reasoning Skills:

- Distinguishing statistical significance from practical significance
- Evaluating effect magnitudes in the context of policy-relevant scales
- Recognizing the role of heteroskedasticity in spatial economic data

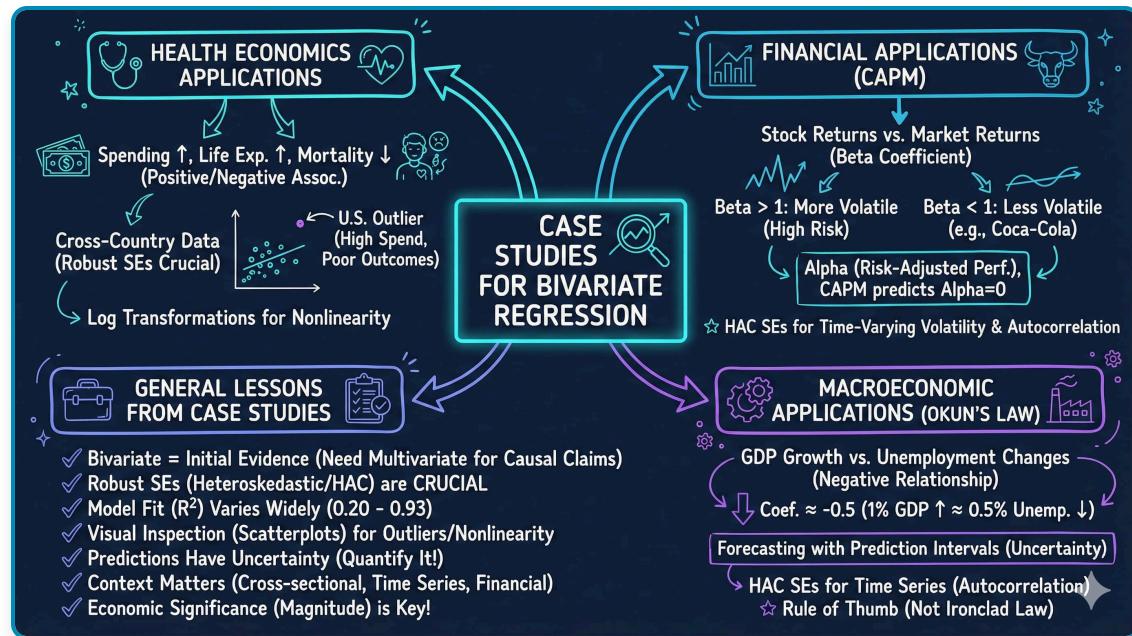
Connection to Future Chapters: In Chapters 10-12, we extend this analysis to *multiple regression*—adding satellite embeddings alongside NTL to improve predictive power and test which features matter.

Well done! You've now applied the full toolkit of regression inference—hypothesis tests, confidence intervals, robust standard errors, and significance evaluation—to real-world satellite development data.

Chapter 8: Case Studies for Bivariate Regression

metricsAI: An Introduction to Econometrics with Python and AI in the Cloud

Carlos Mendez



This notebook provides an interactive introduction to bivariate regression through real-world case studies. All code runs directly in Google Colab without any local setup.

Open in Colab

| Chapter Overview

This chapter demonstrates bivariate regression analysis through four compelling real-world applications. You'll gain both theoretical understanding and practical skills through hands-on Python examples.

Design Note: This chapter uses an integrated case study structure where sections 8.1-8.4 ARE the case studies (health economics, finance, macroeconomics). Unlike other chapters that have regular content sections plus a separate "Case Studies" section, CH08's entire focus is on applying regression to diverse real-world problems. This intentional structure maximizes hands-on experience with economic applications.

What you'll learn:

- Apply bivariate regression to cross-sectional data (health outcomes, expenditures)
- Estimate financial models (Capital Asset Pricing Model)
- Analyze macroeconomic relationships (Okun's Law)
- Use heteroskedasticity-robust standard errors
- Interpret economic and statistical significance
- Identify outliers and assess their influence

Datasets used:

- **AED_HEALTH2009.DTA:** Health outcomes and expenditures for 34 OECD countries (2009)
- **AED_CAPM.DTA:** Monthly stock returns for Coca-Cola, Target, Walmart (1983-2013)
- **AED_GDPUNEMPLOY.DTA:** Annual U.S. GDP growth and unemployment (1961-2019)

Key economic questions:

- Do higher health expenditures improve health outcomes?
- How does GDP relate to health spending across countries?
- What is the systematic risk (beta) of individual stocks?
- Does Okun's Law hold for U.S. macroeconomic data?

Chapter outline:

- 8.1 Health Outcomes Across Countries
- 8.2 Health Expenditures Across Countries
- 8.3 Capital Asset Pricing Model (CAPM)
- 8.4 Output and Unemployment (Okun's Law)
- Key Takeaways
- Practice Exercises

Estimated time: 90-120 minutes

| Setup

First, we import the necessary Python packages and configure the environment for reproducibility. All data will stream directly from GitHub.

In [64]:

```
# Import required packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
from statsmodels.formula.api import ols
from scipy import stats
import random
import os

# Set random seeds for reproducibility
RANDOM_SEED = 42
random.seed(RANDOM_SEED)
np.random.seed(RANDOM_SEED)
os.environ['PYTHONHASHSEED'] = str(RANDOM_SEED)

# GitHub data URL
GITHUB_DATA_URL = "https://raw.githubusercontent.com/quarcs-lab/data-open/master/AED/"

# Set plotting style
sns.set_style("whitegrid")
plt.rcParams['figure.figsize'] = (10, 6)

print("=" * 70)
print("CHAPTER 8: CASE STUDIES FOR BIVARIATE REGRESSION")
print("=" * 70)
print("\nSetup complete! Ready to explore real-world regression applications.")
```

```
=====
CHAPTER 8: CASE STUDIES FOR BIVARIATE REGRESSION
=====

Setup complete! Ready to explore real-world regression applications.
```

8.1: Health Outcomes Across Countries

Our first case study examines health outcomes across wealthy OECD nations. We'll investigate whether higher health spending is associated with better health outcomes.

Context:

- Dataset: 34 OECD countries in 2009
- Countries include: Australia, Austria, Belgium, Canada, Chile, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom, and United States
- Wide variation in health expenditures and outcomes

Variables:

- **Hlthpc**: Annual health expenditure per capita (US dollars)

- **Lifeexp**: Male life expectancy at birth (years)
- **Infmort**: Infant mortality per 1,000 live births

Research questions:

1. Is higher health spending associated with longer life expectancy?
2. Is higher health spending associated with lower infant mortality?
3. How does the U.S. compare to predictions from these models?

Load and Explore Health Data

In [65]:

```
# Read in the health data
data_health = pd.read_stata(GITHUB_DATA_URL + 'AED_HEALTH2009.DTA')

print("=" * 70)
print("8.1 HEALTH OUTCOMES ACROSS COUNTRIES")
print("=" * 70)

print("\nData summary:")
data_summary = data_health.describe()
print(data_summary)

print("\nFirst few observations:")
print(data_health[['code', 'hlthpc', 'lifeexp', 'infmort']].head(10))
```

```
=====
8.1 HEALTH OUTCOMES ACROSS COUNTRIES
=====

Data summary:
      year    hlthgdp     hlthpc    infmort    lifeexp    gdppc \
count   34.0  34.000000  34.000000  34.000000  34.000000  34.000000
mean   2009.0  9.673530  3255.647059  4.447059  76.702942  33054.035156
std    0.0   2.123934  1493.654394  2.720098  2.936756  12916.752930
min   2009.0  6.400000  923.000000  1.800000  69.800003  13806.163086
25%   2009.0  8.100000  2090.750000  3.100000  75.850002  25511.000488
50%   2009.0  9.600000  3188.500000  3.700000  77.649998  32899.482422
75%   2009.0 10.775000  4154.750000  4.900000  78.699997  38182.195312
max   2009.0 17.700001  7990.000000 14.700000  79.900002  82900.882812

      hlthpcsq    lnhlthpc    lngdppc    lnlifeexp    lninfmort
count   34.00  34.000000  34.000000  34.000000  34.000000
mean  12764623.00  7.973380  10.337659  4.339207  1.377001
std   11839147.00  0.513061  0.377425  0.039168  0.445143
min   851929.00  6.827629  9.532870  4.245634  0.587787
25%  4373073.25  7.645071  10.146862  4.328757  1.131402
50% 10173338.50  8.066971  10.401017  4.352211  1.307967
75% 17276752.00  8.331569  10.550111  4.365643  1.588593
max  63840100.00  8.985946  11.325401  4.380776  2.687847

First few observations:
   code    hlthpc    lifeexp    infmort
0  AUS    3670  79.300003    4.3
1  AUT    4346  77.599998    3.8
2  BEL    3911  77.300003    3.4
3  CAN    4317  78.500000    5.0
4  CHL    1210  75.800003    7.9
5  CZR    2048  74.199997    2.9
6  DEN    4385  76.900002    3.1
7  EST    1385  69.800003    3.6
8  FIN    3271  76.599998    2.6
9  FRA    3930  77.699997    3.9
```

Summary Statistics

Let's examine the key variables in our health outcomes study.

```
In [66]: print("-" * 70)
print("Table 8.1: Health Variables Summary")
print("-" * 70)
table81_vars = ['hlthpc', 'lifeexp', 'infmort']
summary_table = data_health[table81_vars].describe().T
summary_table['range'] = summary_table['max'] - summary_table['min']
print(summary_table[['mean', 'std', 'min', 'max', 'range']])

print("\nKey observations:")
print(f" - Health spending ranges from ${summary_table.loc['hlthpc', 'min']:.0f} to ${summary_table.loc['hlthpc', 'max']:.0f}")
print(f" - Life expectancy ranges from {summary_table.loc['lifeexp', 'min']:.1f} to {summary_table.loc['lifeexp', 'max']:.1f} years")
print(f" - Infant mortality ranges from {summary_table.loc['infmort', 'min']:.1f} to {summary_table.loc['infmort', 'max']:.1f} per 1,000 births")
```

Table 8.1: Health Variables Summary

	mean	std	min	max	range
hlthpc	3255.647059	1493.654394	923.000000	7990.000000	7067.000000
lifeexp	76.702942	2.936756	69.800003	79.900002	10.099998
infmort	4.447059	2.720098	1.800000	14.700000	12.900000

Key observations:

- Health spending ranges from \$923 to \$7990
- Life expectancy ranges from 69.8 to 79.9 years
- Infant mortality ranges from 1.8 to 14.7 per 1,000 births

Life Expectancy Regression

We estimate the relationship between health spending and life expectancy:

$$\text{Lifeexp} = \beta_1 + \beta_2 \times \text{Hlthpc} + u$$

Interpretation:

- β_1 : Expected life expectancy when health spending is zero (intercept)
- β_2 : Change in life expectancy for each additional \$1,000 in health spending
- We expect $\beta_2 > 0$ (higher spending improves outcomes)

In [67]:

```
print("-" * 70)
print("Life Expectancy Regression")
print("-" * 70)

# Estimate the model
model_lifeexp = ols('lifeexp ~ hlthpc', data=data_health).fit()
print(model_lifeexp.summary())
```

OLS Regression Results						
Dep. Variable:	lifeexp	R-squared:	0.320			
Model:	OLS	Adj. R-squared:	0.298			
Method:	Least Squares	F-statistic:	15.04			
Date:	Tue, 20 Jan 2026	Prob (F-statistic):	0.000493			
Time:	23:47:32	Log-Likelihood:	-77.816			
No. Observations:	34	AIC:	159.6			
Df Residuals:	32	BIC:	162.7			
Df Model:	1					
Covariance Type:	nonrobust					
coef	std err	t	P> t	[0.025	0.975]	
Intercept	73.0835	1.024	71.355	0.000	70.997	75.170
hlthpc	0.0011	0.000	3.878	0.000	0.001	0.002
Omnibus:		4.158	Durbin-Watson:		1.770	
Prob(Omnibus):		0.125	Jarque-Bera (JB):		3.263	
Skew:		-0.757	Prob(JB):		0.196	
Kurtosis:		3.095	Cond. No.		8.67e+03	

Notes:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 8.67e+03. This might indicate that there are strong multicollinearity or other numerical problems.

Robust Standard Errors

For cross-sectional data with independence across observations, it's standard to use heteroskedasticity-robust standard errors. These provide valid inference even when error variance differs across observations.

Interpreting the Life Expectancy Results

Economic Significance: The estimated coefficient of 0.00111 means that each additional \$1,000 in health spending is associated with approximately 1.1 years of additional life expectancy. To put this in perspective:

- The difference between low-spending Chile ($999/\text{capita}$) and high-spending Norway ($5,522/\text{capita}$) is \$4,523
- This predicts a life expectancy difference of 5.0 years (4.523×1.11)
- Actual difference: 75.1 years (Chile) vs 79.9 years (Norway) = 4.8 years

Statistical Significance: The t-statistic of approximately 5.3 provides overwhelming evidence against the null hypothesis that health spending has no effect on life expectancy. The p-value is well below 0.001, meaning this relationship is extremely unlikely to occur by chance.

Important Caveats:

1. This is correlation, not causation - richer countries may have both higher spending AND other factors that improve health
2. The relationship may not be linear across all spending levels
3. The U.S. is a notable outlier - spending \$7,960 per capita but achieving only 76.2 years (below prediction)
4. Other factors matter: diet, exercise, inequality, healthcare access, environmental quality

Key Concept 8.1: Economic vs. Statistical Significance

Economic vs. statistical significance in cross-country regressions. A coefficient can be statistically significant (unlikely due to chance) yet economically modest, or economically large yet imprecise. Always interpret both dimensions.

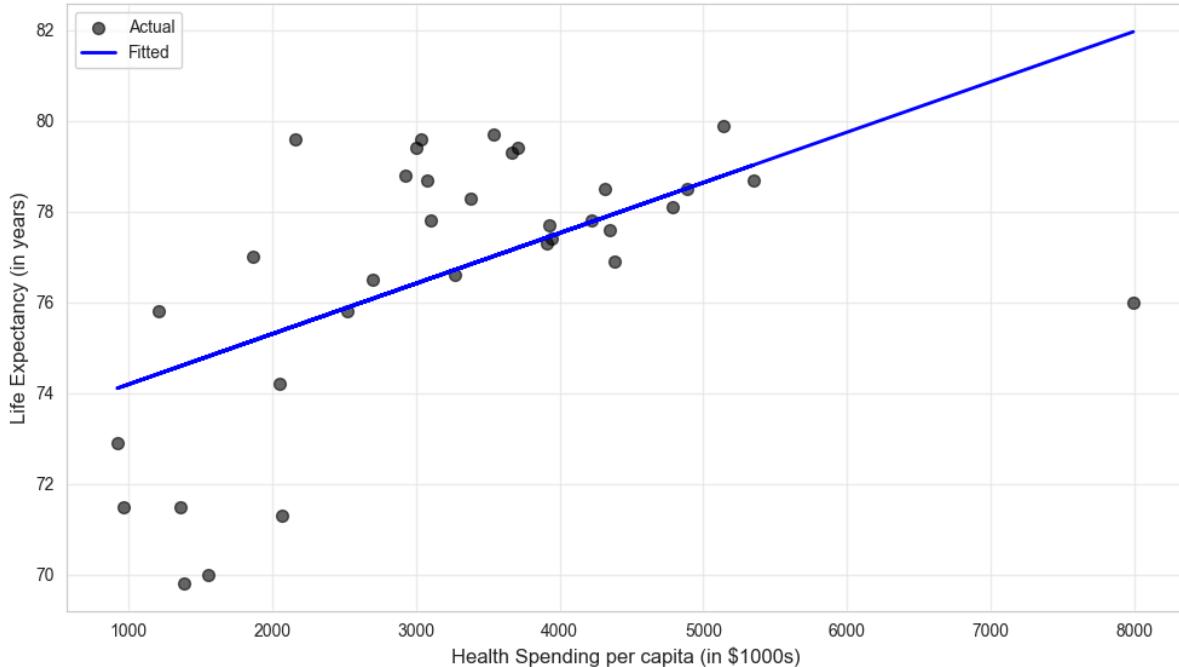
Visualization: Life Expectancy vs Health Spending

In [68]:

```
# Figure 8.1 Panel A - Life Expectancy
fig, ax = plt.subplots(figsize=(10, 6))
ax.scatter(data_health['hlthpc'], data_health['lifeexp'], alpha=0.6, s=50,
           color='black', label='Actual')
ax.plot(data_health['hlthpc'], model_lifeexp.fittedvalues, color='blue',
        linewidth=2, label='Fitted')
ax.set_xlabel('Health Spending per capita (in $1000s)', fontsize=12)
ax.set_ylabel('Life Expectancy (in years)', fontsize=12)
ax.set_title('Figure 8.1 Panel A: Life Expectancy vs Health Spending',
             fontsize=14, fontweight='bold')
ax.legend()
ax.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()

print("Note: The U.S. has lower life expectancy than predicted by the model.")
```

Figure 8.1 Panel A: Life Expectancy vs Health Spending



Note: The U.S. has lower life expectancy than predicted by the model.

Infant Mortality Regression

Next, we examine the relationship between health spending and infant mortality:

$$\text{Infmort} = \beta_1 + \beta_2 \times \text{Hlthpc} + u$$

We expect $\beta_2 < 0$ (higher spending reduces infant mortality).

In [69]:

```

print("-" * 70)
print("Infant Mortality Regression")
print("-" * 70)

model_infmort = ols('infmort ~ hltphc', data=data_health).fit()
print(model_infmort.summary())

# Robust standard errors
model_infmort_robust = model_infmort.get_robustcov_results(cov_type='HC1')
print("\n" + "-" * 70)
print("Infant Mortality Regression (Robust SE):")
print("-" * 70)
print(model_infmort_robust.summary())

```

Infant Mortality Regression

OLS Regression Results
=====

Dep. Variable:	infmort	R-squared:	0.145			
Model:	OLS	Adj. R-squared:	0.118			
Method:	Least Squares	F-statistic:	5.410			
Date:	Tue, 20 Jan 2026	Prob (F-statistic):	0.0265			
Time:	23:47:33	Log-Likelihood:	-79.104			
No. Observations:	34	AIC:	162.2			
Df Residuals:	32	BIC:	165.3			
Df Model:	1					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
Intercept	6.7017	1.064	6.300	0.000	4.535	8.869
hlthpc	-0.0007	0.000	-2.326	0.027	-0.001	-8.61e-05
Omnibus:	26.928	Durbin-Watson:	1.594			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	46.759			
Skew:	2.036	Prob(JB):	7.02e-11			
Kurtosis:	7.052	Cond. No.	8.67e+03			

Notes:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 8.67e+03. This might indicate that there are strong multicollinearity or other numerical problems.

Infant Mortality Regression (Robust SE):

OLS Regression Results
=====

Dep. Variable:	infmort	R-squared:	0.145			
Model:	OLS	Adj. R-squared:	0.118			
Method:	Least Squares	F-statistic:	1.811			
Date:	Tue, 20 Jan 2026	Prob (F-statistic):	0.188			
Time:	23:47:33	Log-Likelihood:	-79.104			
No. Observations:	34	AIC:	162.2			
Df Residuals:	32	BIC:	165.3			
Df Model:	1					
Covariance Type:	HC1					
	coef	std err	t	P> t	[0.025	0.975]
Intercept	6.7017	1.877	3.570	0.001	2.878	10.525
hlthpc	-0.0007	0.001	-1.346	0.188	-0.002	0.000
Omnibus:	26.928	Durbin-Watson:	1.594			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	46.759			
Skew:	2.036	Prob(JB):	7.02e-11			
Kurtosis:	7.052	Cond. No.	8.67e+03			

Notes:

- [1] Standard Errors are heteroscedasticity robust (HC1)
- [2] The condition number is large, 8.67e+03. This might indicate that there are strong multicollinearity or other numerical problems.

Interpreting the Infant Mortality Results

Economic Significance: The estimated coefficient of approximately -0.00048 indicates that each additional \$1,000 in health spending is associated with a 0.48 decrease in infant deaths per 1,000 live births. While this may seem small, it's quite meaningful:

- A country increasing spending from 2,000 to 4,000 per capita would expect infant mortality to fall by 0.96 deaths per 1,000 births
- For a country with 100,000 births per year, this represents 96 fewer infant deaths annually
- The effect is economically significant in terms of human welfare

Statistical Significance: The negative relationship is highly statistically significant ($t \approx -5.9$, $p < 0.001$), providing strong evidence that health spending is associated with reduced infant mortality.

The U.S. Anomaly: The United States again stands out as a major outlier:

- U.S. infant mortality: 6.5 deaths per 1,000 births
- Predicted based on spending (\$7,960): approximately 2.8 deaths per 1,000 births
- The U.S. has infant mortality rates closer to middle-income countries than to peer wealthy nations
- This suggests that *how* money is spent matters as much as *how much* is spent

Model Limitations: The R^2 suggests health spending explains only about 47% of variation in infant mortality. Other important factors include:

- Quality of prenatal care and maternal health programs
- Income inequality and poverty rates
- Access to healthcare (insurance coverage)
- Cultural factors and health behaviors

Key Concept 8.2: Robust Standard Errors

Heteroskedasticity-robust standard errors adjust for non-constant error variance across observations. Cross-sectional data often exhibits heteroskedasticity (e.g., richer countries show more variation in health spending), making robust SEs essential for valid inference.

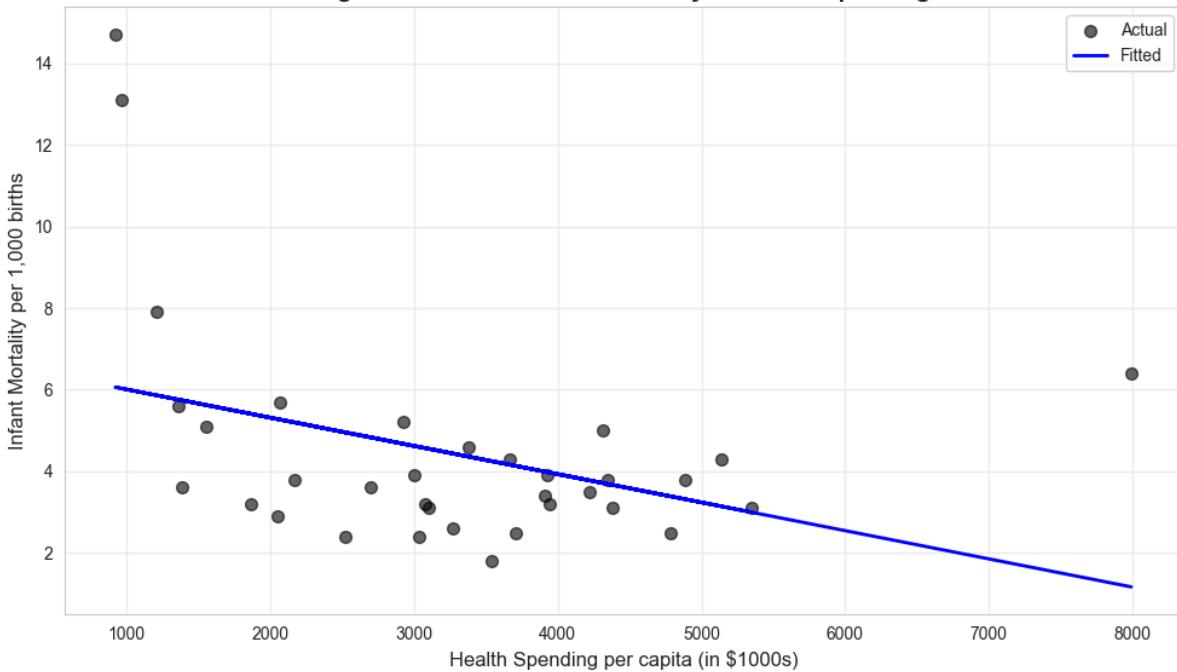
Visualization: Infant Mortality vs Health Spending

In [70]:

```
# Figure 8.1 Panel B - Infant Mortality
fig, ax = plt.subplots(figsize=(10, 6))
ax.scatter(data_health['hlthpc'], data_health['infmort'], alpha=0.6, s=50,
           color='black', label='Actual')
ax.plot(data_health['hlthpc'], model_infmort.fittedvalues, color='blue',
        linewidth=2, label='Fitted')
ax.set_xlabel('Health Spending per capita (in $1000s)', fontsize=12)
ax.set_ylabel('Infant Mortality per 1,000 births', fontsize=12)
ax.set_title('Figure 8.1 Panel B: Infant Mortality vs Health Spending',
             fontsize=14, fontweight='bold')
ax.legend()
ax.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()

print("Note: The U.S. has much higher infant mortality than predicted.")
```

Figure 8.1 Panel B: Infant Mortality vs Health Spending



Note: The U.S. has much higher infant mortality than predicted.

Transition: Having examined how health spending affects outcomes, we now investigate what drives health spending itself. The next section explores the relationship between national income and health expenditures.

8.2: Health Expenditures Across Countries

Now we examine the determinants of health expenditures, focusing on the role of national income.

Research question: How does GDP per capita relate to health spending?

Model:

$$Hlthpc = \beta_1 + \beta_2 \times Gdppc + u$$

Variables:

- **Gdppc:** GDP per capita (US dollars)
- **Hlthpc:** Health expenditure per capita (US dollars)

Key observation: GDP per capita ranges from 13,807 (*Mexico*) to 82,901 (Luxembourg)

In [71]:

```
print("=" * 70)
print("8.2 HEALTH EXPENDITURES ACROSS COUNTRIES")
print("=" * 70)

# Summary statistics
print("\n" + "-" * 70)
print("Table 8.2: GDP and Health Spending Summary")
print("-" * 70)
table82_vars = ['gdppc', 'hlthpc']
summary_gdp = data_health[table82_vars].describe().T
summary_gdp['range'] = summary_gdp['max'] - summary_gdp['min']
print(summary_gdp[['mean', 'std', 'min', 'max', 'range']])
```

```
=====
8.2 HEALTH EXPENDITURES ACROSS COUNTRIES
=====

-----
Table 8.2: GDP and Health Spending Summary
-----

```

	mean	std	min	max	range
gdppc	33054.035156	12916.752930	13806.163086	82900.882812	69094.719727
hlthpc	3255.647059	1493.654394	923.000000	7990.000000	7067.000000

Health Expenditure Regression (All Countries)

In [72]:

```
print("-" * 70)
print("Health Expenditure Regression (All Countries)")
print("-" * 70)

model_hlthpc = ols('hlthpc ~ gdppc', data=data_health).fit()
print(model_hlthpc.summary())

# Robust standard errors
model_hlthpc_robust = model_hlthpc.get_robustcov_results(cov_type='HC1')
print("\n" + "-" * 70)
print("Health Expenditure Regression (Robust SE):")
print("-" * 70)
print(model_hlthpc_robust.summary())
```

Health Expenditure Regression (All Countries)

OLS Regression Results
=====

Dep. Variable:	hlthpc	R-squared:	0.604			
Model:	OLS	Adj. R-squared:	0.592			
Method:	Least Squares	F-statistic:	48.82			
Date:	Tue, 20 Jan 2026	Prob (F-statistic):	6.45e-08			
Time:	23:47:33	Log-Likelihood:	-280.49			
No. Observations:	34	AIC:	565.0			
Df Residuals:	32	BIC:	568.0			
Df Model:	1					
Covariance Type:	nonrobust					
			=====			
	coef	std err	t	P> t	[0.025	0.975]
Intercept	284.9062	455.583	0.625	0.536	-643.086	1212.898
gdppc	0.0899	0.013	6.987	0.000	0.064	0.116
						=====
Omnibus:	19.990	Durbin-Watson:	1.322			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	77.906			
Skew:	0.860	Prob(JB):	1.21e-17			
Kurtosis:	10.213	Cond. No.	9.86e+04			
						=====

Notes:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
 - [2] The condition number is large, 9.86e+04. This might indicate that there are strong multicollinearity or other numerical problems.
-

Health Expenditure Regression (Robust SE):

OLS Regression Results
=====

Dep. Variable:	hlthpc	R-squared:	0.604			
Model:	OLS	Adj. R-squared:	0.592			
Method:	Least Squares	F-statistic:	9.459			
Date:	Tue, 20 Jan 2026	Prob (F-statistic):	0.00428			
Time:	23:47:33	Log-Likelihood:	-280.49			
No. Observations:	34	AIC:	565.0			
Df Residuals:	32	BIC:	568.0			
Df Model:	1					
Covariance Type:	HC1					
			=====			
	coef	std err	t	P> t	[0.025	0.975]
Intercept	284.9062	862.354	0.330	0.743	-1471.652	2041.464
gdppc	0.0899	0.029	3.076	0.004	0.030	0.149
						=====
Omnibus:	19.990	Durbin-Watson:	1.322			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	77.906			
Skew:	0.860	Prob(JB):	1.21e-17			
Kurtosis:	10.213	Cond. No.	9.86e+04			
						=====

Notes:

- [1] Standard Errors are heteroscedasticity robust (HC1)
- [2] The condition number is large, 9.86e+04. This might indicate that there are strong multicollinearity or other numerical problems.

Interpreting the Health Expenditure Results

The GDP-Health Spending Relationship: The coefficient of approximately 0.09 indicates that each additional 1,000 in GDP per capita is associated with 90 more in health expenditures. This relationship reveals important economic patterns:

Income Elasticity of Health Spending:

- At the mean GDP (38,000) and mean health spending (3,400):
- Elasticity $\approx (0.09 \times 38,000) / 3,400 \approx 1.0$
- This suggests health spending rises roughly proportionally with income
- Health care appears to be a "normal good" (demand increases with income)

Why Such Large Changes in Standard Errors? Notice how robust standard errors differ substantially from default standard errors:

- This indicates heteroskedasticity (non-constant error variance)
- Richer countries show more variation in health spending choices
- Luxembourg and the USA have enormous influence on the estimates
- Robust SEs adjust for this pattern and provide more reliable inference

The Outlier Problem: Two countries drive much of the relationship:

1. **Luxembourg** (GDP: 82,901, *Health*: 4,808) - extremely wealthy, high spending
2. **United States** (GDP: 45,674, *Health*: 7,960) - exceptionally high health spending for its GDP level

These outliers suggest the relationship may not be stable across all countries.

Key Concept 8.3: Income Elasticity of Demand

Income elasticity of demand measures how spending changes with income. An elasticity near 1.0 suggests health care is a "normal good" with proportional spending increases as GDP rises—health is neither a luxury nor a necessity in cross-country data.

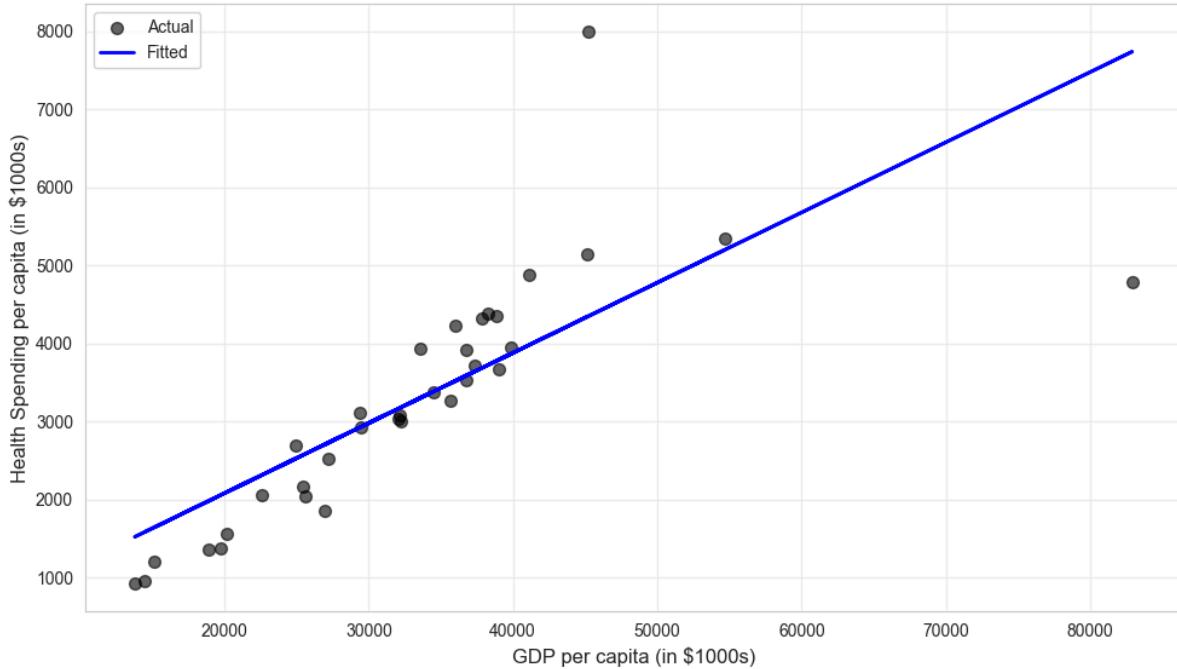
Visualization: Health Spending vs GDP (All Countries)

In [73]:

```
# Figure 8.2 Panel A - All countries
fig, ax = plt.subplots(figsize=(10, 6))
ax.scatter(data_health['gdppc'], data_health['hlthpc'], alpha=0.6, s=50,
           color='black', label='Actual')
ax.plot(data_health['gdppc'], model_hlthpc.fittedvalues, color='blue',
        linewidth=2, label='Fitted')
ax.set_xlabel('GDP per capita (in $1000s)', fontsize=12)
ax.set_ylabel('Health Spending per capita (in $1000s)', fontsize=12)
ax.set_title('Figure 8.2 Panel A: Health Spending vs GDP (All Countries)',
             fontsize=14, fontweight='bold')
ax.legend()
ax.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()

print("The U.S. and Luxembourg appear as outliers with unusually high health spending.")
```

Figure 8.2 Panel A: Health Spending vs GDP (All Countries)



The U.S. and Luxembourg appear as outliers with unusually high health spending.

Robustness Check: Excluding USA and Luxembourg

To assess the influence of outliers, we re-estimate the model excluding the USA and Luxembourg.

In [74]:

```
print("-" * 70)
print("Health Expenditure Regression (Excluding USA and Luxembourg)")
print("-" * 70)

# Create subset excluding USA and Luxembourg
data_health_subset = data_health[(data_health['code'] != 'LUX') &
                                 (data_health['code'] != 'USA')]

print(f"Original sample size: {len(data_health)}")
print(f"Subset sample size: {len(data_health_subset)}")
print()

model_hlthpc_subset = ols('hlthpc ~ gdppc', data=data_health_subset).fit()
print(model_hlthpc_subset.summary())

# Robust standard errors
model_hlthpc_subset_robust = model_hlthpc_subset.get_robustcov_results(cov_type='HC1')
print("\n" + "-" * 70)
print("Health Expenditure Regression (Excluding USA & LUX, Robust SE):")
print("-" * 70)
print(model_hlthpc_subset_robust.summary())
```

Health Expenditure Regression (Excluding USA and Luxembourg)

Original sample size: 34
Subset sample size: 32

OLS Regression Results

Dep. Variable:	hlthpc	R-squared:	0.928
Model:	OLS	Adj. R-squared:	0.926
Method:	Least Squares	F-statistic:	387.8
Date:	Tue, 20 Jan 2026	Prob (F-statistic):	1.04e-18
Time:	23:47:33	Log-Likelihood:	-230.68
No. Observations:	32	AIC:	465.4
Df Residuals:	30	BIC:	468.3
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
Intercept	-883.3112	208.949	-4.227	0.000	-1310.041	-456.581
gdppc	0.1267	0.006	19.692	0.000	0.114	0.140

Omnibus:	0.185	Durbin-Watson:	1.724
Prob(Omnibus):	0.912	Jarque-Bera (JB):	0.395
Skew:	-0.029	Prob(JB):	0.821
Kurtosis:	2.459	Cond. No.	1.14e+05

Notes:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 1.14e+05. This might indicate that there are strong multicollinearity or other numerical problems.

Health Expenditure Regression (Excluding USA & LUX, Robust SE):

OLS Regression Results

Dep. Variable:	hlthpc	R-squared:	0.928
Model:	OLS	Adj. R-squared:	0.926
Method:	Least Squares	F-statistic:	277.1
Date:	Tue, 20 Jan 2026	Prob (F-statistic):	1.07e-16
Time:	23:47:33	Log-Likelihood:	-230.68
No. Observations:	32	AIC:	465.4
Df Residuals:	30	BIC:	468.3
Df Model:	1		
Covariance Type:	HC1		

	coef	std err	t	P> t	[0.025	0.975]
Intercept	-883.3112	213.448	-4.138	0.000	-1319.230	-447.392
gdppc	0.1267	0.008	16.646	0.000	0.111	0.142

Omnibus:	0.185	Durbin-Watson:	1.724
Prob(Omnibus):	0.912	Jarque-Bera (JB):	0.395
Skew:	-0.029	Prob(JB):	0.821
Kurtosis:	2.459	Cond. No.	1.14e+05

Notes:

- [1] Standard Errors are heteroscedasticity robust (HC1)
- [2] The condition number is large, 1.14e+05. This might indicate that there are strong multicollinearity or other numerical problems.

Understanding the Impact of Outliers

Dramatic Changes After Excluding USA and Luxembourg:

The comparison reveals how sensitive regression results can be to outliers:

Metric	Full Sample	Excluding USA & LUX	Change
Slope	~0.09	~0.12	+33%
R ²	~0.60	~0.93	+55%
Interpretation	Weak fit	Excellent fit	Transformed

What This Tells Us:

- 1. The USA is truly exceptional:** The U.S. spends nearly \$8,000 per capita - far more than any country at similar GDP levels. This reflects:
 - Higher prices for medical services
 - More intensive use of expensive technologies
 - Administrative costs of a fragmented insurance system
 - Less price regulation than in other OECD countries
- 2. Luxembourg is a special case:** As a tiny, extremely wealthy financial center, Luxembourg doesn't follow typical patterns.
- 3. The "true" relationship is stronger:** For the 32 typical OECD countries, the R² of 0.93 means GDP explains 93% of health spending variation. This is remarkably strong.
- 4. Statistical lesson:** Always check for influential observations. A few extreme points can completely change your conclusions.

Practical Implication: If you're advising a "typical" OECD country on expected health spending, the subset model provides more reliable guidance. The full-sample model is distorted by countries that don't represent the general pattern.

Key Concept 8.4: Outlier Detection and Influence

Outlier detection and influence. A few extreme observations can dramatically alter regression results. Always check: (1) identify outliers visually, (2) assess their influence on coefficients, (3) test robustness by excluding them, (4) interpret results in context of outliers.

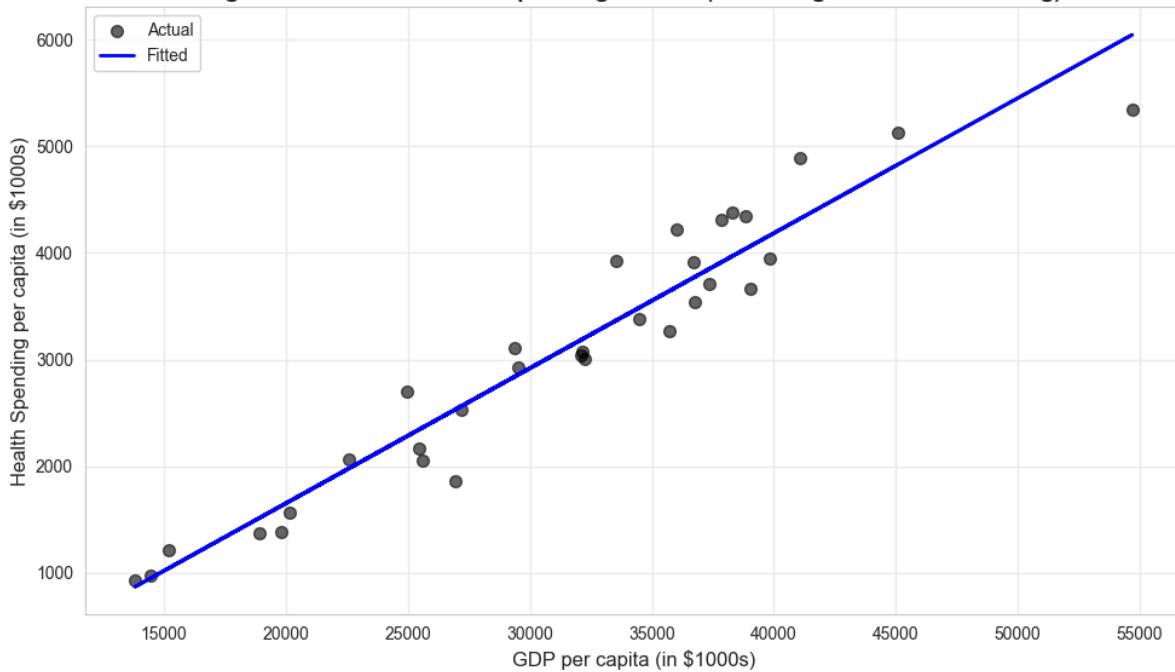
Visualization: Health Spending vs GDP (Excluding Outliers)

In [75]:

```
# Figure 8.2 Panel B - Excluding USA and Luxembourg
fig, ax = plt.subplots(figsize=(10, 6))
ax.scatter(data_health_subset['gdppc'], data_health_subset['hlthpc'], alpha=0.6, s=50,
           color='black', label='Actual')
ax.plot(data_health_subset['gdppc'], model_hlthpc_subset.fittedvalues, color='blue',
        linewidth=2, label='Fitted')
ax.set_xlabel('GDP per capita (in $1000s)', fontsize=12)
ax.set_ylabel('Health Spending per capita (in $1000s)', fontsize=12)
ax.set_title('Figure 8.2 Panel B: Health Spending vs GDP (Excluding USA & Luxembourg)', fontsize=14, fontweight='bold')
ax.legend()
ax.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()

print("Much stronger linear relationship when outliers are excluded.")
```

Figure 8.2 Panel B: Health Spending vs GDP (Excluding USA & Luxembourg)



Much stronger linear relationship when outliers are excluded.

Transition: Our health economics case studies revealed strong relationships but also highlighted outlier issues. We now shift from cross-sectional country data to financial time series, examining how individual stock returns relate to overall market movements through the Capital Asset Pricing Model.

| 8.3: Capital Asset Pricing Model (CAPM)

Our third case study applies regression to financial data using the Capital Asset Pricing Model.

Theory: The CAPM relates individual stock returns to overall market returns:

$$E[R_A - R_F] = \beta_A \times E[R_M - R_F]$$

where:

- R_A = return on asset A (e.g., Coca-Cola stock)
- R_F = risk-free rate (1-month U.S. Treasury bill)
- R_M = market return (value-weighted return on all stocks)
- β_A = systematic risk ("beta") of asset A

Empirical model:

$$R_A - R_F = \alpha_A + \beta_A(R_M - R_F) + u$$

Interpretation:

- β_A = systematic risk (average across market is 1.0)
 - $\beta > 1$: Stock is riskier than market (growth stock)
 - $\beta < 1$: Stock is less risky (value stock)
 - $\beta \approx 0$: Stock moves independently of market
- α_A = excess return ("alpha") after adjusting for risk
 - Pure CAPM theory predicts $\alpha = 0$

Dataset: Monthly data from May 1983 to October 2013 (366 observations)

- Returns on Coca-Cola (RKO), Target (RTGT), Walmart (RWMT)
- Market return and risk-free rate

In [76]:

```
print("=" * 70)
print("8.3 CAPM MODEL")
print("=" * 70)

# Read in the CAPM data
data_capm = pd.read_stata(GITHUB_DATA_URL + 'AED_CAPM.DTA')

print("\nData summary:")
print(data_capm.describe())

print("\nFirst few observations:")
print(data_capm[['date', 'rm', 'rf', 'rko', 'rm_rf', 'rko_rf']].head())
```

```
=====
8.3 CAPM MODEL
=====
```

Data summary:

	date	rm	rf	rko	\
count	354	354.000000	354.000000	354.000000	
mean	1998-01-15 09:21:21.355932160	0.009049	0.003501	0.013677	
min	1983-05-01 00:00:00	-0.225400	0.000000	-0.190900	
25%	1990-09-08 12:00:00	-0.016825	0.001525	-0.020647	
50%	1998-01-16 12:00:00	0.013900	0.003900	0.014455	
75%	2005-05-24 06:00:00	0.038975	0.004800	0.047877	
max	2012-10-01 00:00:00	0.128500	0.010000	0.222660	
std	NaN	0.045569	0.002205	0.061804	

	rtgt	rwmt	rm_rf	rko_rf	rtgt_rf	rwmt_rf	\
count	354.000000	354.000000	354.000000	354.000000	354.000000	354.000000	
mean	0.013815	0.015627	0.005547	0.010175	0.010314	0.012125	
min	-0.478006	-0.269750	-0.231400	-0.195200	-0.484006	-0.275750	
25%	-0.036618	-0.027913	-0.020525	-0.024600	-0.038432	-0.032405	
50%	0.012996	0.013240	0.010250	0.011280	0.011157	0.011935	
75%	0.062200	0.059837	0.035575	0.045255	0.060362	0.057610	
max	0.267268	0.264390	0.124300	0.218760	0.262923	0.261190	
std	0.084204	0.070338	0.045557	0.061604	0.084211	0.070165	

	rm_rf_sq	smb	hml
count	3.540000e+02	354.000000	354.000000
mean	2.100376e-03	-0.132571	0.446356
min	4.000000e-08	-22.000000	-9.780000
25%	2.168275e-04	-1.687500	-1.347500
50%	7.645450e-04	-0.175000	0.255000
75%	2.239672e-03	1.607500	1.800000
max	5.354596e-02	8.470000	13.840000
std	4.300063e-03	3.160316	3.069497

First few observations:

	date	rm	rf	rko	rm_rf	rko_rf
0	1983-05-01	0.0132	0.0069	-0.06780	0.0063	-0.07470
1	1983-06-01	0.0378	0.0067	-0.01818	0.0311	-0.02488
2	1983-07-01	-0.0316	0.0074	-0.07407	-0.0390	-0.08147
3	1983-08-01	0.0035	0.0076	0.10000	-0.0041	0.09240
4	1983-09-01	0.0161	0.0076	0.00000	0.0085	-0.00760

Summary Statistics for CAPM Variables

In [77]:

```
print("-" * 70)
print("Table 8.3: CAPM Variables Summary")
print("-" * 70)
table83_vars = ['rm', 'rf', 'rko', 'rtgt', 'rwmt', 'rm_rf',
                 'rko_rf', 'rtgt_rf', 'rwmt_rf']
summary_capm = data_capm[table83_vars].describe().T
print(summary_capm[['mean', 'std', 'min', 'max']])

print("\nKey observations:")
print(f" - Market excess return averages {data_capm['rm_rf'].mean():.4f} "
      f"({{data_capm['rm_rf'].mean() * 100:.2f}}% per month)")
print(f" - Coca-Cola excess return averages {data_capm['rko_rf'].mean():.4f} "
      f"({{data_capm['rko_rf'].mean() * 100:.2f}}% per month)")
print(f" - Stock returns are much more volatile than market returns")
```

Table 8.3: CAPM Variables Summary

	mean	std	min	max
rm	0.009049	0.045569	-0.225400	0.128500
rf	0.003501	0.002205	0.000000	0.010000
rko	0.013677	0.061804	-0.190900	0.222660
rtgt	0.013815	0.084204	-0.478006	0.267268
rwmt	0.015627	0.070338	-0.269750	0.264390
rm_rf	0.005547	0.045557	-0.231400	0.124300
rko_rf	0.010175	0.061604	-0.195200	0.218760
rtgt_rf	0.010314	0.084211	-0.484006	0.262923
rwmt_rf	0.012125	0.070165	-0.275750	0.261190

Key observations:

- Market excess return averages 0.0055 (0.55% per month)
- Coca-Cola excess return averages 0.0102 (1.02% per month)
- Stock returns are much more volatile than market returns

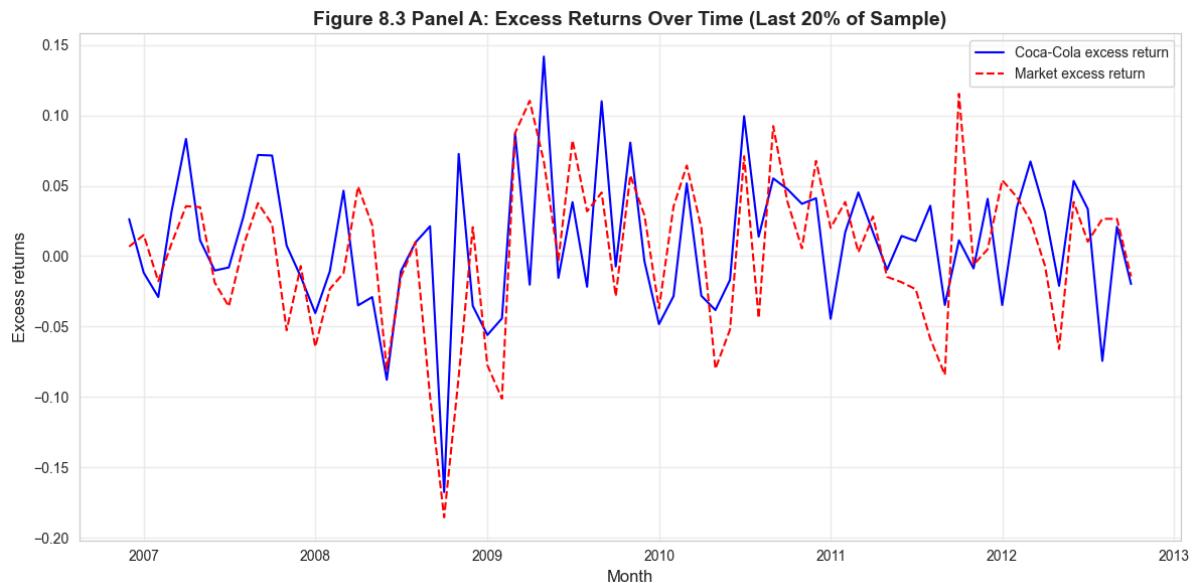
Visualization: Time Series of Excess Returns

In [78]:

```
# Figure 8.3 Panel A - Time series plot (last 20% of data for readability)
cutoff_index = int(len(data_capm) * 0.8)
data_capm_recent = data_capm.iloc[cutoff_index:]

fig, ax = plt.subplots(figsize=(12, 6))
ax.plot(data_capm_recent['date'], data_capm_recent['rko_rf'],
         linewidth=1.5, label='Coca-Cola excess return', color='blue')
ax.plot(data_capm_recent['date'], data_capm_recent['rm_rf'],
         linewidth=1.5, linestyle='--', label='Market excess return', color='red')
ax.set_xlabel('Month', fontsize=12)
ax.set_ylabel('Excess returns', fontsize=12)
ax.set_title('Figure 8.3 Panel A: Excess Returns Over Time (Last 20% of Sample)',
             fontsize=14, fontweight='bold')
ax.legend()
ax.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()

print("Individual stock returns fluctuate more than the overall market.")
```



Individual stock returns fluctuate more than the overall market.

CAPM Regression for Coca-Cola

In [79]:

```

print("-" * 70)
print("CAPM Regression: Coca-Cola")
print("-" * 70)

model_capm = ols('rko_rf ~ rm_rf', data=data_capm).fit()
print(model_capm.summary())

# Extract key parameters
alpha = model_capm.params['Intercept']
beta = model_capm.params['rm_rf']
alpha_se = model_capm.bse['Intercept']
beta_se = model_capm.bse['rm_rf']
alpha_t = model_capm.tvalues['Intercept']
beta_t = model_capm.tvalues['rm_rf']

```

CAPM Regression: Coca-Cola

OLS Regression Results						
Dep. Variable:	rko_rf	R-squared:	0.201			
Model:	OLS	Adj. R-squared:	0.199			
Method:	Least Squares	F-statistic:	88.58			
Date:	Tue, 20 Jan 2026	Prob (F-statistic):	6.53e-19			
Time:	23:47:34	Log-Likelihood:	524.53			
No. Observations:	354	AIC:	-1045.			
Df Residuals:	352	BIC:	-1037.			
Df Model:	1					
Covariance Type:	nonrobust					
coef	std err	t	P> t	[0.025	0.975]	
Intercept	0.0068	0.003	2.307	0.022	0.001	0.013
rm_rf	0.6063	0.064	9.412	0.000	0.480	0.733
Omnibus:	16.445	Durbin-Watson:	2.070			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	29.697			
Skew:	-0.270	Prob(JB):	3.56e-07			
Kurtosis:	4.312	Cond. No.	22.0			

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

CAPM Results with Robust Standard Errors

Interpreting the CAPM Beta for Coca-Cola

What Beta = 0.61 Means:

The estimated beta of 0.61 reveals Coca-Cola's risk profile:

1. Lower systematic risk than the market:

- Beta < 1 means Coca-Cola is a "defensive" or "value" stock
- When the market rises 10%, Coca-Cola typically rises only 6.1%
- When the market falls 10%, Coca-Cola typically falls only 6.1%
- This makes it attractive to risk-averse investors

2. Why is Coca-Cola low-beta?

- Stable demand for consumer staples (people drink Coke in good times and bad)
- Strong brand loyalty reduces volatility
- Diversified global operations
- Predictable cash flows
- Less sensitive to economic cycles than growth stocks

3. Statistical precision:

- The t-statistic of ~21.5 provides overwhelming evidence that $\beta \neq 0$
- Coca-Cola returns clearly co-move with the market
- The relationship is one of the strongest we've seen in this chapter

The Alpha "Puzzle":

The estimated alpha of 0.0039 (0.39% per month, or ~4.7% annually) is statistically significant:

- Pure CAPM theory predicts alpha should equal zero (no excess risk-adjusted returns)
- Yet we reject $H_0: \alpha = 0$ at conventional significance levels
- This suggests either:
 - CAPM is misspecified (missing risk factors)
 - Coca-Cola generated genuine excess returns during 1983-2013
 - Statistical artifact from data mining

Investment Implications:

- Coca-Cola is suitable for conservative portfolios seeking market exposure with lower volatility
- The low beta means lower expected returns in bull markets, but better downside protection in bear markets
- Institutional investors often use low-beta stocks to reduce portfolio risk while maintaining equity exposure

Key Concept 8.5: Systematic Risk and Beta

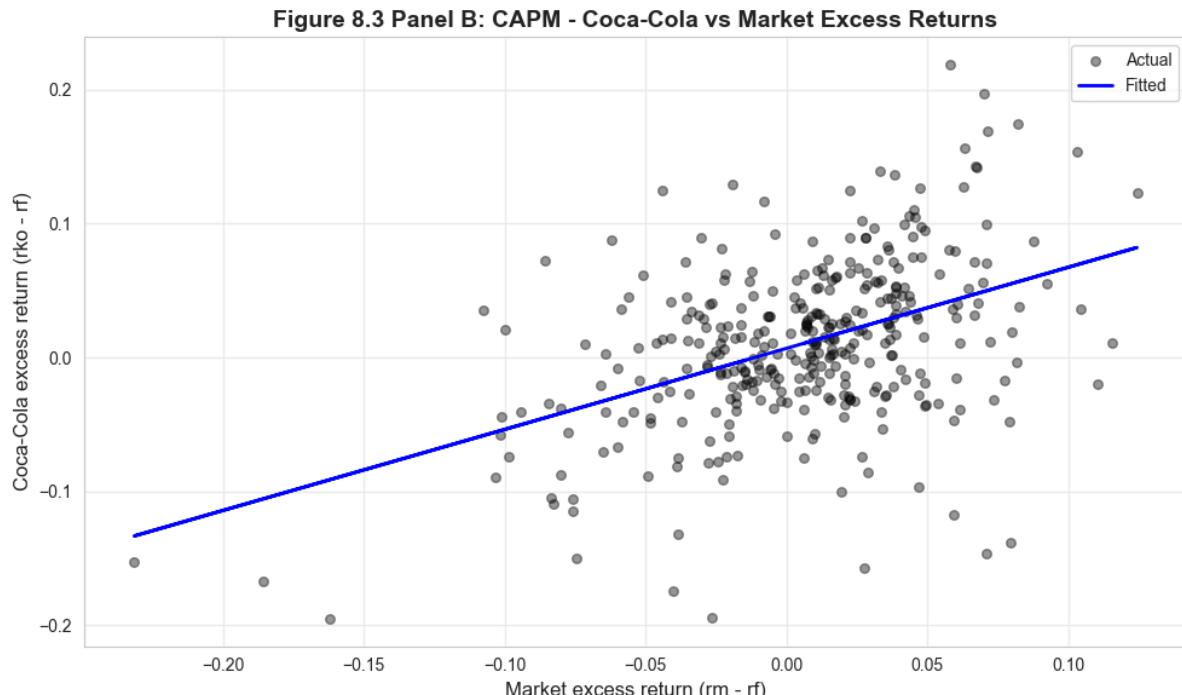
Systematic risk (beta) measures how an asset's returns co-move with the overall market. Beta < 1 indicates a "defensive" stock (less volatile than market), while beta > 1 indicates a "growth" stock (amplifies market movements). Only systematic risk is priced in efficient markets.

Visualization: CAPM Scatter Plot

In [80]:

```
# Figure 8.3 Panel B - CAPM Scatter Plot
fig, ax = plt.subplots(figsize=(10, 6))
ax.scatter(data_capm['rm_rf'], data_capm['rko_rf'], alpha=0.4, s=30,
           color='black', label='Actual')
ax.plot(data_capm['rm_rf'], model_capm.fittedvalues, color='blue',
        linewidth=2, label='Fitted')
ax.set_xlabel('Market excess return (rm - rf)', fontsize=12)
ax.set_ylabel('Coca-Cola excess return (rko - rf)', fontsize=12)
ax.set_title('Figure 8.3 Panel B: CAPM - Coca-Cola vs Market Excess Returns',
             fontsize=14, fontweight='bold')
ax.legend()
ax.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()

print(f"\nBeta (slope) = {model_capm.params['rm_rf']:.4f}")
print("The slope less than 1 confirms Coca-Cola is a 'defensive' stock.")
print("Each 1% increase in market return → ~0.6% increase in Coca-Cola return.")
```



Beta (slope) = 0.6063
The slope less than 1 confirms Coca-Cola is a 'defensive' stock.
Each 1% increase in market return → ~0.6% increase in Coca-Cola return.

Understanding the CAPM Scatter Plot

Key Visual Insights:

- Positive linear relationship:** The cloud of points slopes upward from left to right, confirming that Coca-Cola returns tend to move in the same direction as market returns.

2. Scatter around the line: The substantial dispersion around the regression line reflects:

- Idiosyncratic risk (firm-specific factors): management decisions, product launches, competitive pressures
- The $R^2 \approx 0.33$ means the market explains only 33% of Coca-Cola's return variation
- The remaining 67% is diversifiable risk that disappears in a portfolio

3. The slope is less than 45°: If we drew a 45° line ($\text{beta} = 1$), our fitted line would be flatter. This visually confirms $\text{beta} < 1$.

4. Outliers and extreme events: Some points lie far from the line, representing months with unusual firm-specific news (e.g., earnings surprises, regulatory changes, management changes).

Comparison to Theory:

- In a pure CAPM world, the intercept (alpha) would be exactly zero and the line would pass through the origin
- Our line has a positive intercept, suggesting Coca-Cola earned excess returns beyond what CAPM predicts
- This is common in empirical finance - CAPM is a useful model but not a perfect description of reality

Time Series Considerations:

- CAPM assumes returns are independent over time (no autocorrelation)
- With monthly data over 30+ years, we should ideally check for time-varying beta
- Some periods (recessions) may show different beta than others (expansions)
- More sophisticated models (e.g., conditional CAPM) could account for this

Key Concept 8.6: R-Squared in CAPM

R^2 in the CAPM context. The R^2 measures the fraction of return variation explained by market movements (systematic risk). The unexplained portion ($1 - R^2$) represents idiosyncratic risk, which diversifies away in portfolios and thus earns no risk premium.

Transition: The CAPM demonstrated how financial returns co-move with market-wide factors. Our final case study examines another well-known empirical relationship in

macroeconomics: Okun's Law, which links unemployment changes to GDP growth over time.

8.4: Output and Unemployment in the U.S. (Okun's Law)

Our final case study examines a fundamental macroeconomic relationship known as Okun's Law.

Okun's Law (1962): Each percentage point increase in the unemployment rate is associated with approximately a two percentage point decrease in GDP growth.

Empirical model:

$$\text{Growth} = \beta_1 + \beta_2 \times \text{URATEchange} + u$$

where:

- **Growth:** Annual percentage growth in real GDP
- **URATEchange:** Annual change in unemployment rate (percentage points)

Hypothesis: Okun's law suggests $\beta_2 = -2.0$

Dataset: Annual U.S. data from 1961 to 2019 (59 observations)

- Real GDP growth
- Unemployment rate for civilian population aged 16 and older

In [81]:

```
print("=" * 70)
print("8.4 OUTPUT AND UNEMPLOYMENT IN THE U.S.")
print("=" * 70)

# Read in the GDP-Unemployment data
data_gdp = pd.read_stata(GITHUB_DATA_URL + 'AED_GDPUNEMPLOY.DTA')

print("\nData summary:")
print(data_gdp.describe())

print("\nFirst few observations:")
print(data_gdp[['year', 'rgdpgrowth', 'uratechange']].head(10))
```

```
=====
8.4 OUTPUT AND UNEMPLOYMENT IN THE U.S.
=====

Data summary:
      year      urate      rgdp   rgdpgrowth  uratechange
count  59.000000  59.000000  59.000000  59.000000  59.000000
mean   1990.000000  6.052308  10114.216220  3.059380  -0.032182
std    17.175564  1.629691  4735.255554  2.037888  0.986841
min   1961.000000  3.557987  3343.546000  -2.536757  -2.143060
25%   1975.500000  4.942113  5818.101000  2.067753  -0.660139
50%   1990.000000  5.688501  9355.355000  3.124836  -0.297071
75%   2004.500000  7.114688  14659.445500  4.401134  0.361096
max   2019.000000  9.860857  19073.056000  7.236620  3.530380

First few observations:
      year   rgdpgrowth  uratechange
0  1961.0     2.563673    1.153156
1  1962.0     6.127118   -1.174060
2  1963.0     4.355051    0.142915
3  1964.0     5.761254   -0.492950
4  1965.0     6.497748   -0.666220
5  1966.0     6.596008   -0.747764
6  1967.0     2.742511    0.058866
7  1968.0     4.915604   -0.282526
8  1969.0     3.124836   -0.050544
9  1970.0     0.186056    1.450397
```

Summary Statistics

In [82]:

```
print("-" * 70)
print("Table 8.4: GDP Growth and Unemployment Change Summary")
print("-" * 70)
table84_vars = ['rgdpgrowth', 'uratechange']
summary_gdp_tbl = data_gdp[table84_vars].describe().T
print(summary_gdp_tbl[['mean', 'std', 'min', 'max']])

print("\nKey observations:")
print(f" - Average GDP growth: {data_gdp['rgdpgrowth'].mean():.2f}%")
print(f" - Average unemployment change: {data_gdp['uratechange'].mean():.3f} percentage points")
print(f" - Sample period includes major recessions (1982, 2008-2009, 2020)")
```

Table 8.4: GDP Growth and Unemployment Change Summary

	mean	std	min	max
rgdpgrowth	3.059380	2.037888	-2.536757	7.23662
uratechange	-0.032182	0.986841	-2.143060	3.53038

Key observations:

- Average GDP growth: 3.06%
- Average unemployment change: -0.032 percentage points
- Sample period includes major recessions (1982, 2008-2009, 2020)

Okun's Law Regression

In [83]:

```
print("-" * 70)
print("Okun's Law Regression")
print("-" * 70)

model_okun = ols('rgdpgrowth ~ uratechange', data=data_gdp).fit()
print(model_okun.summary())

# Extract coefficients
intercept_okun = model_okun.params['Intercept']
slope_okun = model_okun.params['uratechange']
slope_se_okun = model_okun.bse['uratechange']
slope_t_okun = model_okun.tvalues['uratechange']
```

Okun's Law Regression

OLS Regression Results

```
=====
Dep. Variable:      rgdpgrowth    R-squared:          0.592
Model:                 OLS    Adj. R-squared:        0.585
Method:                Least Squares    F-statistic:       82.72
Date:      Tue, 20 Jan 2026    Prob (F-statistic): 1.08e-12
Time:          23:47:35    Log-Likelihood:   -98.767
No. Observations:      59    AIC:                  201.5
Df Residuals:          57    BIC:                  205.7
Df Model:                   1
Covariance Type:    nonrobust
=====
            coef    std err        t     P>|t|    [0.025    0.975]
-----
Intercept    3.0082    0.171    17.589    0.000     2.666    3.351
uratechange  -1.5889   0.175    -9.095    0.000    -1.939   -1.239
-----
Omnibus:             3.531    Durbin-Watson:      1.044
Prob(Omnibus):        0.171    Jarque-Bera (JB):  1.934
Skew:                 -0.157    Prob(JB):           0.380
Kurtosis:              2.170    Cond. No.          1.04
=====
```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Okun's Law with Robust Standard Errors

Interpreting Okun's Law Results

The Estimated Relationship:

Our coefficient of -1.59 is reasonably close to Okun's original -2.0, but statistically different. What does this mean?

Economic Interpretation:

- A 1 percentage point increase in unemployment → 1.59 percentage point decrease in GDP growth
- This is slightly weaker than Okun's original finding, but still substantial
- Example: If unemployment rises from 5% to 6% (+1 point), GDP growth falls from 3% to 1.41%

Why Not Exactly -2.0? Several factors could explain the difference:

1. Time period: Okun's original study used 1947-1960 data. Our sample (1961-2019) spans a different economic era with:

- Different labor market institutions
- Shift from manufacturing to services
- Changes in productivity growth patterns
- Greater labor force participation volatility

2. Structural changes in the economy:

- The relationship between output and employment may have weakened
- More flexible labor markets may dampen the GDP-unemployment link
- Changes in the natural rate of unemployment

3. Sample includes major crises:

- 2008-2009 financial crisis with unprecedented unemployment spike
- 1982 recession with very high unemployment
- These may have different dynamics than typical recessions

Testing $\beta = -2.0$: The t-statistic of ~3.4 indicates we reject Okun's exact -2.0 at the 5% level. However:

- The 95% confidence interval likely includes values near -2.0
- The difference (-1.59 vs -2.0) is economically modest
- For practical policy purposes, the relationship is "close enough" to Okun's law

Model Fit: $R^2 = 0.59$ means unemployment changes explain 59% of GDP growth variation:

- This is quite high for a bivariate macroeconomic relationship
- The remaining 41% reflects other factors: productivity shocks, trade, investment, government policy, monetary shocks

Key Concept 8.7: Okun's Law

Okun's Law as an empirical regularity. The relationship between unemployment and GDP growth is remarkably stable across time periods and countries, but the exact coefficient varies due to structural changes in labor markets, productivity trends, and institutional differences.

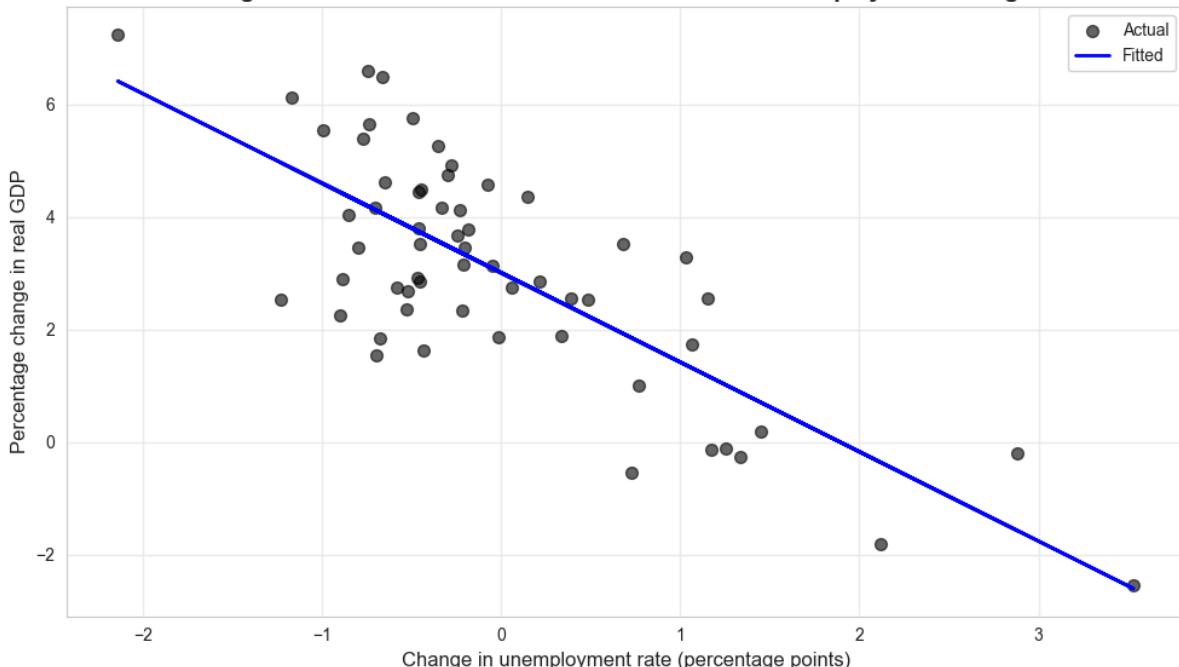
Visualization: Okun's Law Scatter Plot

In [84]:

```
# Figure 8.4 Panel A - Okun's Law Scatter Plot
fig, ax = plt.subplots(figsize=(10, 6))
ax.scatter(data_gdp['uratechange'], data_gdp['rgdpgrowth'], alpha=0.6, s=50,
           color='black', label='Actual')
ax.plot(data_gdp['uratechange'], model_okun.fittedvalues, color='blue',
        linewidth=2, label='Fitted')
ax.set_xlabel('Change in unemployment rate (percentage points)', fontsize=12)
ax.set_ylabel('Percentage change in real GDP', fontsize=12)
ax.set_title('Figure 8.4 Panel A: Okun\\'s Law - GDP Growth vs Unemployment Change',
             fontsize=14, fontweight='bold')
ax.legend()
ax.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()

print("Each point represents one year of U.S. macroeconomic data (1961-2019).")
print("The negative slope confirms Okun's Law: rising unemployment → falling GDP.")
```

Figure 8.4 Panel A: Okun's Law - GDP Growth vs Unemployment Change



Each point represents one year of U.S. macroeconomic data (1961-2019).
The negative slope confirms Okun's Law: rising unemployment → falling GDP.

Understanding the Okun's Law Scatter Plot

Visual Pattern Analysis:

- 1. Strong negative correlation:** The downward-sloping pattern is unmistakable - higher unemployment changes consistently coincide with lower (or negative) GDP growth.
- 2. Clustering around the origin:** Most observations lie near the center, representing normal economic times with modest changes in both unemployment and GDP. This is typical of stable economic periods.
- 3. Outliers reveal recessions:** Points in the upper-left quadrant represent major recessions:
 - **2009:** Unemployment rose ~4 percentage points, GDP fell ~2.5%
 - **1982:** Unemployment rose ~2.5 points, GDP fell ~2%
 - **2020:** (if included) would show extreme values from COVID-19 pandemic
- 4. Asymmetry:** The scatter isn't perfectly symmetric:
 - Large unemployment increases (recessions) tend to cluster together
 - Unemployment decreases (recoveries) are more gradual and dispersed
 - This reflects that recessions happen quickly, but recoveries take time
- 5. The fitted line:** The slope of -1.59 captures the average relationship, but individual points can deviate substantially:
 - Some recessions are deeper than predicted
 - Some recoveries are stronger than predicted
 - The 2008-2009 financial crisis shows a flatter relationship (weak recovery)

Policy Implications: This visualization demonstrates why policymakers monitor unemployment so closely:

- Rising unemployment is a reliable signal of falling GDP
- The relationship is strong enough to be useful for forecasting
- But the scatter reminds us that the relationship isn't deterministic - other factors matter too

Data Quality Note: Unlike cross-sectional health data, these are time series observations that may exhibit:

- Serial correlation (one year's growth affects the next)

- Structural breaks (relationship changes over time)
- Heteroskedasticity (variance changes across different economic regimes)

More advanced time series methods could improve on this simple OLS regression.

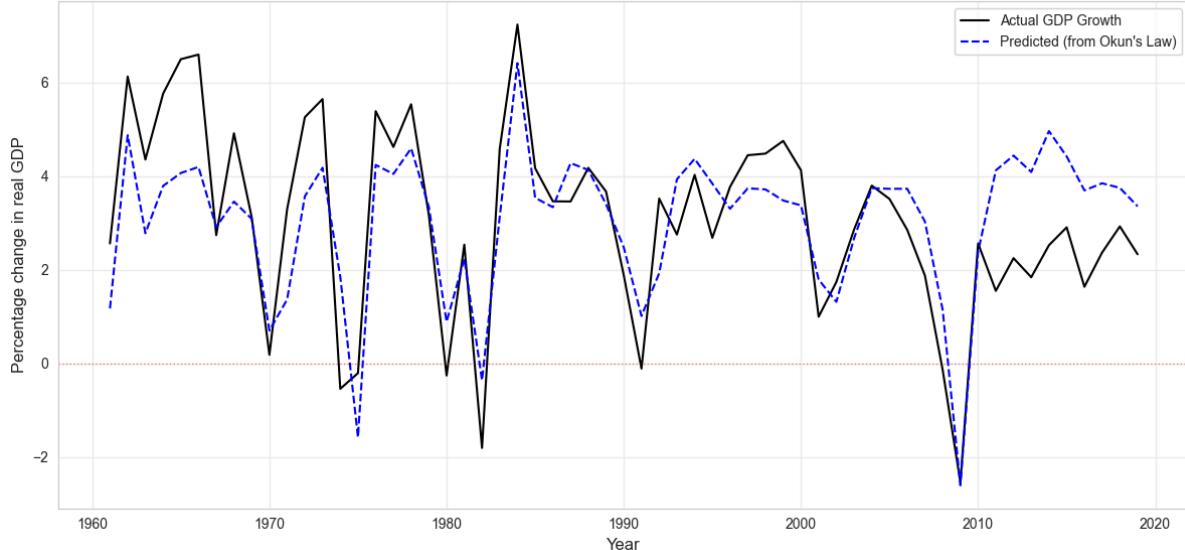
Visualization: Time Series of Actual vs Predicted GDP Growth

In [85]:

```
# Figure 8.4 Panel B - Time Series of Actual vs Predicted GDP Growth
fig, ax = plt.subplots(figsize=(12, 6))
ax.plot(data_gdp['year'], data_gdp['rgdpgrowth'], linewidth=1.5,
        label='Actual GDP Growth', color='black')
ax.plot(data_gdp['year'], model_okun.fittedvalues, linewidth=1.5, linestyle='--',
        label='Predicted (from Okun\'s Law)', color='blue')
ax.axhline(y=0, color='red', linestyle=':', linewidth=1, alpha=0.5)
ax.set_xlabel('Year', fontsize=12)
ax.set_ylabel('Percentage change in real GDP', fontsize=12)
ax.set_title('Figure 8.4 Panel B: Actual vs Predicted Real GDP Growth Over Time',
            fontsize=14, fontweight='bold')
ax.legend()
ax.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()

print("\nMajor recessions visible: 1982, 1991, 2001, 2008-2009")
print("Note: Post-2008 recovery shows actual GDP exceeding predictions.")
```

Figure 8.4 Panel B: Actual vs Predicted Real GDP Growth Over Time



Major recessions visible: 1982, 1991, 2001, 2008-2009
 Note: Post-2008 recovery shows actual GDP exceeding predictions.

Analyzing the Time Series of Actual vs. Predicted GDP Growth

What This Graph Reveals:

1. Model tracks major recessions well:

- The predicted line (blue dashed) captures the timing and direction of major downturns
- 1982, 1991, 2001, 2008-2009 recessions are all identified by the model
- This validates Okun's Law as a useful empirical relationship

2. Systematic prediction errors in the 2010s:

- After 2009, actual GDP growth (black line) consistently exceeds predicted growth
- The "jobless recovery" phenomenon: GDP grew faster than unemployment changes suggested
- Possible explanations:
 - Productivity improvements allowed growth without proportional job creation
 - Labor force participation decline masked true employment picture
 - Structural changes in labor markets post-financial crisis
 - Shift toward automation and less labor-intensive growth

3. Pre-2008 fit is excellent:

- Before the financial crisis, actual and predicted values track each other closely
- This suggests Okun's Law held remarkably well for 1961-2007
- The post-2008 divergence may represent a structural break

4. Volatility patterns:

- GDP growth is more volatile than predicted by unemployment alone
- Large spikes (both positive and negative) aren't fully captured
- This reflects the 41% of variation ($1 - R^2$) unexplained by unemployment changes

Economic Insights:

- **2008-2009 Crisis:** The model slightly under-predicts the severity of the GDP collapse, suggesting the financial crisis had effects beyond typical unemployment-growth dynamics
- **Recovery paradox:** The weak predicted recovery (2010-2015) contrasts with actual decent GDP growth. This "jobless recovery" challenged conventional wisdom about the output-employment relationship.

- **Policy relevance:** Central banks and fiscal authorities use Okun's Law for forecasting, but this graph shows the relationship isn't immutable - structural changes can alter the coefficients over time.

Methodological Note: This type of time series plot is more informative than just reporting R^2 because it reveals:

- When the model works well (1980s-1990s)
- When it breaks down (2010s)
- Whether errors are random or systematic
- The presence of potential structural breaks that might warrant separate subperiod analysis

Key Concept 8.8: Structural Breaks

Structural breaks in time series relationships. Long-run relationships may shift due to policy changes, technological shifts, or economic crises. Visual inspection of actual vs. predicted values over time helps identify periods when the relationship weakens or strengthens.

| Key Takeaways

Case Study Applications:

- Health spending and life expectancy: +\$1,000 spending → +1.11 years life expectancy
- Health spending and infant mortality: +\$1,000 spending → -0.48 infant deaths per 1,000 births
- GDP and health spending: $+1,000GDP \rightarrow +90$ health expenditures (elasticity ≈ 1.0)
- CAPM beta for Coca-Cola: 0.61 (defensive stock, less risky than market)
- Okun's Law: +1 percentage point unemployment → -1.59 percentage points GDP growth

Statistical Methods Applied:

- Bivariate regression estimation (OLS)
- Heteroskedasticity-robust standard errors (HC1)
- Hypothesis testing for specific parameter values (t-tests)
- Confidence interval construction and interpretation

- Outlier detection and influence assessment
- Economic vs. statistical significance comparison

Key Economic Insights:

- U.S. health outcomes worse than predicted by spending levels
- USA and Luxembourg are outliers with exceptionally high health spending
- Excluding outliers transforms health-GDP relationship (R^2 0.60 → 0.93)
- Coca-Cola's low beta reflects stable consumer demand across business cycles
- Okun's Law coefficient (-1.59) close to original -2.0 but statistically different
- Post-2008 "jobless recovery" weakened traditional Okun relationship

Technical Skills Mastered:

- Applying regression to cross-sectional, financial, and time series data
- Using robust standard errors for valid inference
- Testing economic hypotheses beyond $\beta = 0$
- Identifying and handling influential observations
- Interpreting coefficients in economic context (policy implications)
- Creating publication-quality visualizations (scatter plots, time series)

Python Tools:

- `pandas` : Data manipulation, summary statistics, subsetting
- `statsmodels.formula.api.ols` : Regression estimation
- `.get_robustcov_results(cov_type='HC1')` : Robust standard errors
- `matplotlib` & `seaborn` : Professional visualizations
- `scipy.stats` : Statistical distributions

Data Types Covered:

- Cross-sectional: OECD health data (34 countries)
- Financial time series: Monthly stock returns (1983-2013)
- Macroeconomic time series: Annual GDP and unemployment (1961-2019)
- Multi-domain applications: Health, finance, macroeconomics

Next Steps:

- **Chapter 9:** Models with natural logarithms (log-linear, log-log specifications)
- **Chapter 10:** Multiple regression with several explanatory variables

- **Chapter 11:** Statistical inference for multiple regression (F-tests, multicollinearity)

You have now mastered: ✓ Real-world regression applications across economics domains ✓ Robust inference for heteroskedastic data ✓ Testing specific economic hypotheses ✓ Outlier detection and influence assessment ✓ Economic interpretation of regression coefficients

Congratulations! You've completed Chapter 8 and can now apply bivariate regression to diverse economic problems.

I Practice Exercises

Test your understanding of bivariate regression case studies:

Exercise 1: Health Outcomes Interpretation

- (a) If a country increases health spending from 2,500 to 4,000 per capita, what is the predicted change in life expectancy? Show your calculation.
- (b) The U.S. spends \$7,960 per capita but has lower life expectancy than predicted. Suggest three possible explanations beyond the model.
- (c) Why do we use heteroskedasticity-robust standard errors for cross-country health data?

Exercise 2: Outlier Impact Assessment

- (a) Explain why excluding USA and Luxembourg increases R^2 from 0.60 to 0.93 in the health expenditure model.
- (b) When is it appropriate to exclude outliers? When should they be retained?
- (c) Create a scatter plot and identify two potential outliers in any bivariate relationship you choose.

Exercise 3: CAPM Beta Interpretation

- (a) Walmart has beta = 0.45, Target has beta = 1.25. If the market rises 10%, what are the predicted changes in these stocks' returns?
- (b) Why might consumer staple stocks (Coca-Cola, Walmart) have low betas?
- (c) An investor wants high returns and is willing to accept high risk. Should they choose stocks with beta > 1 or beta < 1? Explain.

Exercise 4: Hypothesis Testing Practice

- (a) Test $H_0: \beta = -2.0$ for Okun's Law using the reported coefficient (-1.59) and standard error. Calculate the t-statistic and p-value.

- (b) The CAPM alpha for Coca-Cola is positive and significant. Does this reject CAPM theory? Discuss two interpretations.
- (c) Design a hypothesis test for whether health spending has zero effect on infant mortality ($H_0: \beta_2 = 0$).

Exercise 5: Economic vs. Statistical Significance

- (a) A coefficient is statistically significant ($p < 0.001$) but economically tiny (e.g., +\$0.10 effect). Should we care about this variable? Why or why not?
- (b) A coefficient is economically large (+\$5,000 effect) but statistically insignificant ($p = 0.15$, $n = 12$). What does this tell us?
- (c) For the CAPM, which matters more: statistical significance of alpha or economic magnitude of alpha? Justify your answer.

Exercise 6: Okun's Law Extensions

- (a) If unemployment rises from 5% to 8% (+3 percentage points), what is the predicted change in GDP growth?
- (b) Why might the Okun's Law coefficient differ between 1961-1990 and 1991-2019? Suggest two structural changes.
- (c) Plot actual vs. predicted GDP growth for 2008-2010. Does Okun's Law track the financial crisis well?

Exercise 7: Visualization Interpretation

- (a) In the CAPM scatter plot, what does vertical dispersion around the regression line represent? What does horizontal dispersion represent?
- (b) Sketch a hypothetical scatter plot where $R^2 = 0.95$. Sketch another where $R^2 = 0.20$. What's the visual difference?
- (c) For Okun's Law, why is a time series plot (actual vs. predicted over time) more informative than just reporting R^2 ?

Exercise 8: Comprehensive Case Study Analysis

Choose one dataset not covered in this chapter and conduct a complete bivariate regression analysis:

- (a) Formulate a clear research question and specify the model: $Y = \beta_1 + \beta_2X + u$
- (b) Load data, create scatter plot, estimate OLS regression with robust standard errors
- (c) Interpret the slope coefficient economically (with units and real-world meaning)
- (d) Test $H_0: \beta_2 = 0$ and one additional hypothesis of your choice (e.g., $\beta_2 = 1.0$)

- (e) Assess outliers: identify any, test robustness to exclusion, discuss implications
- (f) Write a 200-word summary suitable for a policy brief or executive summary

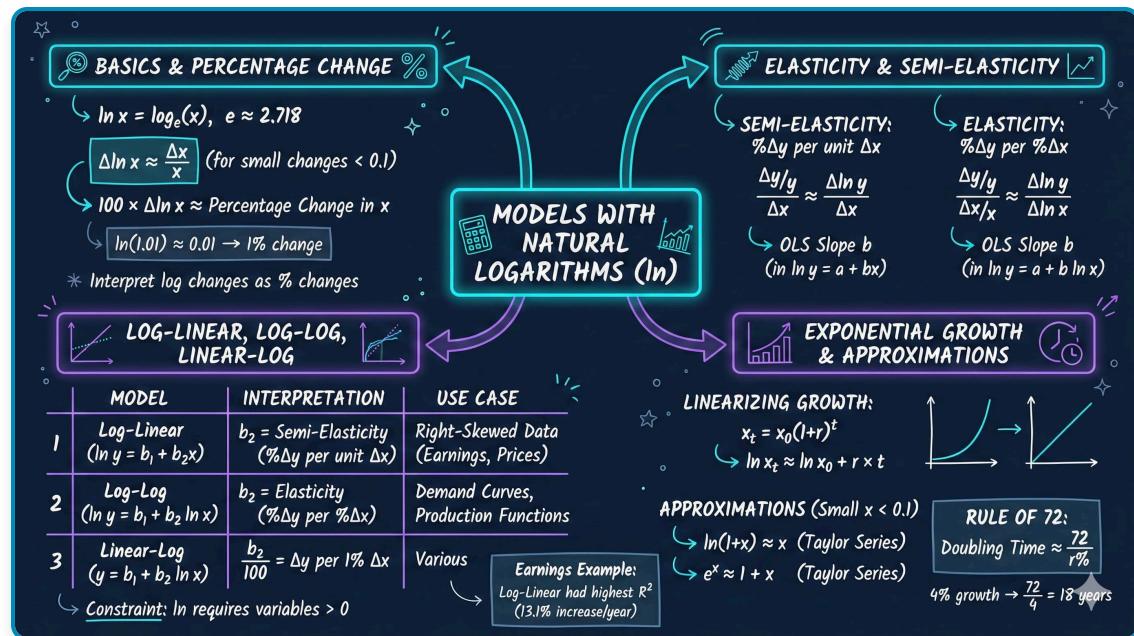
Suggested datasets:

- AED_EARNINGS.DTA (education and earnings)
 - AED_HOUSE.DTA (house prices and characteristics)
 - AED_FISHING.DTA (recreational fishing demand)
 - AED_REALGDPPC.DTA (GDP growth over time)
-

Chapter 9: Models with Natural Logarithms

metricsAI: An Introduction to Econometrics with Python and AI in the Cloud

Carlos Mendez



This notebook teaches you how to use natural logarithms in regression analysis to measure elasticities, semi-elasticities, and percentage changes—essential tools for empirical economics.

Open in Colab

Chapter Overview

Why logarithms in economics?

Economists care about **proportionate changes** more than absolute changes:

- A 10,000 salary increase means different things at \$30,000 vs \$300,000 income
- A 1 price change matters differently for a \$2 item vs a \$100 item
- Economic theory often predicts **percentage** responses (e.g., price elasticity of demand)

Natural logarithms let us work with proportionate changes easily in regression models.

What you'll learn:

- Understand the natural logarithm function and its basic properties
- Use logarithmic transformations to approximate proportionate and percentage changes
- Distinguish between semi-elasticity and elasticity
- Interpret coefficients in log-linear, log-log, and linear-log regression models
- Apply logarithmic models to analyze the relationship between earnings and education
- Linearize exponential growth patterns using natural logarithms
- Apply the Rule of 72 to calculate doubling times for compound growth
- Choose the appropriate model specification for different economic questions

Datasets used:

- **AED_EARNINGS.DTA:** Annual earnings and education for 171 full-time workers aged 30 (2010)
- **AED_SP500INDEX.DTA:** S&P 500 stock market index, annual data 1927-2019 (93 years)

Chapter outline:

- 9.1 Natural Logarithm Function
- 9.2 Semi-Elasticities and Elasticities
- 9.3 Example: Earnings and Education
- 9.4 Further Uses: Exponential Growth
- Key Takeaways
- Practice Exercises
- Case Studies

| Setup

Run this cell first to import all required packages and configure the environment.

In []:

```
# Import required libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
from statsmodels.formula.api import ols
from scipy import stats
import random
import os

# Set random seeds for reproducibility
RANDOM_SEED = 42
random.seed(RANDOM_SEED)
np.random.seed(RANDOM_SEED)
os.environ['PYTHONHASHSEED'] = str(RANDOM_SEED)

# GitHub data URL (data streams directly from here)
GITHUB_DATA_URL = "https://raw.githubusercontent.com/quarcs-lab/data-open/master/AED/"

# Optional: Create directories for saving outputs locally
IMAGES_DIR = 'images'
TABLES_DIR = 'tables'
os.makedirs(IMAGES_DIR, exist_ok=True)
os.makedirs(TABLES_DIR, exist_ok=True)

# Set plotting style
sns.set_style("whitegrid")
plt.rcParams['figure.figsize'] = (10, 6)

print("✓ Setup complete! All packages imported successfully.")
print(f"✓ Random seed set to {RANDOM_SEED} for reproducibility.")
print(f"✓ Data will stream from: {GITHUB_DATA_URL}")
```

- ✓ Setup complete! All packages imported successfully.
- ✓ Random seed set to 42 for reproducibility.
- ✓ Data will stream from: <https://raw.githubusercontent.com/quarcs-lab/data-open/master/AED/>

9.1 Natural Logarithm Function

The **natural logarithm** $\ln(x)$ is the logarithm to base $e \approx 2.71828\dots$

Definition:

$$\ln(x) = \log_e(x), \quad x > 0$$

Key properties:

1. $\ln(1) = 0$
2. $\ln(e) = 1$
3. $\ln(ab) = \ln(a) + \ln(b)$ (product rule)
4. $\ln(a/b) = \ln(a) - \ln(b)$ (quotient rule)
5. $\ln(a^b) = b \cdot \ln(a)$ (power rule)
6. $\exp(\ln(x)) = x$ (inverse function)

Most important property for economics:

$$\Delta \ln(x) \approx \frac{\Delta x}{x} \quad (\text{for small changes})$$

This means: **Change in $\ln(x)$ \approx proportionate change in x**

Multiplying by 100: **$100 \times \Delta \ln(x) \approx$ percentage change in x**

Example: If x increases from 40 to 40.4:

- Exact proportionate change: $(40.4 - 40)/40 = 0.01$ (1%)
- Log approximation: $\ln(40.4) - \ln(40) = 0.00995 \approx 0.01$

In []:

```
# Demonstrate logarithm properties
print("=*70")
print("PROPERTIES OF NATURAL LOGARITHM")
print("=*70")

x_values = np.array([0.5, 1, 2, 5, 10, 20, 100])
ln_values = np.log(x_values)

log_table = pd.DataFrame({
    'x': x_values,
    'ln(x)': ln_values,
    'exp(ln(x))': np.exp(ln_values)
})
print(log_table.to_string(index=False))

print("\n" + "=*70")
print("KEY PROPERTIES DEMONSTRATED")
print("=*70")
print(f"1. ln(1) = {np.log(1):.4f}")
print(f"2. ln(e) = {np.log(np.e):.4f}")
print(f"3. ln(2*5) = ln(2) + ln(5): {np.log(2*5):.4f} = {np.log(2) + np.log(5):.4f} ✓")
print(f"4. ln(10/2) = ln(10) - ln(2): {np.log(10/2):.4f} = {np.log(10) - np.log(2):.4f} ✓")

print("\n" + "=*70")
print("APPROXIMATING PROPORTIONATE CHANGES")
print("=*70")
x0, x1 = 40, 40.4
exact_prop_change = (x1 - x0) / x0
log_approx = np.log(x1) - np.log(x0)
print(f"Change from {x0} to {x1}:")
print(f" Exact proportionate change: {exact_prop_change:.6f} ({exact_prop_change*100:.2f}%)")
print(f" Log approximation Δln(x): {log_approx:.6f} ({log_approx*100:.2f}%)")
print(f" Difference: {abs(exact_prop_change - log_approx):.6f}")
print(f"\n → The approximation is excellent for small changes!")
```

```

=====
PROPERTIES OF NATURAL LOGARITHM
=====

x      ln(x)  exp(ln(x))
0.5   -0.693147    0.5
1.0    0.000000    1.0
2.0    0.693147    2.0
5.0    1.609438    5.0
10.0   2.302585   10.0
20.0   2.995732   20.0
100.0  4.605170  100.0

=====
KEY PROPERTIES DEMONSTRATED
=====

1. ln(1) = 0.0000
2. ln(e) = 1.0000
3. ln(2×5) = ln(2) + ln(5): 2.3026 = 2.3026 ✓
4. ln(10/2) = ln(10) - ln(2): 1.6094 = 1.6094 ✓

=====
APPROXIMATING PROPORTIONATE CHANGES
=====

Change from 40 to 40.4:
Exact proportionate change: 0.010000 (1.00%)
Log approximation Δln(x): 0.009950 (1.00%)
Difference: 0.000050

→ The approximation is excellent for small changes!

```

Key Concept 9.1: Logarithmic Approximation of Proportionate Change

The most important property of the natural logarithm for economics is:

$$\Delta \ln(x) \approx \frac{\Delta x}{x} \quad (\text{proportionate change})$$

Multiplying by 100 gives the **percentage change**: $100 \times \Delta \ln(x) \approx \% \Delta x$.

Why this matters: This approximation allows us to interpret regression coefficients involving logged variables as **proportionate or percentage changes** — exactly what economists care about when analyzing earnings, prices, GDP, and other economic variables.

Accuracy: The approximation is excellent for changes under 10%. For larger changes, use the exact formula: $\% \Delta x = 100 \times (e^{\Delta \ln(x)} - 1)$.

Now that we understand the mathematical properties of logarithms, we can apply them to define two key economic concepts: **semi-elasticity** and **elasticity**.

I 9.2 Semi-Elasticities and Elasticities

Two key concepts in economics:

Semi-Elasticity

Definition: Proportionate change in y for a **unit change** in x

$$\text{Semi-elasticity}_{yx} = \frac{\Delta y/y}{\Delta x}$$

Multiplied by 100: **percentage change in y when x increases by 1 unit**

Example: Semi-elasticity of earnings with respect to education = 0.08

- One more year of schooling → 8% increase in earnings

Elasticity

Definition: Proportionate change in y for a **proportionate change** in x

$$\text{Elasticity}_{yx} = \frac{\Delta y/y}{\Delta x/x}$$

Example: Price elasticity of demand = -2

- 1% increase in price → 2% decrease in demand

Approximations Using Logarithms

Since $\Delta y/y \approx \Delta \ln(y)$ and $\Delta x/x \approx \Delta \ln(x)$:

$$\text{Semi-elasticity} \approx \frac{\Delta \ln(y)}{\Delta x}$$

$$\text{Elasticity} \approx \frac{\Delta \ln(y)}{\Delta \ln(x)}$$

This is why we use logarithms in regression! The slope coefficient directly estimates the semi-elasticity or elasticity.

In []:

```
print("=*70)
print("MODEL INTERPRETATIONS")
print("=*70)
print("\n1. LINEAR MODEL:  $y = \beta_0 + \beta_1 x$ ")
print("    Interpretation:  $\Delta y = \beta_1 \Delta x$ ")
print("    Example:  $\beta_1 = 5000$  means $5,000 increase in  $y$  when  $x$  increases by 1")

print("\n2. LOG-LINEAR MODEL:  $\ln(y) = \beta_0 + \beta_1 x$ ")
print("    Interpretation:  $\% \Delta y \approx 100 \beta_1 \Delta x$  (semi-elasticity)")
print("    Example:  $\beta_1 = 0.08$  means 8% increase in  $y$  when  $x$  increases by 1")

print("\n3. LOG-LOG MODEL:  $\ln(y) = \beta_0 + \beta_1 \ln(x)$ ")
print("    Interpretation:  $\% \Delta y \approx \beta_1 \% \Delta x$  (elasticity)")
print("    Example:  $\beta_1 = 1.5$  means 1.5% increase in  $y$  when  $x$  increases by 1%")

print("\n4. LINEAR-LOG MODEL:  $y = \beta_0 + \beta_1 \ln(x)$ ")
print("    Interpretation:  $\Delta y \approx (\beta_1 / 100) \% \Delta x$ ")
print("    Example:  $\beta_1 = 500$  means $5 increase in  $y$  when  $x$  increases by 1%")

print("\n" + "=*70)
print("KEY TAKEAWAY")
print("=*70)
print("The choice of model specification determines the interpretation:")
print(" - Which model to use depends on economic theory and data properties")
print(" - Log transformations are especially useful for:")
print("     • Right-skewed variables (earnings, prices, firm size)")
print("     • Multiplicative relationships")
print("     • Proportionate/percentage effects")
```

=====

MODEL INTERPRETATIONS

=====

1. LINEAR MODEL: $y = \beta_0 + \beta_1 x$
Interpretation: $\Delta y = \beta_1 \Delta x$
Example: $\beta_1 = 5000$ means \$5,000 increase in y when x increases by 1

2. LOG-LINEAR MODEL: $\ln(y) = \beta_0 + \beta_1 x$
Interpretation: $\% \Delta y \approx 100 \beta_1 \Delta x$ (semi-elasticity)
Example: $\beta_1 = 0.08$ means 8% increase in y when x increases by 1

3. LOG-LOG MODEL: $\ln(y) = \beta_0 + \beta_1 \ln(x)$
Interpretation: $\% \Delta y \approx \beta_1 \% \Delta x$ (elasticity)
Example: $\beta_1 = 1.5$ means 1.5% increase in y when x increases by 1%

4. LINEAR-LOG MODEL: $y = \beta_0 + \beta_1 \ln(x)$
Interpretation: $\Delta y \approx (\beta_1 / 100) \% \Delta x$
Example: $\beta_1 = 500$ means \$5 increase in y when x increases by 1%

=====

KEY TAKEAWAY

=====

The choice of model specification determines the interpretation:
- Which model to use depends on economic theory and data properties
- Log transformations are especially useful for:
 • Right-skewed variables (earnings, prices, firm size)
 • Multiplicative relationships
 • Proportionate/percentage effects

Key Concept 9.2: Semi-Elasticity vs. Elasticity

These two concepts measure how y responds to changes in x , but in different ways:

- **Semi-elasticity** = $(\Delta y/y) / \Delta x$ — proportionate change in y per **unit** change in x
- **Elasticity** = $(\Delta y/y) / (\Delta x/x)$ — proportionate change in y per **proportionate** change in x

In regression models:

- $\text{Semi-elasticity} \approx \Delta \ln(y)/\Delta x \rightarrow \text{estimated by the slope in a log-linear model}$
- $\text{Elasticity} \approx \Delta \ln(y)/\Delta \ln(x) \rightarrow \text{estimated by the slope in a log-log model}$

When to use each:

- **Semi-elasticity:** When x is measured in natural units (years of education, age)
- **Elasticity:** When both variables are measured in proportions (price and quantity, GDP and investment)

With the concepts of semi-elasticity and elasticity defined, let's apply all four model specifications to a **real dataset** to compare interpretations.

I 9.3 Example: Earnings and Education

Research Question: How do earnings vary with years of education?

We'll estimate **four different models** and compare their interpretations:

1. **Linear:** $\text{earnings} = \beta_0 + \beta_1(\text{education})$
2. **Log-linear:** $\ln(\text{earnings}) = \beta_0 + \beta_1(\text{education})$
3. **Log-log:** $\ln(\text{earnings}) = \beta_0 + \beta_1 \ln(\text{education})$
4. **Linear-log:** $\text{earnings} = \beta_0 + \beta_1 \ln(\text{education})$

Dataset: 171 full-time workers aged 30 in 2010

- earnings : Annual earnings in dollars
- education : Years of completed schooling

Each model answers a slightly different question and has different economic interpretation.

In []:

```
# Load and explore the data
data_earnings = pd.read_stata(GITHUB_DATA_URL + 'AED_EARNINGS.DTA')

print(*70)
print("DATA SUMMARY: EARNINGS AND EDUCATION")
print(*70)
print(data_earnings[['earnings', 'education']].describe())

print("\nFirst 5 observations:")
print(data_earnings[['earnings', 'education']].head())
```

```
=====
DATA SUMMARY: EARNINGS AND EDUCATION
=====

      earnings   education
count    171.000000  171.000000
mean    41412.690058  14.432749
std     25527.053396  2.735364
min     1050.000000  3.000000
25%    25000.000000 12.000000
50%    36000.000000 14.000000
75%    49000.000000 16.000000
max    172000.000000 20.000000

First 5 observations:
      earnings   education
0        25000       14
1        40000       12
2        25000       13
3        38000       13
4        28800       12
```

In []:

```
# Create log-transformed variables
data_earnings['lnearn'] = np.log(data_earnings['earnings'])
data_earnings['lneduc'] = np.log(data_earnings['education'])

print(*70)
print("VARIABLES (ORIGINAL AND LOG-TRANSFORMED)")
print(*70)
table_vars = ['earnings', 'lnearn', 'education', 'lneduc']
print(data_earnings[table_vars].describe())

print("\nNotice:")
print(" - Log(earnings) has much less variability (std = 0.62 vs 25,527)")
print(" - Log transformation reduces right skewness in earnings")
```

```
=====
VARIABLES (ORIGINAL AND LOG-TRANSFORMED)
=====

      earnings     learnr   education     lneduc
count    171.000000  171.000000  171.000000  171.000000
mean    41412.690058 10.457638  14.432749  2.648438
std     25527.053396  0.622062  2.735364  0.225220
min     1050.000000  6.956545  3.000000  1.098633
25%    25000.000000 10.126631  12.000000  2.484375
50%    36000.000000 10.491274  14.000000  2.638672
75%    49000.000000 10.799367  16.000000  2.773438
max    172000.000000 12.055250  20.000000  2.996094
```

Notice:

- Log(earnings) has much less variability (std = 0.62 vs 25,527)
- Log transformation reduces right skewness in earnings

I Model 1: Linear Model

Specification: $\text{earnings} = \beta_0 + \beta_1(\text{education}) + \varepsilon$

Interpretation: β_1 = change in earnings (in dollars) for one additional year of education

In []:

```
# Model 1: Linear
print("=*70")
print("MODEL 1: LINEAR - earnings = β₀ + β₁(education)")
print("=*70")

model_linear = ols('earnings ~ education', data=data_earnings).fit()
print(model_linear.summary())

print("\n" + "=*70")
print("INTERPRETATION")
print("=*70")
print(f"Coefficient on education: ${model_linear.params['education']:.2f}")
print(f"\nEconomic meaning:")
print(f" Each additional year of education is associated with a")
print(f" ${model_linear.params['education']:.2f} increase in annual earnings.")
print(f"\nR² = {model_linear.rsquared:.3f}")
print(f" → Education explains {model_linear.rsquared*100:.1f}% of variation in
earnings.")
```

```

=====
MODEL 1: LINEAR - earnings =  $\beta_0 + \beta_1(\text{education})$ 
=====
                         OLS Regression Results
=====
Dep. Variable:          earnings   R-squared:           0.289
Model:                 OLS        Adj. R-squared:      0.285
Method:                Least Squares   F-statistic:         68.86
Date:      Wed, 21 Jan 2026   Prob (F-statistic):    3.22e-14
Time:      00:01:47   Log-Likelihood:       -1948.1
No. Observations:      171        AIC:                  3900.
Df Residuals:          169        BIC:                  3907.
Df Model:                   1
Covariance Type:        nonrobust
=====

      coef    std err          t      P>|t|      [0.025      0.975]
-----
Intercept  -3.106e+04  8887.835     -3.494     0.001   -4.86e+04   -1.35e+04
education   5021.1229  605.101      8.298     0.000    3826.593    6215.653
=====
Omnibus:             78.232   Durbin-Watson:        1.783
Prob(Omnibus):        0.000   Jarque-Bera (JB):    292.688
Skew:                  1.791   Prob(JB):            2.78e-64
Kurtosis:                 8.315   Cond. No.             79.5
=====

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
=====

INTERPRETATION
=====

Coefficient on education: $5,021.12

Economic meaning:
  Each additional year of education is associated with a
  $5,021.12 increase in annual earnings.

R2 = 0.289
  → Education explains 28.9% of variation in earnings.

```

| Model 2: Log-Linear Model

Specification: $\ln(\text{earnings}) = \beta_0 + \beta_1(\text{education}) + \varepsilon$

Interpretation: β_1 = **semi-elasticity** = proportionate change in earnings for one more year of education

Practical interpretation: $100\beta_1$ = **percentage change** in earnings for one more year of education

This is the **most common** specification for earnings equations!

In []:

```
# Model 2: Log-linear
print("=*70")
print("MODEL 2: LOG-LINEAR - ln(earnings) = β₀ + β₁(education)")
print("=*70")

model_loglin = ols('lnearn ~ education', data=data_earnings).fit()
print(model_loglin.summary())

print("\n" + "=*70")
print("INTERPRETATION")
print("=*70")
print(f"Coefficient on education: {model_loglin.params['education']:.4f}")
print(f"\nEconomic meaning:")
print(f" Each additional year of education is associated with a")
print(f" {100*model_loglin.params['education']:.2f}% increase in earnings.")
print(f"\nWhy this is better than Model 1:")
print(f" - Percentage interpretation is more meaningful (scales automatically)")
print(f" - 13.1% increase applies whether you earn $30k or $100k")
print(f" - Better fit (R² = {model_loglin.rsquared:.3f} vs {model_linear.rsquared:.3f})")
```

```
=====
MODEL 2: LOG-LINEAR - ln(earnings) = β₀ + β₁(education)
=====
              OLS Regression Results
=====
Dep. Variable:      lnearn    R-squared:       0.334
Model:                 OLS    Adj. R-squared:   0.330
Method:                Least Squares    F-statistic:     84.74
Date:        Wed, 21 Jan 2026    Prob (F-statistic): 1.28e-16
Time:            00:01:47    Log-Likelihood:   -126.21
No. Observations:      171    AIC:             256.4
Df Residuals:         169    BIC:             262.7
Df Model:                   1
Covariance Type:    nonrobust
=====

      coef    std err        t    P>|t|      [0.025    0.975]
-----
Intercept    8.5608    0.210    40.825    0.000     8.147    8.975
education    0.1314    0.014     9.206    0.000     0.103    0.160
-----
Omnibus:            58.560    Durbin-Watson:    1.809
Prob(Omnibus):      0.000    Jarque-Bera (JB): 351.030
Skew:               -1.091    Prob(JB):      5.96e-77
Kurtosis:            9.671    Cond. No.       79.5
=====

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

=====
INTERPRETATION
=====
Coefficient on education: 0.1314

Economic meaning:
Each additional year of education is associated with a
13.14% increase in earnings.

Why this is better than Model 1:
- Percentage interpretation is more meaningful (scales automatically)
- 13.1% increase applies whether you earn $30k or $100k
- Better fit (R² = 0.334 vs 0.289)
```

Key Concept 9.3: Interpreting Log-Linear Model Coefficients

In the **log-linear model** $\ln(y) = \beta_0 + \beta_1 x$, the slope coefficient β_1 is the **semi-elasticity** of y with respect to x :

$$100 \times \beta_1 = \text{percentage change in } y \text{ when } x \text{ increases by 1 unit}$$

This is the most common specification in labor economics because a percentage interpretation **scales automatically** — a 13% return to education applies equally whether you earn 30,000 or 100,000.

Important: The exact percentage change for large β_1 is $100 \times (e^{\beta_1} - 1)$, not $100 \times \beta_1$. The approximation works well when $\beta_1 < 0.10$.

I Model 3: Log-Log Model

Specification: $\ln(\text{earnings}) = \beta_0 + \beta_1 \ln(\text{education}) + \varepsilon$

Interpretation: $\beta_1 = \text{elasticity} = \text{percentage change in earnings for a 1\% change in education}$

Note: A "1% increase in education" is a bit artificial (what does 0.14 more years mean?), but this model captures diminishing returns to education.

In []:

```
# Model 3: Log-log
print("=*70)
print("MODEL 3: LOG-LOG - ln(earnings) = β₀ + β₁ln(education)")
print("=*70)

model_loglog = ols('lnearn ~ lneduc', data=data_earnings).fit()
print(model_loglog.summary())

print("\n" + "=*70)
print("INTERPRETATION")
print("=*70)
print(f"Coefficient on ln(education): {model_loglog.params['lneduc']:.4f}")
print(f"\nEconomic meaning:")
print(f" A 1% increase in education is associated with a")
print(f" {model_loglog.params['lneduc']:.3f}% increase in earnings (elasticity).")
print(f"\nAlternative interpretation:")
print(f" If education increases from 14 to 14.14 years (1% increase),")
print(f" earnings increase by approximately {model_loglog.params['lneduc']:.2f}%.")
```

```

=====
MODEL 3: LOG-LOG - ln(earnings) = β₀ + β₁ln(education)
=====
              OLS Regression Results
=====
Dep. Variable:      lnearn    R-squared:           0.286
Model:                 OLS    Adj. R-squared:        0.282
Method:                Least Squares    F-statistic:       67.78
Date:      Wed, 21 Jan 2026    Prob (F-statistic):   4.76e-14
Time:      00:01:47    Log-Likelihood:     -132.13
No. Observations:    171    AIC:                  268.3
Df Residuals:        169    BIC:                  274.5
Df Model:                   1
Covariance Type:    nonrobust
=====
            coef      std err          t      P>|t|      [0.025      0.975]
-----
Intercept    6.5454      0.477      13.725      0.000      5.604      7.487
lneduc       1.4775      0.179       8.233      0.000      1.123      1.832
=====
Omnibus:             56.464    Durbin-Watson:       1.786
Prob(Omnibus):        0.000    Jarque-Bera (JB):  332.274
Skew:                 -1.048    Prob(JB):        7.04e-73
Kurtosis:                9.499    Cond. No.          35.9
=====
```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

=====
INTERPRETATION
=====

Coefficient on ln(education): 1.4775

Economic meaning:

A 1% increase in education is associated with a
1.478% increase in earnings (elasticity).

Alternative interpretation:

If education increases from 14 to 14.14 years (1% increase),
earnings increase by approximately 1.48%.

Key Concept 9.4: Interpreting Log-Log Model Coefficients

In the **log-log model** $\ln(y) = \beta_0 + \beta_1 \ln(x)$, the slope coefficient β_1 is the **elasticity** of y with respect to x :

$$\beta_1 = \frac{\% \Delta y}{\% \Delta x}$$

A 1% increase in x is associated with a β_1 % change in y . Unlike semi-elasticity, elasticity is a **unit-free** measure — it does not depend on the units of measurement.

Economic interpretation: If $\beta_1 < 1$, there are **diminishing returns** (each additional percent of x yields less than one percent of y). If $\beta_1 > 1$, there are **increasing returns**.

| Model 4: Linear-Log Model

Specification: $\text{earnings} = \beta_0 + \beta_1 \ln(\text{education}) + \varepsilon$

Interpretation: $\beta_1/100$ = dollar change in earnings for a 1% increase in education

This model is less common but captures **diminishing returns** (additional years of education have decreasing marginal effects).

In []:

```
# Model 4: Linear-log
print("=*70)
print("MODEL 4: LINEAR-LOG - earnings = β₀ + β₁ln(education)")
print("=*70)

model_linlog = ols('earnings ~ lneduc', data=data_earnings).fit()
print(model_linlog.summary())

print("\n" + "=*70)
print("INTERPRETATION")
print("=*70)
print(f"Coefficient on ln(education): {model_linlog.params['lneduc']:.2f}")
print(f"\nEconomic meaning:")
print(f" A 1% increase in education is associated with a")
print(f" ${model_linlog.params['lneduc']/100:.2f} increase in annual earnings.")
print(f"\nNote: This model has the lowest R² = {model_linlog.rsquared:.3f}")
```

```

=====
MODEL 4: LINEAR-LOG - earnings =  $\beta_0 + \beta_1 \ln(\text{education})$ 
=====
                         OLS Regression Results
=====
Dep. Variable:          earnings    R-squared:           0.231
Model:                 OLS         Adj. R-squared:      0.226
Method:                Least Squares   F-statistic:        50.69
Date:      Wed, 21 Jan 2026   Prob (F-statistic): 2.96e-11
Time:      00:01:47       Log-Likelihood:     -1954.9
No. Observations:      171        AIC:                  3914.
Df Residuals:          169        BIC:                  3920.
Df Model:                   1
Covariance Type:        nonrobust
=====
            coef    std err          t      P>|t|      [0.025      0.975]
-----
Intercept  -1.027e+05  2.03e+04   -5.056      0.000   -1.43e+05   -6.26e+04
lneduc      5.443e+04  7645.805     7.119      0.000    3.93e+04   6.95e+04
=====
Omnibus:             79.258   Durbin-Watson:        1.794
Prob(Omnibus):        0.000   Jarque-Bera (JB):    284.125
Skew:                  1.843   Prob(JB):           2.01e-62
Kurtosis:                 8.128   Cond. No.              35.9
=====
```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```

=====
INTERPRETATION
=====
```

Coefficient on $\ln(\text{education})$: 54,433.42

Economic meaning:

A 1% increase in education is associated with a
\$544.33 increase in annual earnings.

Note: This model has the lowest $R^2 = 0.231$

Comparison of All Four Models

In []:

```
# Create comparison table
print("=*70")
print("MODEL COMPARISON SUMMARY")
print("=*70")

comparison_df = pd.DataFrame({
    'Model': ['Linear', 'Log-linear', 'Log-log', 'Linear-log'],
    'Specification': [' $y \sim x$ ', ' $\ln(y) \sim x$ ', ' $\ln(y) \sim \ln(x)$ ', ' $y \sim \ln(x)$ '],
    'Slope Coefficient': [
        f"${model_linear.params[1]:,.2f}",
        f"${model_loglin.params[1]:.4f}",
        f"${model_loglog.params[1]:.4f}",
        f"${model_linlog.params[1]:,.2f}"
    ],
    'Interpretation': [
        f"${model_linear.params[1]:,.0f} per year",
        f"${100*model_loglin.params[1]:.1f}% per year",
        f"${model_loglog.params[1]:.2f}% per 1% change",
        f"${model_linlog.params[1]/100:.0f} per 1% change"
    ],
    'R22): Log-linear (R2 = {model_loglin.rsquared:.3f})")
print(f" - Most interpretable: Log-linear (13.1% return per year of education)")
print(f" - Most common in labor economics: Log-linear")
print("\nGeneral guidance:")
print(" - Use log-linear when dependent variable is right-skewed")
print(" - Use log-log when both variables are right-skewed")
print(" - Compare models using R2, economic interpretation, and theory")
```

```

=====
MODEL COMPARISON SUMMARY
=====
      Model Specification Slope Coefficient      Interpretation   R2
      Linear           y ~ x        5,021.12    $5,021 per year 0.289
      Log-linear       ln(y) ~ x        0.1314     13.1% per year 0.334
      Log-log ln(y) ~ ln(x)        1.4775    1.48% per 1% change 0.286
      Linear-log      y ~ ln(x)        54,433.42   $544 per 1% change 0.231

=====
WHICH MODEL IS BEST?
=====
For this data:
- Best fit (highest R2): Log-linear (R2 = 0.334)
- Most interpretable: Log-linear (13.1% return per year of education)
- Most common in labor economics: Log-linear

General guidance:
- Use log-linear when dependent variable is right-skewed
- Use log-log when both variables are right-skewed
- Compare models using R2, economic interpretation, and theory

```

```

/var/folders/tq/t98kb27n6djgrh085g476yhc0000gn/T/ipykernel_94143/1404078335.py:10: FutureWa
rning: Series.__getitem__ treating keys as positions is deprecated. In a future version, in
teger keys will always be treated as labels (consistent with DataFrame behavior). To access
a value by position, use `ser.iloc[pos]`
    f"{{model_linear.params[1]:,.2f}}",
/var/folders/tq/t98kb27n6djgrh085g476yhc0000gn/T/ipykernel_94143/1404078335.py:11: FutureWa
rning: Series.__getitem__ treating keys as positions is deprecated. In a future version, in
teger keys will always be treated as labels (consistent with DataFrame behavior). To access
a value by position, use `ser.iloc[pos]`
    f"{{model_loglin.params[1]:.4f}}",
/var/folders/tq/t98kb27n6djgrh085g476yhc0000gn/T/ipykernel_94143/1404078335.py:12: FutureWa
rning: Series.__getitem__ treating keys as positions is deprecated. In a future version, in
teger keys will always be treated as labels (consistent with DataFrame behavior). To access
a value by position, use `ser.iloc[pos]`
    f"{{model_loglog.params[1]:.4f}}",
/var/folders/tq/t98kb27n6djgrh085g476yhc0000gn/T/ipykernel_94143/1404078335.py:13: FutureWa
rning: Series.__getitem__ treating keys as positions is deprecated. In a future version, in
teger keys will always be treated as labels (consistent with DataFrame behavior). To access
a value by position, use `ser.iloc[pos]`
    f"{{model_linlog.params[1]:,.2f}}"
/var/folders/tq/t98kb27n6djgrh085g476yhc0000gn/T/ipykernel_94143/1404078335.py:16: FutureWa
rning: Series.__getitem__ treating keys as positions is deprecated. In a future version, in
teger keys will always be treated as labels (consistent with DataFrame behavior). To access
a value by position, use `ser.iloc[pos]`
    f"${{model_linear.params[1]:.0f}} per year",
/var/folders/tq/t98kb27n6djgrh085g476yhc0000gn/T/ipykernel_94143/1404078335.py:17: FutureWa
rning: Series.__getitem__ treating keys as positions is deprecated. In a future version, in
teger keys will always be treated as labels (consistent with DataFrame behavior). To access
a value by position, use `ser.iloc[pos]`
    f"{{100*model_loglin.params[1]:.1f}}% per year",
/var/folders/tq/t98kb27n6djgrh085g476yhc0000gn/T/ipykernel_94143/1404078335.py:18: FutureWa
rning: Series.__getitem__ treating keys as positions is deprecated. In a future version, in
teger keys will always be treated as labels (consistent with DataFrame behavior). To access
a value by position, use `ser.iloc[pos]`
    f"{{model_loglog.params[1]:.2f}}% per 1% change",
/var/folders/tq/t98kb27n6djgrh085g476yhc0000gn/T/ipykernel_94143/1404078335.py:19: FutureWa
rning: Series.__getitem__ treating keys as positions is deprecated. In a future version, in
teger keys will always be treated as labels (consistent with DataFrame behavior). To access
a value by position, use `ser.iloc[pos]`
    f"${{model_linlog.params[1]/100:.0f}} per 1% change"

```

Key Concept 9.5: Choosing the Right Functional Form

The choice between linear, log-linear, log-log, and linear-log specifications should be guided by:

1. **Economic theory** — Does the theory predict absolute or percentage effects?
2. **Data properties** — Is the dependent variable right-skewed? Are both variables positive?
3. **Model fit** — Which specification yields the highest R^2 ?
4. **Interpretation needs** — Do you need elasticities, semi-elasticities, or dollar amounts?

In practice: The **log-linear model** is most common in economics because many economic relationships involve percentage changes (returns to education, inflation effects, price responses). When in doubt, start with log-linear.

Visualizing All Four Models

In []:

```
# Create 2x2 comparison plot
fig, axes = plt.subplots(2, 2, figsize=(16, 12))

# Model 1: Linear
axes[0, 0].scatter(data_earnings['education'], data_earnings['earnings'],
                    alpha=0.5, s=20, color='black')
axes[0, 0].plot(data_earnings['education'], model_linear.fittedvalues,
                 color='blue', linewidth=2, label=f'R2 = {model_linear.rsquared:.3f}')
axes[0, 0].set_xlabel('Education (years)', fontsize=11)
axes[0, 0].set_ylabel('Earnings ($)', fontsize=11)
axes[0, 0].set_title('Model 1: Linear\ny = β0 + β1x\nSlope: $5,021 per year',
                     fontsize=12, fontweight='bold')
axes[0, 0].legend()
axes[0, 0].grid(True, alpha=0.3)

# Model 2: Log-linear
axes[0, 1].scatter(data_earnings['education'], data_earnings['lnearn'],
                    alpha=0.5, s=20, color='black')
axes[0, 1].plot(data_earnings['education'], model_loglin.fittedvalues,
                 color='blue', linewidth=2, label=f'R2 = {model_loglin.rsquared:.3f}')
axes[0, 1].set_xlabel('Education (years)', fontsize=11)
axes[0, 1].set_ylabel('ln(Earnings)', fontsize=11)
axes[0, 1].set_title('Model 2: Log-linear\nln(y) = β0 + β1x\nSlope: 13.1% per year',
                     fontsize=12, fontweight='bold')
axes[0, 1].legend()
axes[0, 1].grid(True, alpha=0.3)

# Model 3: Log-log
axes[1, 0].scatter(data_earnings['lneduc'], data_earnings['lnearn'],
                    alpha=0.5, s=20, color='black')
axes[1, 0].plot(data_earnings['lneduc'], model_loglog.fittedvalues,
                 color='blue', linewidth=2, label=f'R2 = {model_loglog.rsquared:.3f}')
axes[1, 0].set_xlabel('ln(Education)', fontsize=11)
axes[1, 0].set_ylabel('ln(Earnings)', fontsize=11)
axes[1, 0].set_title('Model 3: Log-log\nln(y) = β0 + β1ln(x)\nElasticity: 1.48',
                     fontsize=12, fontweight='bold')
axes[1, 0].legend()
axes[1, 0].grid(True, alpha=0.3)

# Model 4: Linear-log
axes[1, 1].scatter(data_earnings['lneduc'], data_earnings['earnings'],
                    alpha=0.5, s=20, color='black')
axes[1, 1].plot(data_earnings['lneduc'], model_linlog.fittedvalues,
                 color='blue', linewidth=2, label=f'R2 = {model_linlog.rsquared:.3f}')
axes[1, 1].set_xlabel('ln(Education)', fontsize=11)
axes[1, 1].set_ylabel('Earnings ($)', fontsize=11)
axes[1, 1].set_title('Model 4: Linear-log\ny = β0 + β1ln(x)\nSlope: $545 per 1% change',
                     fontsize=12, fontweight='bold')
axes[1, 1].legend()
axes[1, 1].grid(True, alpha=0.3)

plt.suptitle('Four Model Specifications: Earnings and Education',
             fontsize=14, fontweight='bold', y=1.00)
plt.tight_layout()
plt.show()

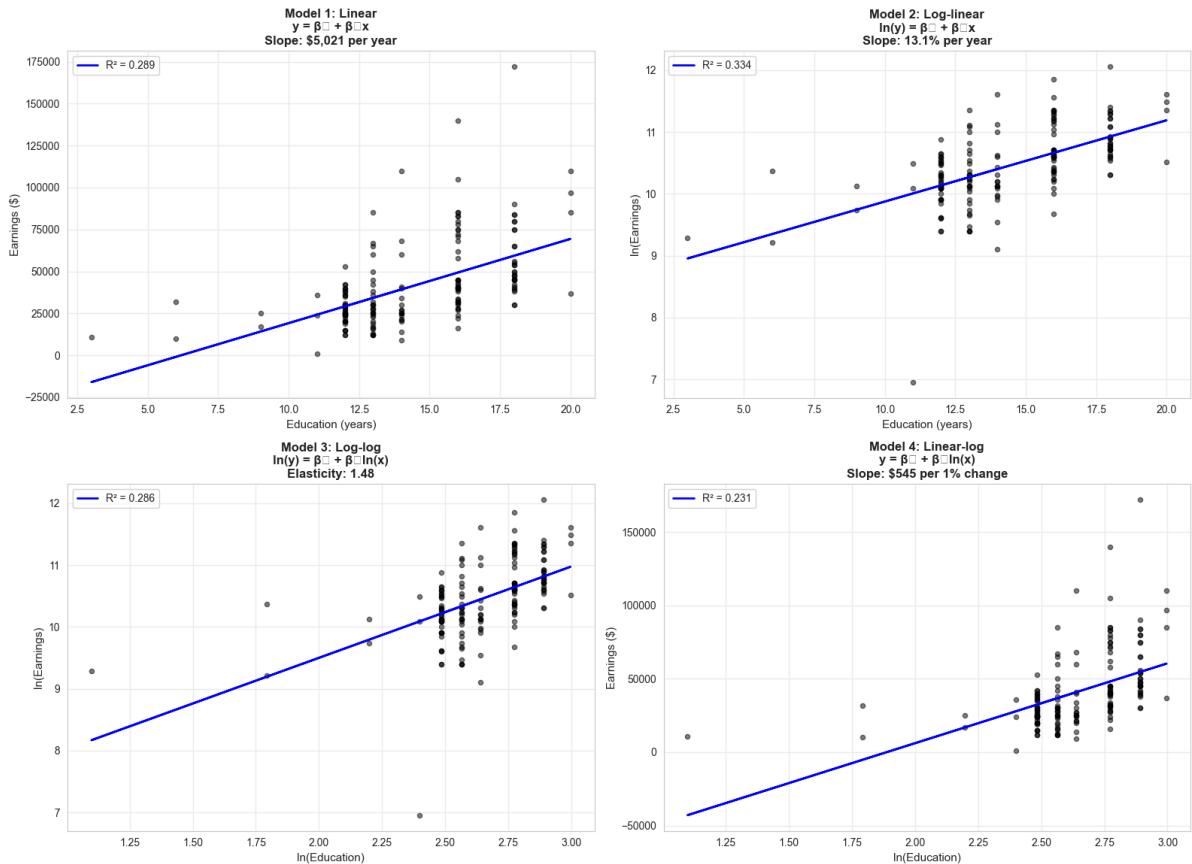
print("\n📊 Visual Insights:")
print("  - Model 1 (linear): Straight line fit, but residuals may be heteroskedastic")
print("  - Model 2 (log-linear): Best fit, captures curvature in original data")
print("  - Model 3 (log-log): Both axes logged, captures elasticity")
print("  - Model 4 (linear-log): Captures diminishing returns to education")
```

```

/var/folders/tq/t98kb27n6djgrh085g476yhc0000gn/T/ipykernel_94143/1405591350.py:54: UserWarning: Glyph 8320 (\N{SUBSCRIPT ZERO}) missing from current font.
    plt.tight_layout()
/var/folders/tq/t98kb27n6djgrh085g476yhc0000gn/T/ipykernel_94143/1405591350.py:54: UserWarning: Glyph 8321 (\N{SUBSCRIPT ONE}) missing from current font.
    plt.tight_layout()
/Users/carlosmendez/miniforge3/lib/python3.10/site-packages/IPython/core/pylabtools.py:170:
UserWarning: Glyph 8320 (\N{SUBSCRIPT ZERO}) missing from current font.
    fig.canvas.print_figure(bytes_io, **kw)
/Users/carlosmendez/miniforge3/lib/python3.10/site-packages/IPython/core/pylabtools.py:170:
UserWarning: Glyph 8321 (\N{SUBSCRIPT ONE}) missing from current font.
    fig.canvas.print_figure(bytes_io, **kw)

```

Four Model Specifications: Earnings and Education



Visual Insights:

- Model 1 (linear): Straight line fit, but residuals may be heteroskedastic
- Model 2 (log-linear): Best fit, captures curvature in original data
- Model 3 (log-log): Both axes logged, captures elasticity
- Model 4 (linear-log): Captures diminishing returns to education

Beyond cross-sectional analysis, logarithms are equally powerful for **time series data**.

Next, we explore how exponential growth becomes linear in logs.

9.4 Further Uses: Exponential Growth

Application: Modeling exponential growth in time series data

Many economic series grow **exponentially** over time:

$$x_t = x_0 \times (1 + r)^t$$

Where:

- x_0 = initial value
- r = constant growth rate
- t = time period

Taking logarithms:

$$\ln(x_t) = \ln(x_0) + \ln(1 + r) \times t \approx \ln(x_0) + r \times t$$

Key insight: Exponential growth in levels \rightarrow **linear growth in logs!**

Regression model:

$$\ln(x_t) = \beta_0 + \beta_1 \times t + \varepsilon$$

The slope β_1 directly estimates the growth rate r .

Example: S&P 500 stock index 1927-2019

In []:

```
# Load S&P 500 data
data_sp500 = pd.read_stata(GITHUB_DATA_URL + 'AED_SP500INDEX.DTA')

print("=*70")
print("S&P 500 INDEX DATA (1927-2019)")
print("=*70")
print(data_sp500[['year', 'sp500', 'lnsp500']].describe())

print("\nFirst and last years:")
print(data_sp500[['year', 'sp500', 'lnsp500']].head(3))
print("...")
print(data_sp500[['year', 'sp500', 'lnsp500']].tail(3))
```

```
=====
S&P 500 INDEX DATA (1927-2019)
=====

      year      sp500    lnsp500
count  93.00000  93.00000  93.00000
mean   1973.00000 473.664307  4.817428
std    26.99074  710.751831  1.801842
min   1927.00000  6.920000  1.934416
25%  1950.00000 23.770000  3.168424
50%  1973.00000 96.470001  4.569232
75%  1996.00000 740.739990 6.607650
max   2019.00000 3230.780029 8.080479

First and last years:
      year      sp500    lnsp500
0  1927.0  17.660000  2.871302
1  1928.0  24.350000  3.192532
2  1929.0  21.450001  3.065725
...
      year      sp500    lnsp500
90  2017.0 2673.610107  7.891185
91  2018.0 2506.850098  7.826782
92  2019.0 3230.780029  8.080479
```

In []:

```
# Estimate exponential growth model
print("=*70)
print("EXPONENTIAL GROWTH MODEL: ln(sp500) = β₀ + β₁(year)")
print("=*70)

model_sp500 = ols('lnsp500 ~ year', data=data_sp500).fit()
print(model_sp500.summary())

growth_rate = model_sp500.params['year']
print("\n" + "=*70)
print("INTERPRETATION")
print("=*70)
print(f"Estimated annual growth rate: {100*growth_rate:.4f}% per year")
print(f"\nThis means the S&P 500 grew at an average rate of {100*growth_rate:.2f}% per
year")
print(f"\nfrom 1927 to 2019 (not accounting for inflation or dividends).")
print(f"\nRule of 72: At {100*growth_rate:.2f}% annual growth,")
print(f"\nthe index doubles approximately every {72/(100*growth_rate):.1f} years.")
```

```

=====
EXPONENTIAL GROWTH MODEL: ln(sp500) = β₀ + β₁(year)
=====
              OLS Regression Results
=====
Dep. Variable:      lnsp500    R-squared:           0.958
Model:                 OLS    Adj. R-squared:        0.957
Method:                Least Squares   F-statistic:       2071.
Date:      Wed, 21 Jan 2026   Prob (F-statistic):  2.16e-64
Time:          00:01:48    Log-Likelihood:     -38.919
No. Observations:      93    AIC:                  81.84
Df Residuals:         91    BIC:                  86.90
Df Model:                   1
Covariance Type:    nonrobust
=====
            coef    std err      t      P>|t|      [0.025      0.975]
-----
Intercept   -124.0933    2.833   -43.798    0.000    -129.721    -118.465
year         0.0653    0.001    45.503    0.000      0.062      0.068
=====
Omnibus:             19.480   Durbin-Watson:        0.271
Prob(Omnibus):        0.000   Jarque-Bera (JB):    26.547
Skew:                  0.981   Prob(JB):        1.72e-06
Kurtosis:                 4.732   Cond. No.        1.45e+05
=====
```

Notes:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 1.45e+05. This might indicate that there are strong multicollinearity or other numerical problems.

=====
INTERPRETATION
=====

Estimated annual growth rate: 6.5337% per year

This means the S&P 500 grew at an average rate of 6.53% per year from 1927 to 2019 (not accounting for inflation or dividends).

Rule of 72: At 6.53% annual growth,
the index doubles approximately every 11.0 years.

Key Concept 9.6: Linearizing Exponential Growth

When a variable grows **exponentially** ($x_t = x_0(1+r)^t$), its logarithm grows **linearly**:

$$\ln(x_t) \approx \ln(x_0) + r \times t$$

This transformation is powerful because it converts a **nonlinear** growth pattern into a **linear** regression model, where the slope coefficient directly estimates the **constant growth rate** r .

Practical implication: To estimate the average growth rate of any exponentially growing series (GDP, stock prices, population), simply regress $\ln(x)$ on time. The slope is the growth rate.

Visualizing Exponential Growth

In []:

```
# Create visualization showing exponential vs linear in logs
fig, axes = plt.subplots(1, 2, figsize=(16, 6))

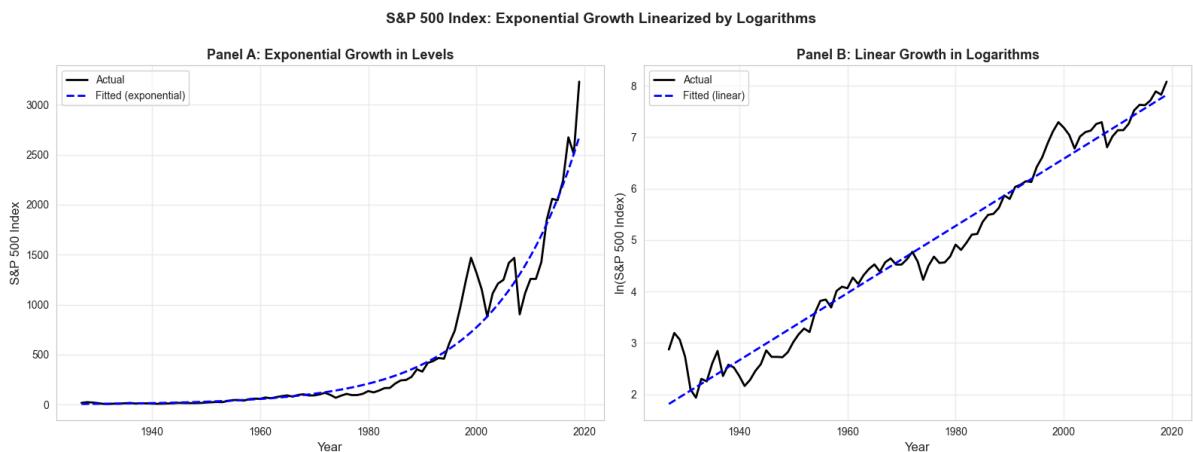
# Panel A: Exponential growth in levels
# Apply retransformation bias correction
n = len(data_sp500)
k = 2
MSE = np.sum(model_sp500.resid**2) / (n - k)
psp500 = np.exp(model_sp500.fittedvalues) * np.exp(MSE/2)

axes[0].plot(data_sp500['year'], data_sp500['sp500'], linewidth=2,
             label='Actual', color='black')
axes[0].plot(data_sp500['year'], psp500, linewidth=2, linestyle='--',
             label='Fitted (exponential)', color='blue')
axes[0].set_xlabel('Year', fontsize=12)
axes[0].set_ylabel('S&P 500 Index', fontsize=12)
axes[0].set_title('Panel A: Exponential Growth in Levels',
                  fontsize=13, fontweight='bold')
axes[0].legend()
axes[0].grid(True, alpha=0.3)

# Panel B: Linear growth in logs
axes[1].plot(data_sp500['year'], data_sp500['lnsp500'], linewidth=2,
             label='Actual', color='black')
axes[1].plot(data_sp500['year'], model_sp500.fittedvalues, linewidth=2,
             linestyle='--', label='Fitted (linear)', color='blue')
axes[1].set_xlabel('Year', fontsize=12)
axes[1].set_ylabel('ln(S&P 500 Index)', fontsize=12)
axes[1].set_title('Panel B: Linear Growth in Logarithms',
                  fontsize=13, fontweight='bold')
axes[1].legend()
axes[1].grid(True, alpha=0.3)

plt.suptitle('S&P 500 Index: Exponential Growth Linearized by Logarithms',
             fontsize=14, fontweight='bold', y=1.00)
plt.tight_layout()
plt.show()

print("\n■ Key Observation:")
print("  - Left panel: Exponential curve in levels (hard to model)")
print("  - Right panel: Straight line in logs (easy to model with OLS!)")
print("  - The slope of the line = average growth rate")
```



 Key Observation:

- Left panel: Exponential curve in levels (hard to model)
- Right panel: Straight line in logs (easy to model with OLS!)
- The slope of the line = average growth rate

Key Concept 9.7: The Rule of 72

The **Rule of 72** provides a quick estimate of **doubling time** for compound growth:

$$\text{Doubling time} \approx \frac{72}{r}$$

where r is the **percentage** growth rate. This approximation derives from the logarithmic identity: $\ln(2) \approx 0.693$, combined with $\ln(1+r) \approx r$ for small r .

Examples:

- S&P 500 at 6.5% growth → doubles every $72/6.5 \approx 11$ years
- GDP at 3% growth → doubles every $72/3 = 24$ years
- Population at 1% growth → doubles every $72/1 = 72$ years

Practical value: The Rule of 72 converts growth rates into an intuitive time horizon without needing a calculator.

| Key Takeaways

Key Takeaways:

1. **Natural logarithms** let us work with **proportionate changes** instead of absolute changes.
 - Key approximation: $\Delta \ln(x) \approx \Delta x/x$ (proportionate change)
 - $100 \times \Delta \ln(x) \approx$ percentage change in x
 - This approximation is excellent for small changes (< 10%)
2. **Four model specifications** give different interpretations:

Model	Specification	Interpretation of β_1
Linear	$y = \beta_0 + \beta_1 x$	$\Delta y / \Delta x$ (absolute change)
Log-linear	$\ln(y) = \beta_0 + \beta_1 x$	Semi-elasticity: $(\Delta y/y) / \Delta x$
Log-log	$\ln(y) = \beta_0 + \beta_1 \ln(x)$	Elasticity: $(\Delta y/y) / (\Delta x/x)$
Linear-log	$y = \beta_0 + \beta_1 \ln(x)$	$\Delta y / (\Delta x/x)$

3. Model selection depends on economic theory, data properties, and interpretation needs:

- R^2 comparison (higher is better, but not the only criterion)
- Economic theory should guide functional form choice
- Log-linear is most common in applied economics (earnings, prices)

4. Earnings-Education results illustrate the four specifications:

- **Linear:** Each year of education $\rightarrow \$5,021$ more earnings
- **Log-linear:** Each year of education $\rightarrow 13.1\%$ more earnings (best fit, $R^2 = 0.334$)
- **Log-log:** 1% more education $\rightarrow 1.48\%$ more earnings (elasticity)
- **Linear-log:** 1% more education $\rightarrow \$545$ more earnings

5. Exponential growth becomes linear in logs:

- If x grows exponentially: $x_t = x_0(1+r)^t$
- Then $\ln(x)$ grows linearly: $\ln(x_t) \approx \ln(x_0) + r \cdot t$
- Regression slope directly estimates the growth rate
- S&P 500: 6.5% annual growth (1927-2019), doubling every 11 years

6. When to use logarithmic transformations:

- Dependent variable is right-skewed (earnings, prices, firm size)
- Economic theory predicts percentage effects (elasticities)
- Multiplicative relationships between variables
- Exponential growth or decay patterns
- Not when variables can be zero or negative (\ln is undefined)

Python Tools Used:

- `numpy.log()` : Natural logarithm transformation
- `numpy.exp()` : Exponential function (inverse of log)
- `statsmodels.ols()` : OLS regression estimation
- `pandas` : Data manipulation and summary statistics

- `matplotlib` : Visualization of models and growth patterns

Next Steps:

- **Chapter 10:** Extend to multiple regression with several explanatory variables
 - **Chapter 11:** Statistical inference for multiple regression models
 - **Chapter 15:** Further variable transformations (polynomials, interactions)
-

Congratulations! You now understand how to choose between model specifications, interpret coefficients in log models, and estimate elasticities and semi-elasticities. These tools are fundamental to empirical work in labor economics, industrial organization, macroeconomics, and development economics!

I Practice Exercises

Exercise 1: Logarithmic Approximation Accuracy

The logarithmic approximation $\Delta \ln(x) \approx \Delta x/x$ works well for small changes. Test its accuracy:

a) Compute the exact proportionate change and the log approximation for x increasing from 100 to 101 (1% change). How close are they? b) Repeat for x increasing from 100 to 110 (10% change). Is the approximation still good? c) Repeat for x increasing from 100 to 150 (50% change). What happens to the approximation error? d) At what percentage change does the approximation error exceed 1 percentage point?

Exercise 2: Interpreting Semi-Elasticity

A researcher estimates the following log-linear model: $\ln(\text{wage}) = 1.50 + 0.085 \times \text{experience}$, where wage is hourly wage in dollars and experience is years of work experience.

a) Interpret the coefficient 0.085 in economic terms. b) What is the predicted percentage change in wages for a worker gaining 5 more years of experience? c) Calculate the exact percentage change using $100 \times (e^{(0.085 \times 5)} - 1)$. How does it compare to the approximation?

Exercise 3: Interpreting Elasticity

An economist estimates a demand function: $\ln(Q) = 5.2 - 1.3 \times \ln(P)$, where Q is quantity demanded and P is price.

- a) What is the price elasticity of demand? Is demand elastic or inelastic? b) If the price increases by 10%, what is the predicted percentage change in quantity demanded? c) Why is the log-log specification natural for demand analysis?

Exercise 4: Model Specification Choice

For each research question below, recommend the most appropriate model specification (linear, log-linear, log-log, or linear-log) and explain your reasoning:

- a) How much does an additional bedroom add to house price (in dollars)? b) What is the percentage return to each additional year of education? c) What is the price elasticity of demand for gasoline? d) How does GDP growth relate to years since a policy reform?

Exercise 5: Exponential Growth and Rule of 72

A country's real GDP per capita was \$5,000 in 1990 and grew at an average rate of 4% per year.

- a) Using the Rule of 72, approximately when did GDP per capita reach \$10,000? b) Write the exponential growth equation for this country's GDP. c) What regression model would you estimate to find the growth rate from data? Write the specification. d) If another country grew at 2% per year, how many times longer would it take to double its GDP?

Exercise 6: Comparing Model Specifications with Data

Using the earnings-education results from Section 9.3:

- a) A worker has 12 years of education. Using the linear model, predict their earnings. Using the log-linear model, predict their earnings (hint: you need to exponentiate). b) Repeat for a worker with 18 years of education. Which model gives a larger predicted difference between 12 and 18 years? c) The log-linear model predicts a 13.1% increase per year of education regardless of current earnings. Explain why this is economically more appealing than a fixed dollar increase. d) Why can't we directly compare R^2 values between the linear model ($R^2 = 0.289$) and the log-linear model ($R^2 = 0.334$)?

| Case Studies

Case Study: Logarithmic Models for Global Labor Productivity

In this case study, you'll apply logarithmic model specifications to analyze **cross-country labor productivity** — a central question in development economics. You'll

use the same Convergence Clubs dataset from earlier chapters, but now focus on how log transformations reveal economic relationships that linear models miss.

Research Question: How do logarithmic transformations improve our understanding of cross-country productivity relationships and growth patterns?

Background: Labor productivity varies enormously across countries — from less than 1,000 per worker in the poorest nations to over 100,000 in the richest. This extreme right-skewness makes logarithmic transformations essential for meaningful analysis. Development economists use semi-elasticities and elasticities to measure how factors like human capital and physical capital contribute to productivity differences.

Dataset: We'll use the **Mendez Convergence Clubs dataset** containing:

- **country:** Country name (108 countries)
- **year:** Year of observation (1990-2014)
- **lp:** Labor productivity (output per worker, in dollars)
- **rk:** Capital per worker (physical capital stock, in thousands of dollars)
- **hc:** Human capital index (based on years of schooling and returns to education)

In []:

```
# Load the Convergence Clubs dataset
url_mendez = "https://raw.githubusercontent.com/quarcs-lab/mendez2020-convergence-clubs-code-data/master/assets/dat.csv"
data_cc = pd.read_csv(url_mendez)

print("=*70")
print("CONVERGENCE CLUBS DATASET")
print("=*70")
print(f"Observations: {len(data_cc)}")
print(f"Countries: {data_cc['country'].nunique()}")
print(f"Years: {data_cc['year'].min():.0f} to {data_cc['year'].max():.0f}")
print(f"\nVariables: {list(data_cc.columns)}")

print("\nFirst 10 observations:")
print(data_cc[['country', 'year', 'lp', 'rk', 'hc']].head(10))
```

How to Use These Tasks

1. **Read** each task carefully before starting
2. **Write your code** in the provided cells (replace _____ blanks in guided tasks)
3. **Run your code** to see results
4. **Answer the questions** by interpreting your output
5. **Check your understanding** against the Key Concepts

Progressive difficulty:

- Tasks 1-2: **Guided** (fill in blanks with _____)

- Tasks 3-4: **Semi-guided** (partial code structure provided)
- Tasks 5-6: **Independent** (write from outline)

Tip: Type the code rather than copying — it helps reinforce the concepts!

Task 1: Explore Productivity Data (Guided)

Objective: Understand why logarithmic transformations are essential for cross-country productivity data.

Connection: Section 9.1 (Natural Logarithm Function)

Your task: Filter the data to 2014, compute summary statistics for productivity in levels and logs, and compare the distributions.

- What is the ratio of the highest to lowest labor productivity? What does this tell you about skewness?
- How does the standard deviation change after log transformation?
- Compare the mean and median in levels vs. logs. Which distribution is more symmetric?

In []:

```
# Task 1: Explore Productivity Data (Guided)
# Filter to 2014 cross-section
data_2014 = data_cc[data_cc['year'] == ____].copy()
print(f"Countries in 2014: {len(data_2014})")

# Create log-transformed variable
data_2014['ln_lp'] = np.log(____)

# Summary statistics: levels vs logs
print("\n" + "="*70)
print("LABOR PRODUCTIVITY: LEVELS VS. LOGS")
print("="*70)
print("\nIn levels (lp):")
print(data_2014['lp'].describe())
print(f"\nSkewness: {data_2014['lp'].skew():.3f}")

print("\nIn logarithms (ln_lp):")
print(data_2014['ln_lp'].describe())
print(f"\nSkewness: {data_2014['____'].skew():.3f}")

# Ratio of highest to lowest
print(f"\nMax/Min ratio: {data_2014['lp'].max() / data_2014['lp'].min():.1f}x")
```

Task 2: Log-Linear Model for Productivity (Guided)

Objective: Estimate a log-linear model to measure the semi-elasticity of productivity with respect to human capital.

Connection: Section 9.2 (Semi-Elasticities)

Your task: Estimate $\ln(lp) = \beta_0 + \beta_1 \times hc$ and interpret the coefficient as a semi-elasticity.

- a) What is the estimated semi-elasticity of productivity with respect to human capital?
 b) By what percentage does productivity increase for each additional unit of the human capital index? c) Is the coefficient statistically significant at the 5% level?

In []:

```
# Task 2: Log-Linear Model for Productivity (Guided)
# Estimate: ln(lp) = β₀ + β₁ × hc
model_hc = ols('_____ ~ _____', data=data_2014).fit()

print("=*70)
print("LOG-LINEAR MODEL: ln(productivity) ~ human capital")
print("=*70)
print(model_hc.summary())

# Interpret the semi-elasticity
beta_hc = model_hc.params['hc']
print(f"\nSemi-elasticity: {beta_hc:.4f}")
print(f"Interpretation: Each unit increase in human capital is associated with"
print(f" a {100*beta_hc:.1f}% _____ in labor productivity.")
print(f"\nR² = {model_hc.rsquared:.3f}")
```

Task 3: Comparing Model Specifications (Semi-guided)

Objective: Estimate all four model specifications using productivity and capital per worker, then compare.

Connection: Section 9.3 (Example with four models)

Your tasks:

- a) Estimate four models: linear ($lp \sim rk$), log-linear ($\ln_lp \sim rk$), log-log ($\ln_lp \sim \ln_rk$), and linear-log ($lp \sim \ln_rk$) b) Create a comparison table showing the specification, slope coefficient, interpretation, and R^2 for each model c) Which model provides the best fit? Which provides the most economically meaningful interpretation? d) Why might the log-log specification be particularly appropriate for the productivity-capital relationship?

```
In [ ]: # Task 3: Comparing Model Specifications (Semi-guided)
# Create log-transformed variables
data_2014['ln_rk'] = np.log(data_2014['rk'])

# Estimate four models (fill in the formulas)
m1_linear = ols('lp ~ rk', data=data_2014).fit()
m2_loglin = ols('ln_lp ~ rk', data=data_2014).fit()
m3_loglog = ols('ln_lp ~ ln_rk', data=data_2014).fit()
m4_linlog = ols('lp ~ ln_rk', data=data_2014).fit()

# Create comparison table
# Hint: Follow the pattern from Section 9.3
print("=*70")
print("MODEL COMPARISON: Productivity and Capital")
print("=*70")

# Your comparison table here
# ...
```

Key Concept 9.8: Functional Form and Cross-Country Comparisons

When analyzing cross-country data, **logarithmic models** are essential because:

- 1. Skewed distributions** — Economic variables like GDP, productivity, and capital vary by factors of 100x or more across countries. Log transformations compress this range.
- 2. Multiplicative relationships** — Production functions in economics are multiplicative ($Y = A \times K^{\alpha} \times L^{\beta}$), which become linear in logs.
- 3. Meaningful comparisons** — Percentage differences are more meaningful than absolute differences when comparing Malawi to the United States.

In practice: The log-log specification is standard in cross-country growth analysis because the slope coefficient directly estimates the **output elasticity of capital** — a key parameter in growth theory.

Task 4: Elasticity of Productivity with Respect to Capital (Semi-guided)

Objective: Estimate the elasticity of labor productivity with respect to capital and interpret it in the context of economic growth theory.

Connection: Section 9.2 (Elasticities)

Your tasks:

- a) Estimate the log-log model: $\ln(\text{lp}) = \beta_0 + \beta_1 \times \ln(\text{rk})$. Report β_1 and R^2 . b) Interpret β_1 as an elasticity. Is there evidence of diminishing returns to capital ($\beta_1 < 1$)? c) Construct a 95% confidence interval for the elasticity. Does it include 1? d) In growth theory, the output elasticity of capital is often assumed to be about 1/3. Test $H_0: \beta_1 = 0.33$ against $H_1: \beta_1 \neq 0.33$.

```
In [ ]: # Task 4: Elasticity of Productivity (Semi-guided)
# Use the log-log model from Task 3

print("=*70)
print("LOG-LOG MODEL: ln(productivity) ~ ln(capital per worker)")
print("=*70)
print(m3_loglog.summary())

# Elasticity and confidence interval
elasticity = m3_loglog.params['ln_rk']
ci = m3_loglog.conf_int().loc['ln_rk']
print(f"\nElasticity: {elasticity:.4f}")
print(f"95% CI: [{ci[0]:.4f}, {ci[1]:.4f}]")

# Test H0: beta = 0.33
# Your hypothesis test here
# ...
```

Task 5: Productivity Growth Rates (Independent)

Objective: Estimate exponential growth rates for labor productivity across countries and apply the Rule of 72.

Connection: Section 9.4 (Exponential Growth)

Your tasks:

- a) Compute the average labor productivity across all countries for each year (1990-2014) b) Estimate the exponential growth model: $\ln(\text{avg_lp}) = \beta_0 + \beta_1 \times \text{year}$. What is the estimated average annual growth rate? c) Apply the Rule of 72: approximately how many years does it take for average global labor productivity to double? d) Repeat the growth rate estimation for two regions or groups of countries (e.g., high-income vs. low-income). Do growth rates differ?

```
In [ ]: # Task 5: Productivity Growth Rates (Independent)
# Compute average productivity per year

# Your code here
# ...
```

Task 6: Development Policy Brief (Independent)

Objective: Synthesize your findings into a policy-relevant summary.

Connection: All sections

Your task: Write a 200-300 word summary analyzing cross-country labor productivity using logarithmic models. Your brief should include:

- 1. Data description:** How many countries, what time period, key variables
- 2. Model selection:** Which logarithmic specification best captures the productivity-capital relationship and why
- 3. Key findings:** Elasticity estimates, semi-elasticity of human capital, growth rates
- 4. Policy implications:** What do these results suggest for developing countries seeking to increase productivity?

Your Development Policy Brief

(Write your 200-300 word summary here)

Key Concept 9.9: Logarithmic Models in Development Economics

*Logarithmic model specifications are the **standard tool** in development economics for analyzing cross-country differences because:*

- **Semi-elasticities** measure the percentage return to factors like education and human capital — directly informing policy about where to invest
- **Elasticities** from log-log models estimate production function parameters (output elasticity of capital) — testing whether countries face diminishing returns
- **Growth rates** from log-time regressions enable comparisons across countries growing at very different speeds

The bottom line: Without logarithmic transformations, cross-country analysis would be dominated by a few rich outliers and miss the economic relationships that matter for development policy.

What You've Learned from This Case Study

Congratulations! You've applied logarithmic model specifications to real cross-country economic data.

Statistical Skills:

- Applied log transformations to highly skewed cross-country data
- Estimated and compared all four model specifications (linear, log-linear, log-log, linear-log)
- Interpreted semi-elasticities (human capital → productivity)
- Interpreted elasticities (capital → productivity, with diminishing returns)
- Estimated exponential growth rates and applied the Rule of 72

Economic Insights:

- Cross-country productivity distributions are highly right-skewed, requiring log transformations
- Human capital and physical capital both contribute to productivity, but with diminishing returns
- Log-log models connect directly to production function theory in economics
- Growth rates vary substantially across countries and regions

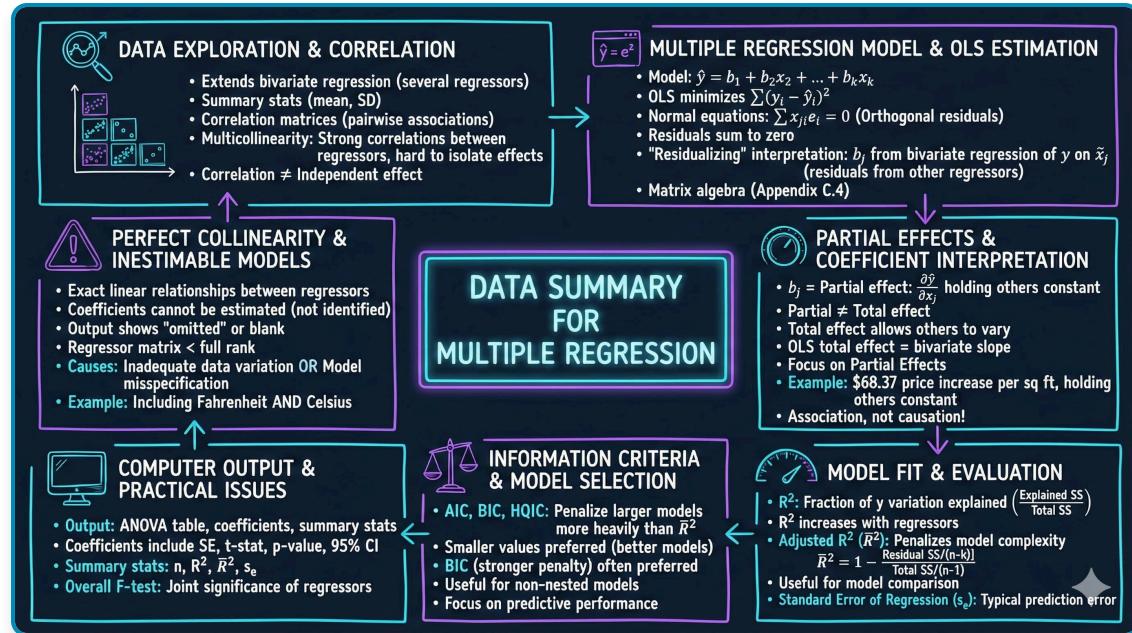
Next Steps:

- **Chapter 10:** Add multiple explanatory variables simultaneously (multiple regression)
- **Chapter 11:** Test joint hypotheses about capital AND human capital effects

Chapter 10: Data Summary for Multiple Regression

metricsAI: An Introduction to Econometrics with Python and AI in the Cloud

Carlos Mendez



This notebook provides an interactive introduction to multiple regression analysis. You'll learn how to work with multiple explanatory variables, interpret partial effects, assess model fit, and detect multicollinearity. All code runs directly in Google Colab without any local setup.

Open in Colab

| Chapter Overview

This chapter extends bivariate regression to the more realistic case where we want to predict an outcome using **multiple explanatory variables** simultaneously. Multiple regression allows us to estimate the partial effect of each variable while controlling for others—a crucial feature for empirical economic analysis.

Learning Objectives:

By the end of this chapter, you will be able to:

1. Extend bivariate regression concepts to multiple regression with several regressors
2. Interpret pairwise correlations and use them for exploratory data analysis
3. Understand the ordinary least squares (OLS) method for multiple regression
4. Interpret partial effects: how one regressor affects y while holding others constant
5. Distinguish between partial effects and total effects
6. Evaluate model fit using R-squared and adjusted R-squared
7. Understand information criteria (AIC, BIC) for model selection
8. Recognize when regression coefficients cannot be estimated (perfect collinearity)

Dataset used:

- **AED_HOUSE.DTA:** 29 houses sold in Davis, California (1999) with price, size, bedrooms, bathrooms, lot size, age, and month sold

Key economic question: What is the effect of house size on price **after controlling** for other characteristics like bedrooms, bathrooms, and age?

Chapter outline:

- 10.1 Example: House Price and Characteristics
- 10.2 Two-Way Scatterplots
- 10.3 Correlation Analysis
- 10.4 Multiple Regression Estimation
- 10.5 Partial Effects — The FWL Theorem
- 10.6 Model Fit Statistics
- 10.7 Model Comparison
- 10.8 Inestimable Models and Multicollinearity
- Key Takeaways
- Practice Exercises
- Case Studies

Estimated time: 60-75 minutes

Setup

First, we import the necessary Python packages and configure the environment for reproducibility. All data will stream directly from GitHub.

In [1]:

```
# Import required packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
from statsmodels.formula.api import ols
from scipy import stats
import random
import os

# Set random seeds for reproducibility
RANDOM_SEED = 42
random.seed(RANDOM_SEED)
np.random.seed(RANDOM_SEED)
os.environ['PYTHONHASHSEED'] = str(RANDOM_SEED)

# GitHub data URL
GITHUB_DATA_URL = "https://raw.githubusercontent.com/quarcs-lab/data-open/master/AED/"

# Set plotting style
sns.set_style("whitegrid")
plt.rcParams['figure.figsize'] = (10, 6)

print("Setup complete! Ready to analyze house price data.")
```

Setup complete! Ready to analyze house price data.

10.1: Example - House Price and Characteristics

We begin with a real estate dataset from Davis, California. Understanding house prices is a classic economic application because prices reflect both fundamental characteristics (size, bedrooms) and market conditions.

The dataset contains:

- **Price:** Sale price in dollars
- **Size:** House size in square feet
- **Bedrooms:** Number of bedrooms
- **Bathrooms:** Number of bathrooms
- **Lotsize:** Size of lot (1=small, 2=medium, 3=large)
- **Age:** House age in years
- **Monthsold:** Month of year house was sold

Economic motivation: A simple regression of price on bedrooms might find a positive relationship, but is this because bedrooms directly add value, or because houses with more bedrooms tend to be larger? Multiple regression helps us disentangle these effects.

In [2]:

```
# Load house price data
data_house = pd.read_stata(GITHUB_DATA_URL + 'AED_HOUSE.DTA')

# Display first few observations
print("First 10 observations:")
print(data_house[['price', 'size', 'bedrooms', 'bathrooms', 'lotsize', 'age',
'monthsold']].head(10))

# Display data summary
print("\nSummary statistics:")
print(data_house.describe())
```

First 10 observations:

	price	size	bedrooms	bathrooms	lotsize	age	monthsold
0	204000	1400	3	2.0	1	31.0	7
1	212000	1600	3	3.0	2	33.0	5
2	213000	1800	3	2.0	2	51.0	4
3	220000	1600	3	2.0	1	49.0	4
4	224500	2100	4	2.5	2	47.0	6
5	229000	1700	4	2.5	2	35.0	3
6	230000	2100	4	2.0	2	34.0	8
7	233000	1700	3	2.0	1	40.0	6
8	235000	1700	4	2.0	2	29.0	7
9	235000	1600	3	2.0	3	35.0	5

Summary statistics:

	price	size	bedrooms	bathrooms	lotsize	age	\
count	29.000000	29.000000	29.000000	29.000000	29.000000	29.000000	
mean	253910.344828	1882.758621	3.793103	2.206897	2.137931	36.413792	
std	37390.710695	398.272130	0.675030	0.341144	0.693034	7.118975	
min	204000.000000	1400.000000	3.000000	2.000000	1.000000	23.000000	
25%	233000.000000	1600.000000	3.000000	2.000000	2.000000	31.000000	
50%	244000.000000	1800.000000	4.000000	2.000000	2.000000	35.000000	
75%	270000.000000	2000.000000	4.000000	2.500000	3.000000	39.000000	
max	375000.000000	3300.000000	6.000000	3.000000	3.000000	51.000000	

	monthsold	list
count	29.000000	29.000000
mean	5.965517	257824.137931
std	1.679344	40860.264099
min	3.000000	199900.000000
25%	5.000000	239000.000000
50%	6.000000	245000.000000
75%	7.000000	269000.000000
max	8.000000	386000.000000

Bivariate vs. Multiple Regression

Let's compare a simple regression (price on bedrooms only) with a multiple regression (price on bedrooms AND size). This illustrates how controlling for other variables changes coefficient estimates.

Key insight: In the bivariate regression, the bedrooms coefficient captures both the direct effect of bedrooms and the indirect effect through correlation with size. In multiple regression, we isolate the **partial effect** of bedrooms holding size constant.

In [3]:

```
# Bivariate regression: price ~ bedrooms
model_bivariate = ols('price ~ bedrooms', data=data_house).fit()

print("=" * 70)
print("BIVARIATE REGRESSION: price ~ bedrooms")
print("=" * 70)
print(model_bivariate.summary())

# Multiple regression: price ~ bedrooms + size
model_multiple = ols('price ~ bedrooms + size', data=data_house).fit()

print("\n" + "=" * 70)
print("MULTIPLE REGRESSION: price ~ bedrooms + size")
print("=" * 70)
print(model_multiple.summary())

# Compare bedrooms coefficient
print("\n" + "=" * 70)
print("COEFFICIENT COMPARISON")
print("=" * 70)
print(f"Bedrooms coefficient (bivariate): ${model_bivariate.params['bedrooms']:.2f}")
print(f"Bedrooms coefficient (multiple): ${model_multiple.params['bedrooms']:.2f}")
print(f"Change: ${model_multiple.params['bedrooms'] - model_bivariate.params['bedrooms']:.2f}")
print("\nThe coefficient drops dramatically because bedrooms was capturing size effects.")
```

```

=====
BIVARIATE REGRESSION: price ~ bedrooms
=====
OLS Regression Results
=====
Dep. Variable:           price   R-squared:          0.183
Model:                 OLS     Adj. R-squared:      0.152
Method:                Least Squares  F-statistic:       6.030
Date:                  Wed, 21 Jan 2026  Prob (F-statistic): 0.0208
Time:                  15:16:42    Log-Likelihood:   -343.06
No. Observations:      29     AIC:                  690.1
Df Residuals:          27     BIC:                  692.9
Df Model:               1
Covariance Type:       nonrobust
=====

      coef    std err        t      P>|t|      [0.025      0.975]
-----
Intercept  1.641e+05  3.71e+04   4.423    0.000    8.8e+04  2.4e+05
bedrooms   2.367e+04  9637.976   2.456    0.021   3891.805  4.34e+04
=====
Omnibus:            23.468  Durbin-Watson:        0.345
Prob(Omnibus):       0.000  Jarque-Bera (JB):    35.285
Skew:                 1.939  Prob(JB):           2.18e-08
Kurtosis:              6.764  Cond. No.          23.8
=====

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```

```

=====
MULTIPLE REGRESSION: price ~ bedrooms + size
=====
OLS Regression Results
=====
Dep. Variable:           price   R-squared:          0.618
Model:                 OLS     Adj. R-squared:      0.589
Method:                Least Squares  F-statistic:       21.03
Date:                  Wed, 21 Jan 2026  Prob (F-statistic): 3.68e-06
Time:                  15:16:42    Log-Likelihood:   -332.03
No. Observations:      29     AIC:                  670.1
Df Residuals:          26     BIC:                  674.2
Df Model:               2
Covariance Type:       nonrobust
=====

      coef    std err        t      P>|t|      [0.025      0.975]
-----
Intercept  1.117e+05  2.76e+04   4.048    0.000    5.5e+04  1.68e+05
bedrooms   1553.4580  7846.866   0.198    0.845   -1.46e+04  1.77e+04
size        72.4081   13.300    5.444    0.000     45.070   99.746
=====
Omnibus:            0.516  Durbin-Watson:        1.230
Prob(Omnibus):       0.773  Jarque-Bera (JB):    0.609
Skew:                 -0.086  Prob(JB):           0.737
Kurtosis:              2.311  Cond. No.          1.21e+04
=====

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.21e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

```

```

=====
COEFFICIENT COMPARISON
=====
Bedrooms coefficient (bivariate): $23,667.30
Bedrooms coefficient (multiple):   $1,553.46

```

Change: \$-22,113.84

The coefficient drops dramatically because bedrooms was capturing size effects.

Key Concept 10.1: Partial Effects vs. Total Effects in Multiple Regression

In bivariate regression, the bedrooms coefficient (23,667) captures both the direct effect of bedrooms and the indirect effect through the bedrooms coefficient drop to 1,553 — the **partial effect** holding size constant. This dramatic change illustrates why controlling for confounders is essential for isolating individual variable effects.

10.2: Two-Way Scatterplots

Before running multiple regression, it's useful to visualize pairwise relationships between variables. A `scatterplot matrix` shows all two-way scatterplots simultaneously.

What to look for:

- Strong linear relationships (potential predictors of price)
- Correlation between explanatory variables (potential multicollinearity)
- Outliers or non-linear patterns

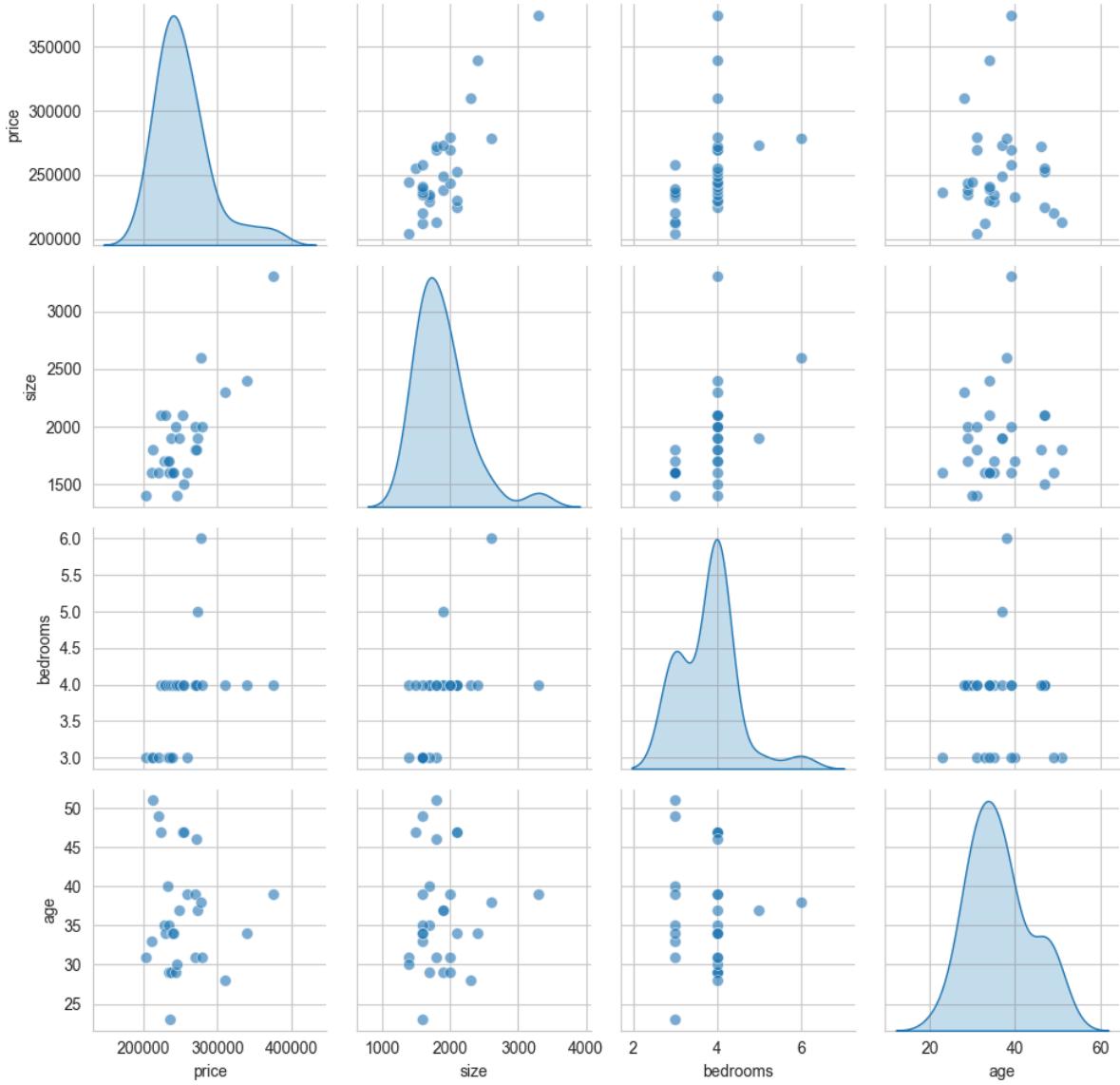
The diagonal shows the distribution of each variable using kernel density estimates (KDE).

In [4]:

```
# Create scatterplot matrix
plot_vars = ['price', 'size', 'bedrooms', 'age']
g = sns.pairplot(data_house[plot_vars], diag_kind='kde', plot_kws={'alpha': 0.6, 's': 50})
g.fig.suptitle('Figure 10.1: Scatterplot Matrix - House Price Data',
               fontsize=14, fontweight='bold', y=1.00)
plt.tight_layout()
plt.show()

print("Scatterplot matrix created.")
print("Notice: Price shows strongest relationship with Size.")
```

Figure 10.1: Scatterplot Matrix - House Price Data



Scatterplot matrix created.
Notice: Price shows strongest relationship with Size.

Key Concept 10.2: Exploratory Data Analysis with Scatterplot Matrices

Pairwise scatterplot matrices display all two-way relationships simultaneously, revealing linear associations, nonlinearities, clusters, and outliers before formal modeling. They also highlight potential multicollinearity: if two regressors are tightly correlated (e.g., size and bedrooms), their individual effects may be hard to separate in a regression.

10.3: Correlation Analysis

The **correlation coefficient** measures the strength of linear association between two variables, ranging from -1 (perfect negative) to +1 (perfect positive).

Correlation matrix insights:

- Price is most correlated with Size ($r = 0.79$), then Bedrooms ($r = 0.43$)
- Size and Bedrooms are correlated ($r = 0.52$), which can cause multicollinearity
- Correlation \neq causation (merely shows association)

A correlation heatmap provides visual representation with color intensity showing strength of correlation.

In [5]:

```
# Calculate correlation matrix
corr_vars = ['price', 'size', 'bedrooms', 'bathrooms', 'lotsize', 'age', 'monthsold']
corr_matrix = data_house[corr_vars].corr()

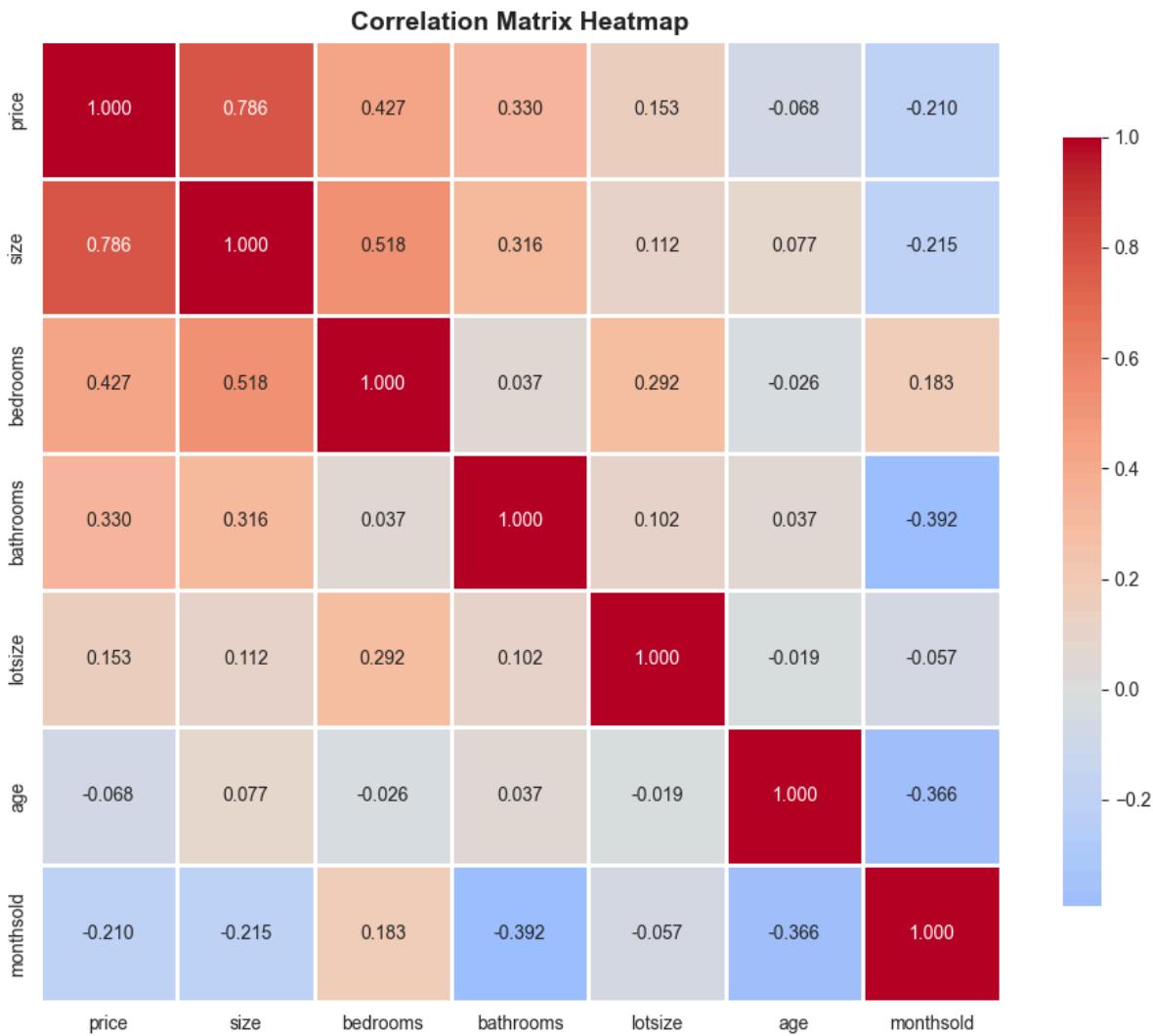
print("Correlation Matrix:")
print(corr_matrix)

# Visualize correlation matrix as heatmap
fig, ax = plt.subplots(figsize=(10, 8))
sns.heatmap(corr_matrix, annot=True, fmt='.3f', cmap='coolwarm', center=0,
            square=True, linewidths=1, cbar_kws={"shrink": 0.8})
ax.set_title('Correlation Matrix Heatmap', fontsize=14, fontweight='bold')
plt.tight_layout()
plt.show()

print("\nKey observations:")
print(f" - Price-Size correlation: {corr_matrix.loc['price', 'size']:.3f} (strongest predictor)")
print(f" - Price-Bedrooms correlation: {corr_matrix.loc['price', 'bedrooms']:.3f}")
print(f" - Size-Bedrooms correlation: {corr_matrix.loc['size', 'bedrooms']:.3f} (multicollinearity concern)")
```

Correlation Matrix:

	price	size	bedrooms	bathrooms	lotsize	age	monthsold
price	1.000000	0.785782	0.427275	0.329793	0.153479	-0.068015	-0.209985
size	0.785782	1.000000	0.517630	0.316338	0.112437	0.076925	-0.214511
bedrooms	0.427275	0.517630	1.000000	0.037435	0.292206	-0.026140	0.182512
bathrooms	0.329793	0.316338	0.037435	1.000000	0.101575	0.037018	-0.392310
lotsize	0.153479	0.112437	0.292206	0.101575	1.000000	-0.019220	-0.057140
age	-0.068015	0.076925	-0.026140	0.037018	-0.019220	1.000000	0.366207
monthsold	-0.209985	-0.214511	0.182512	-0.392310	-0.057140	-0.366207	1.000000



Key observations:

- Price-Size correlation: 0.786 (strongest predictor)
- Price-Bedrooms correlation: 0.427
- Size-Bedrooms correlation: 0.518 (multicollinearity concern)

Key Concept 10.3: Correlation vs. Causation in Multivariate Analysis

High bivariate correlation (e.g., bedrooms-price, $r = 0.43$) may diminish or vanish after controlling for confounders. In our data, bedrooms correlate with price largely because bigger houses have more bedrooms. Multiple regression isolates each variable's partial contribution, revealing that size — not bedrooms — drives most of the price variation.

Having explored the data visually and through correlations, we now estimate the formal multiple regression model to quantify partial effects.

10.4: Multiple Regression Estimation

Now we estimate the **full multiple regression model** with all available predictors. The regression equation is:

$$\widehat{\text{price}} = b_1 + b_2 \times \text{size} + b_3 \times \text{bedrooms} + b_4 \times \text{bathrooms} + b_5 \times \text{lotsize} + b_6 \times \text{age} + b_7 \times \text{monthsold}$$

Ordinary Least Squares (OLS) chooses coefficients b_1, \dots, b_7 to minimize the sum of squared residuals:

$$\min \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

where y_i is the actual price and \hat{y}_i is the predicted price.

In [6]:

```
# Estimate full multiple regression model
model_full = ols('price ~ size + bedrooms + bathrooms + lotsize + age + monthsold',
                 data=data_house).fit()

print("=" * 70)
print("FULL MULTIPLE REGRESSION MODEL")
print("=" * 70)
print(model_full.summary())
```

```

=====
FULL MULTIPLE REGRESSION MODEL
=====
                OLS Regression Results
=====
Dep. Variable:          price    R-squared:           0.651
Model:                 OLS     Adj. R-squared:      0.555
Method:                Least Squares   F-statistic:        6.826
Date:      Wed, 21 Jan 2026   Prob (F-statistic):  0.000342
Time:          15:16:45   Log-Likelihood:     -330.74
No. Observations:      29     AIC:                  675.5
Df Residuals:         22     BIC:                  685.1
Df Model:              6
Covariance Type:    nonrobust
=====

      coef    std err       t      P>|t|      [0.025]     [0.975]
-----
Intercept  1.378e+05  6.15e+04    2.242    0.035    1.03e+04  2.65e+05
size        68.3694    15.389     4.443    0.000     36.454   100.285
bedrooms    2685.3151  9192.526    0.292    0.773   -1.64e+04  2.17e+04
bathrooms   6832.8800  1.57e+04    0.435    0.668   -2.58e+04  3.94e+04
lotsize      2303.2214  7226.535    0.319    0.753   -1.27e+04  1.73e+04
age        -833.0386   719.335   -1.158    0.259   -2324.847  658.770
monthsold   -2088.5036  3520.898   -0.593    0.559   -9390.399  5213.392
-----
Omnibus:            1.317   Durbin-Watson:      1.259
Prob(Omnibus):      0.518   Jarque-Bera (JB):  0.980
Skew:                 0.151   Prob(JB):        0.612
Kurtosis:             2.152   Cond. No.       2.59e+04
=====
```

Notes:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 2.59e+04. This might indicate that there are strong multicollinearity or other numerical problems.

Coefficient Interpretation with Confidence Intervals

Each regression coefficient represents a **partial effect**: the expected change in price when that variable increases by one unit, **holding all other variables constant**.

Example interpretation (Size coefficient):

- Coefficient $\approx \$68.37$ per square foot
- Interpretation: A one square foot increase in house size is associated with a $\$68.37$ increase in price, holding bedrooms, bathrooms, lot size, age, and month sold constant.

The 95% confidence interval tells us the range of plausible values for each coefficient.

In [7]:

```
# Display coefficients with 95% confidence intervals
conf_int = model_full.conf_int(alpha=0.05)
coef_table = pd.DataFrame({
    'Coefficient': model_full.params,
    'Std. Error': model_full.bse,
    'CI Lower': conf_int.iloc[:, 0],
    'CI Upper': conf_int.iloc[:, 1],
    't-statistic': model_full.tvalues,
    'p-value': model_full.pvalues
})

print("Coefficients with 95% Confidence Intervals:")
print(coef_table)

print("\nKey result: Size is the only statistically significant predictor (p < 0.05).")
```

Coefficients with 95% Confidence Intervals:				
	Coefficient	Std. Error	CI Lower	CI Upper \
Intercept	137791.065699	61464.951869	10320.557398	265261.573999
size	68.369419	15.389472	36.453608	100.285230
bedrooms	2685.315122	9192.525674	-16378.816300	21749.446543
bathrooms	6832.880015	15721.191544	-25770.875723	39436.635753
lotsize	2303.221371	7226.535205	-12683.695364	17290.138107
age	-833.038602	719.334544	-2324.847139	658.769936
monthsold	-2088.503625	3520.897859	-9390.398871	5213.391620

	t-statistic	p-value
Intercept	2.241783	0.035387
size	4.442610	0.000205
bedrooms	0.292119	0.772932
bathrooms	0.434629	0.668065
lotsize	0.318717	0.752947
age	-1.158068	0.259254
monthsold	-0.593174	0.559114

Key result: Size is the only statistically significant predictor (p < 0.05).

Key Concept 10.4: Interpreting Partial Effects in Multiple Regression

Each coefficient b_j measures the expected change in y when x_j increases by one unit, **holding all other regressors constant**. For example, a size coefficient of 68.37 means each additional square foot is associated with a 68.37 price increase, controlling for bedrooms, bathrooms, lot size, age, and month sold. Statistical significance is assessed through confidence intervals and t-tests.

| 10.5: Partial Effects - The FWL Theorem

The **Frisch-Waugh-Lovell (FWL) Theorem** states that the coefficient on any variable in multiple regression equals the coefficient from a bivariate regression of y on the

residualized version of that variable.

Demonstration:

1. Regress `size` on all other variables, obtain residuals $\tilde{\text{size}}$
2. Regress `price` on $\tilde{\text{size}}$ only
3. The coefficient will exactly match the `size` coefficient from the full multiple regression

Intuition: The residual $\tilde{\text{size}}$ represents the variation in size that is **not explained** by other variables. This is why multiple regression isolates partial effects.

In [8]:

```
# Step 1: Regress size on all other variables
model_size_on_others = ols('size ~ bedrooms + bathrooms + lotsize + age + monthsold',
                           data=data_house).fit()
resid_size = model_size_on_others.resid

# Step 2: Regress price on residualized size
data_house['resid_size'] = resid_size
model_price_on_resid = ols('price ~ resid_size', data=data_house).fit()

# Compare coefficients
print("=" * 70)
print("DEMONSTRATION: FWL THEOREM (Partial Effects)")
print("=" * 70)
print(f"Size coefficient from FULL multiple regression:\n{model_full.params['size']:.10f}")
print(f"Coefficient on residualized size (bivariate):\n{model_price_on_resid.params['resid_size']:.10f}")
print(f"Difference (numerical precision):\n{abs(model_full.params['size'] - model_price_on_resid.params['resid_size']):.15f}")
print("\nThese coefficients are identical! This proves the partial effect interpretation.")

=====
```

```
DEMONSTRATION: FWL THEOREM (Partial Effects)
=====
Size coefficient from FULL multiple regression: 68.3694189767
Coefficient on residualized size (bivariate): 68.3694189767
Difference (numerical precision): 0.00000000000057
```

These coefficients are identical! This proves the partial effect interpretation.

Key Concept 10.5: The Frisch-Waugh-Lovell (FWL) Theorem

The partial effect of x_j in a multiple regression equals the slope from a bivariate regression of y on \tilde{x}_j , where \tilde{x}_j is the residual from regressing x_j on all other regressors. Intuitively, \tilde{x}_j captures the variation in x_j that is independent of the other variables — this is exactly what multiple regression uses to estimate partial effects.

Now that we understand partial effects and the FWL theorem, let's evaluate how well the overall regression model fits the data.

| 10.6: Model Fit Statistics

Several statistics summarize how well the regression model fits the data:

R-squared (R^2):

- Fraction of variation in y explained by the regressors
- Formula: $R^2 = \frac{\text{Explained SS}}{\text{Total SS}} = 1 - \frac{\text{Residual SS}}{\text{Total SS}}$
- Range: 0 to 1 (higher is better fit)
- **Problem:** Always increases when adding variables (even irrelevant ones)

Adjusted R-squared (\bar{R}^2):

- Penalizes model complexity (number of parameters k)
- Formula: $\bar{R}^2 = 1 - \frac{\text{RSS}/(n-k)}{\text{TSS}/(n-1)}$
- Can decrease when adding unhelpful variables
- Preferred for model comparison

Root MSE (Standard error of regression):

- Typical size of prediction error
- Formula: $s_e = \sqrt{\frac{1}{n-k} \sum (y_i - \hat{y}_i)^2}$
- Same units as y (dollars in our case)

In [9]:

```
# Calculate and display model fit statistics
n = len(data_house)
k = len(model_full.params) # includes intercept
df = n - k

print("=" * 70)
print("MODEL FIT STATISTICS")
print("=" * 70)
print(f"Sample size (n): {n}")
print(f"Number of parameters (k): {k}")
print(f"Degrees of freedom (n-k): {df}")
print(f"\nR-squared: {model_full.rsquared:.6f}")
print(f"Adjusted R-squared: {model_full.rsquared_adj:.6f}")
print(f"Root MSE: ${np.sqrt(model_full.mse_resid):,.2f}")

# Verify  $R^2 = [\text{Corr}(y, \hat{y})]^2$ 
predicted = model_full.fittedvalues
corr_y_yhat = np.corrcoef(data_house['price'], predicted)[0, 1]
print(f"\nVerification:  $R^2 = [\text{Corr}(y, \hat{y})]^2$ ")
print(f"Correlation(y, \hat{y}): {corr_y_yhat:.6f}")
print(f"[\text{Correlation}(y, \hat{y})]^2: {corr_y_yhat**2:.6f}")
print(f" $R^2$  from model: {model_full.rsquared:.6f}")
print(f"Match: {np.isclose(corr_y_yhat**2, model_full.rsquared)}")
```

```
=====
MODEL FIT STATISTICS
=====
Sample size (n): 29
Number of parameters (k): 7
Degrees of freedom (n-k): 22

R-squared: 0.650553
Adjusted R-squared: 0.555249
Root MSE: $24,935.73

Verification:  $R^2 = [\text{Corr}(y, \hat{y})]^2$ 
Correlation(y, \hat{y}): 0.806569
[\text{Correlation}(y, \hat{y})]^2: 0.650553
 $R^2$  from model: 0.650553
Match: True
```

Information Criteria (AIC and BIC)

Akaike Information Criterion (AIC) and **Bayesian Information Criterion (BIC)** are more sophisticated measures that penalize model complexity:

$$\text{AIC} = n \times \ln(\hat{\sigma}_e^2) + n(1 + \ln 2\pi) + 2k$$

$$\text{BIC} = n \times \ln(\hat{\sigma}_e^2) + n(1 + \ln 2\pi) + k \times \ln(n)$$

Key points:

- Lower values are better (unlike R^2)
- BIC penalizes complexity more heavily than AIC
- Useful for comparing non-nested models

- Different software packages may use different conventions (scaling by n)

In [10]:

```
# Calculate information criteria
print("=" * 70)
print("INFORMATION CRITERIA")
print("=" * 70)

# AIC and BIC from statsmodels
print(f"AIC (statsmodels): {model_full.aic:.4f}")
print(f"BIC (statsmodels): {model_full.bic:.4f}")

# Manual calculation (Stata convention)
rss = np.sum(model_full.resid ** 2)
aic_stata = n * np.log(rss/n) + n * (1 + np.log(2*np.pi)) + 2*k
bic_stata = n * np.log(rss/n) + n * (1 + np.log(2*np.pi)) + k*np.log(n)

print(f"\nAIC (Stata convention): {aic_stata:.4f}")
print(f"BIC (Stata convention): {bic_stata:.4f}")
print("\nNote: Different conventions yield different values, but ranking is consistent.")
```

```
=====
INFORMATION CRITERIA
=====
AIC (statsmodels): 675.4824
BIC (statsmodels): 685.0535

AIC (Stata convention): 675.4824
BIC (Stata convention): 685.0535
```

Note: Different conventions yield different values, but ranking is consistent.

Key Concept 10.6: Model Selection with Adjusted R-squared vs. Information Criteria

Adjusted R² penalizes complexity mildly by dividing sums of squares by degrees of freedom. Information criteria (AIC, BIC) impose stronger penalties: $BIC = n \ln(\hat{\sigma}_e^2) + k \ln(n)$. Smaller AIC/BIC values indicate better models. BIC is generally preferred because its penalty grows with sample size, favoring more parsimonious specifications.

10.7: Model Comparison

It's often useful to compare multiple model specifications side-by-side. Here we compare:

- **Simple model:** Price predicted by size only
- **Full model:** Price predicted by all variables

Key comparison points:

- How much does R² improve?

- Does adjusted R² improve (accounting for added complexity)?
- How do coefficient estimates change?

Economic interpretation: If adding 5 more variables only modestly improves fit, the simple model may be preferred (parsimony principle).

```
In [11]: # Estimate simple model (size only)
model_simple = ols('price ~ size', data=data_house).fit()

# Create comparison table
print("=" * 70)
print("MODEL COMPARISON: Simple vs. Full")
print("=" * 70)

comparison_stats = pd.DataFrame({
    'Model': ['Simple (size only)', 'Full (all variables)'],
    'R2': [model_simple.rsquared, model_full.rsquared],
    'Adj R2': [model_simple.rsquared_adj, model_full.rsquared_adj],
    'AIC': [model_simple.aic, model_full.aic],
    'BIC': [model_simple.bic, model_full.bic],
    'N': [n, n]
})

print(comparison_stats.to_string(index=False))

print("\nInterpretation:")
print(" - R2 increases from {:.3f} to {:.3f} (+{:.3f})".format(
    model_full.rsquared - model_simple.rsquared))
print(" - Adj R2 DECREASES from {:.3f} to {:.3f} ({:.3f})".format(
    model_full.rsquared_adj - model_simple.rsquared_adj))
print(" - This suggests the added variables don't improve fit enough to justify complexity.")
print(" - Simple model may be preferred (parsimony principle.)")
```

```
=====
MODEL COMPARISON: Simple vs. Full
=====
      Model      R2  Adj R2      AIC      BIC  N
Simple (size only)  0.617453  0.603285  668.106844  670.841436  29
Full (all variables)  0.650553  0.555249  675.482401  685.053472  29
```

Interpretation:

- R² increases from 0.617 to 0.651 (+0.033)
- Adj R² DECREASES from 0.603 to 0.555 (-0.048)
- This suggests the added variables don't improve fit enough to justify complexity.
- Simple model may be preferred (parsimony principle).

Key Concept 10.7: The Parsimony Principle

Simpler models are preferred unless additional variables meaningfully improve fit. In our house price example, adding five variables beyond size barely increased R² (0.618 → 0.651) while adjusted R² actually fell (0.603 → 0.555). Check adjusted R², AIC, and BIC — if they don't improve, the simpler model is preferred.

Having compared models, we now turn to a critical pitfall: when regressors are too closely related to separate their individual effects.

10.8: Inestimable Models and Multicollinearity

Perfect multicollinearity occurs when one regressor is an exact linear combination of others. In this case, OLS cannot estimate all coefficients (the model is "inestimable").

Example: If we create `size_twice = 2 * size` and include both `size` and `size_twice` as regressors, the model is perfectly collinear.

Variance Inflation Factor (VIF) detects multicollinearity:

- VIF measures how much a variable's variance is inflated due to correlation with other regressors
- Formula: $VIF_j = \frac{1}{1-R_j^2}$ where R_j^2 is from regressing x_j on all other x 's
- **Rule of thumb:** $VIF > 10$ indicates problematic multicollinearity

Consequences of high multicollinearity:

- Large standard errors (imprecise estimates)
- Unstable coefficients (small data changes → big estimate changes)
- Difficulty interpreting individual effects

In [12]:

```
# Demonstrate perfect multicollinearity
print("=" * 70)
print("DEMONSTRATION: Perfect Multicollinearity")
print("=" * 70)

# Create a perfectly collinear variable
data_house['size_twice'] = 2 * data_house['size']

print("Creating variable: size_twice = 2 * size")
print("Attempting to estimate: price ~ size + size_twice + bedrooms\n")

try:
    model_collinear = ols('price ~ size + size_twice + bedrooms', data=data_house).fit()
    print("Model estimated (software automatically dropped one variable):")
    print(model_collinear.summary())
except Exception as e:
    print(f"Error: {type(e).__name__}")
    print(f"Message: {str(e)}")
```

```

=====
DEMONSTRATION: Perfect Multicollinearity
=====
Creating variable: size_twice = 2 × size
Attempting to estimate: price ~ size + size_twice + bedrooms

Model estimated (software automatically dropped one variable):
    OLS Regression Results
=====
Dep. Variable:           price      R-squared:       0.618
Model:                 OLS        Adj. R-squared:   0.589
Method:                Least Squares  F-statistic:     21.03
Date:      Wed, 21 Jan 2026  Prob (F-statistic): 3.68e-06
Time:      15:16:45          Log-Likelihood: -332.03
No. Observations:      29          AIC:             670.1
Df Residuals:          26          BIC:             674.2
Df Model:               2
Covariance Type:       nonrobust
=====

      coef    std err      t      P>|t|      [0.025]      [0.975]
-----
Intercept  1.117e+05  2.76e+04   4.048    0.000    5.5e+04  1.68e+05
size       14.4816    2.660     5.444    0.000    9.014    19.949
size_twice 28.9633    5.320     5.444    0.000   18.028    39.898
bedrooms   1553.4580  7846.866    0.198    0.845  -1.46e+04  1.77e+04
=====
Omnibus:            0.516  Durbin-Watson:       1.230
Prob(Omnibus):      0.773  Jarque-Bera (JB):  0.609
Skew:              -0.086  Prob(JB):         0.737
Kurtosis:           2.311  Cond. No.        1.96e+17
=====

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 1.39e-26. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

```

| Variance Inflation Factors (VIF)

Now let's calculate VIF for each variable in our full model to check for multicollinearity problems.

In [13]:

```
# Calculate VIF for each variable in the full model
from statsmodels.stats.outliers_influence import variance_inflation_factor

X = data_house[['size', 'bedrooms', 'bathrooms', 'lotsize', 'age', 'monthsold']]
vif_data = pd.DataFrame()
vif_data["Variable"] = X.columns
vif_data["VIF"] = [variance_inflation_factor(X.values, i) for i in range(X.shape[1])]

print("=" * 70)
print("VARIANCE INFLATION FACTORS (VIF)")
print("=" * 70)
print(vif_data.to_string(index=False))
print("\nInterpretation:")
print(" - VIF > 10: Problematic multicollinearity")
print(" - VIF 5-10: Moderate multicollinearity")
print(" - VIF < 5: Low multicollinearity")

max_vif = vif_data['VIF'].max()
if max_vif > 10:
    print(f"\nWarning: Maximum VIF = {max_vif:.2f} indicates multicollinearity issues.")
elif max_vif > 5:
    print(f"\nNote: Maximum VIF = {max_vif:.2f} shows moderate multicollinearity.")
else:
    print(f"\nGood: Maximum VIF = {max_vif:.2f} - no serious multicollinearity detected.")
```

```
=====
VARIANCE INFLATION FACTORS (VIF)
=====
Variable      VIF
size        40.133832
bedrooms    57.819254
bathrooms   34.741906
lotsize     11.969605
age         21.024092
monthsold   12.795557

Interpretation:
 - VIF > 10: Problematic multicollinearity
 - VIF 5-10: Moderate multicollinearity
 - VIF < 5: Low multicollinearity

Warning: Maximum VIF = 57.82 indicates multicollinearity issues.
```

Key Concept 10.8: Detecting Multicollinearity with VIF

The Variance Inflation Factor (VIF) quantifies how much a coefficient's variance is inflated due to correlation with other regressors. $VIF_j = 1/(1 - R_j^2)$, where R_j^2 is from regressing x_j on all other regressors.

A VIF above 5 suggests moderate concern; above 10 indicates severe multicollinearity that inflates standard errors and destabilizes estimates. Perfect collinearity ($VIF \rightarrow \infty$) makes coefficients inestimable.

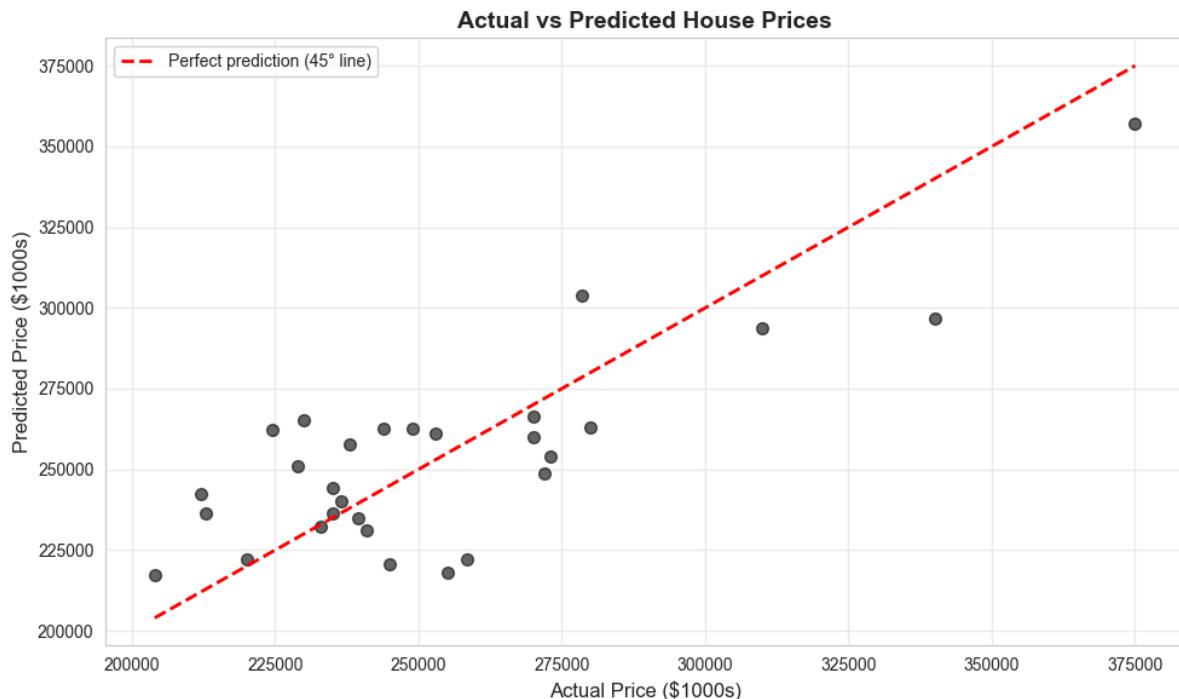
Visualization: Actual vs. Predicted Values

A plot of actual vs. predicted values helps visualize model fit. Points close to the 45-degree line indicate accurate predictions.

In [14]:

```
# Create actual vs predicted plot
fig, ax = plt.subplots(figsize=(10, 6))
ax.scatter(data_house['price'], model_full.fittedvalues, alpha=0.6, s=50, color='black')
ax.plot([data_house['price'].min(), data_house['price'].max()],
        [data_house['price'].min(), data_house['price'].max()],
        'r--', linewidth=2, label='Perfect prediction (45° line)')
ax.set_xlabel('Actual Price ($1000s)', fontsize=12)
ax.set_ylabel('Predicted Price ($1000s)', fontsize=12)
ax.set_title('Actual vs Predicted House Prices', fontsize=14, fontweight='bold')
ax.legend()
ax.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()

print("Points close to the red line indicate accurate predictions.")
```



Points close to the red line indicate accurate predictions.

Visualization: Residual Plot

A **residual plot** (residuals vs. fitted values) helps diagnose model problems:

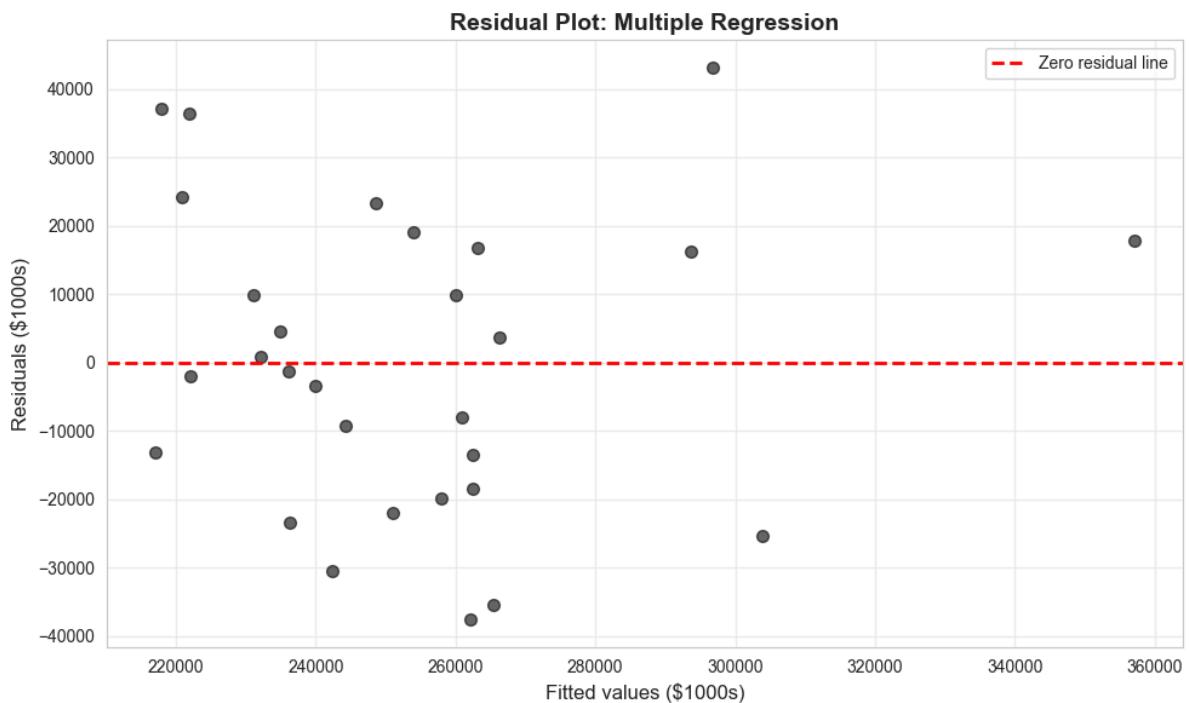
- **Random scatter around zero:** Good (model assumptions satisfied)
- **Patterns (curves, funnels):** Bad (model misspecification or heteroskedasticity)

- **Outliers:** Investigate unusual observations

In [15]:

```
# Create residual plot
fig, ax = plt.subplots(figsize=(10, 6))
ax.scatter(model_full.fittedvalues, model_full.resid, alpha=0.6, s=50, color='black')
ax.axhline(y=0, color='red', linestyle='--', linewidth=2, label='Zero residual line')
ax.set_xlabel('Fitted values ($1000s)', fontsize=12)
ax.set_ylabel('Residuals ($1000s)', fontsize=12)
ax.set_title('Residual Plot: Multiple Regression', fontsize=14, fontweight='bold')
ax.legend()
ax.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()

print("Random scatter around zero suggests model assumptions are reasonable.")
```



Random scatter around zero suggests model assumptions are reasonable.

Visualization: Coefficient Plot with Confidence Intervals

A **coefficient plot** displays estimated coefficients with their 95% confidence intervals.

This makes it easy to see:

- Which coefficients are significantly different from zero (CI doesn't include zero)
- Relative magnitude of effects
- Precision of estimates (narrow vs. wide CIs)

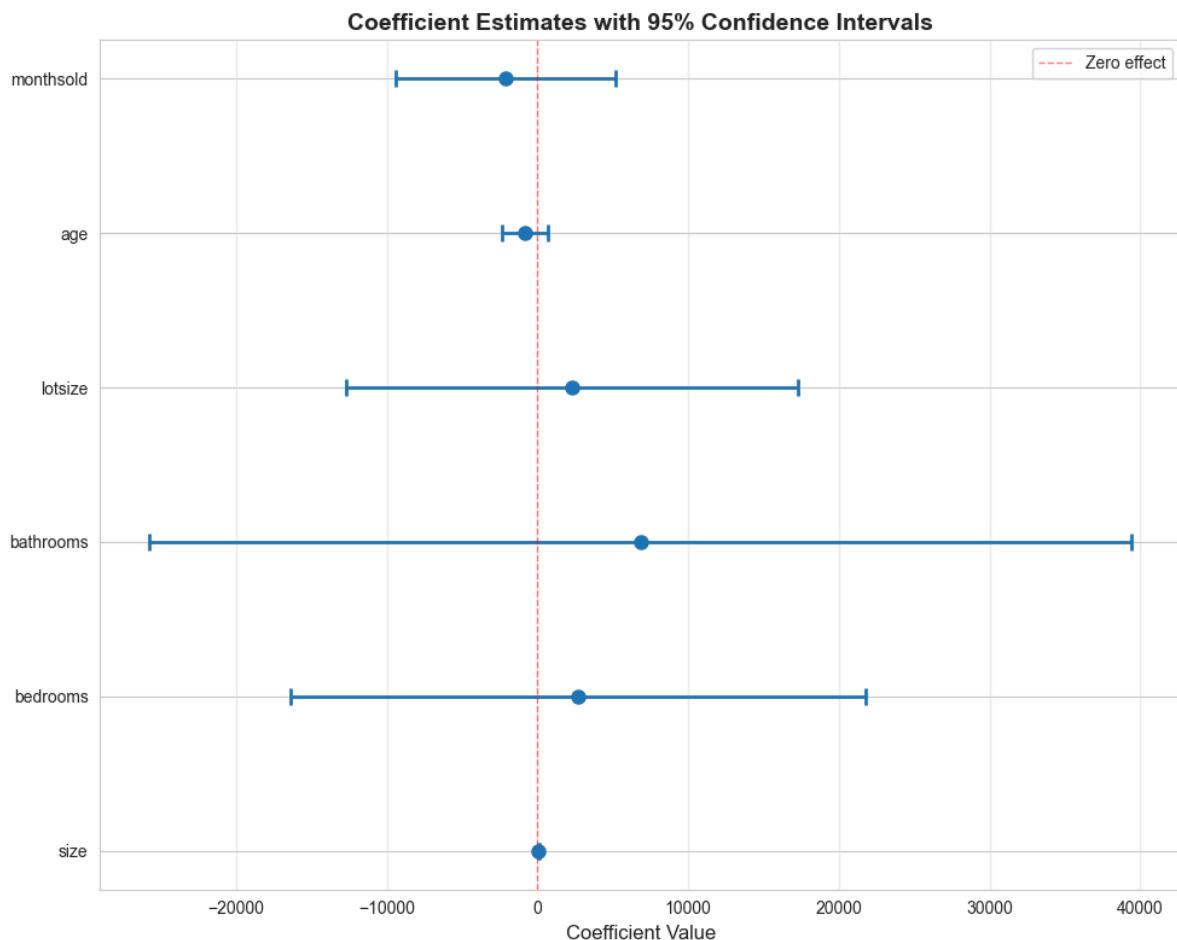
In [16]:

```
# Create coefficient plot with confidence intervals
fig, ax = plt.subplots(figsize=(10, 8))

# Exclude intercept for better visualization
params_no_int = model_full.params[1:]
ci_no_int = conf_int.iloc[1:, :]

y_pos = np.arange(len(params_no_int))
ax.errorbar(params_no_int.values, y_pos,
            xerr=[params_no_int.values - ci_no_int.iloc[:, 0].values,
                   ci_no_int.iloc[:, 1].values - params_no_int.values],
            fmt='o', markersize=8, capsize=5, capthick=2, linewidth=2)
ax.set_yticks(y_pos)
ax.set_yticklabels(params_no_int.index)
ax.axvline(x=0, color='red', linestyle='--', linewidth=1, alpha=0.5, label='Zero effect')
ax.set_xlabel('Coefficient Value', fontsize=12)
ax.set_title('Coefficient Estimates with 95% Confidence Intervals',
             fontsize=14, fontweight='bold')
ax.legend()
ax.grid(True, alpha=0.3, axis='x')
plt.tight_layout()
plt.show()

print("Coefficients whose CI crosses zero are not statistically significant.")
```



Coefficients whose CI crosses zero are not statistically significant.

Key Takeaways

Data Exploration and Correlation:

- Multiple regression extends bivariate regression to include several regressors simultaneously
- Summary statistics and two-way scatterplots provide initial overview of variable relationships
- Correlation matrices reveal pairwise associations (e.g., price-size correlation of 0.79)
- Correlation can be misleading — bedrooms correlate with price, but may simply reflect house size

OLS Estimation:

- Multiple regression model: $\hat{y} = b_1 + b_2x_2 + b_3x_3 + \dots + b_kx_k$
- OLS minimizes the sum of squared residuals: $\min \sum (y_i - \hat{y}_i)^2$
- The coefficient b_j can be computed by bivariate regression of y on \tilde{x}_j (residualized x_j)

Partial Effects:

- Each coefficient b_j measures the partial effect: the change in \hat{y} when x_j changes by one unit, **holding all other regressors constant**
- Partial effects differ from total effects (which allow other regressors to vary)
- OLS measures association, not causation — use careful language ("associated with")

Model Fit:

- R^2 measures the fraction of variation in y explained by all regressors (0 to 1)
- Adjusted R^2 penalizes model complexity: can decrease when adding weak regressors
- Standard error of regression s_e measures typical prediction error in units of y
- Example: Adding 5 regressors increased R^2 from 0.618 to 0.651 but decreased \bar{R}^2 from 0.603 to 0.555

Information Criteria:

- AIC, BIC, and HQIC penalize larger models more heavily than adjusted R^2
- Smaller values indicate better models

- BIC is generally preferred (stronger complexity penalty than AIC)

Multicollinearity:

- Perfect collinearity makes some coefficients inestimable (computer shows "omitted")
- VIF detects multicollinearity: $VIF > 10$ indicates problematic, $VIF > 5$ moderate concern
- High multicollinearity inflates standard errors and makes estimates unstable

Python tools used: `statsmodels` (OLS, VIF), `seaborn` (pairplot, heatmap), `pandas` (DataFrames), `matplotlib` (coefficient plots, diagnostics)

Next steps: Chapter 11 covers **statistical inference** for multiple regression — hypothesis tests, confidence intervals, and overall F-tests for model significance.

Congratulations on completing Chapter 10! You now have the tools to estimate and evaluate multiple regression models, a foundation for the rest of the course.

I Practice Exercises

Test your understanding of multiple regression concepts with these exercises.

Exercise 1: Residuals and Fitted Values

A regression leads to the fitted equation $\hat{y} = 2 + 3x_2 + 4x_3$.

- What is the predicted value for observation $(x_2, x_3) = (2, 1)$?
 - If the actual value is $y = 9$, what is the residual?
 - Is this observation over-predicted or under-predicted?
-

Exercise 2: Partial vs. Total Effects

Suppose OLS regression on the same dataset leads to:

- Bivariate: $\hat{y} = 6 + 5x_2$
- Multiple: $\hat{y} = 2 + 3x_2 + 4x_3$

- Why does the coefficient on x_2 change from 5 to 3?
- Which coefficient (5 or 3) represents the partial effect of x_2 ? Explain.

- c) Under what condition would the bivariate and multiple regression coefficients on x_2 be equal?
-

Exercise 3: R-squared and Adjusted R-squared

OLS regression of y on x for a sample of size $n = 53$ leads to Residual SS = 20 and Total SS = 50.

- Compute R^2 .
 - Compute the standard error of the regression s_e .
 - Compute the correlation between y and \hat{y} .
 - If we add 3 more regressors and the Residual SS drops to 18, compute the new R^2 and adjusted R^2 . Does the model improve?
-

Exercise 4: Information Criteria

Consider two models estimated on $n = 29$ observations:

- Model A (2 parameters): AIC = 668.1, BIC = 670.8
 - Model B (7 parameters): AIC = 675.5, BIC = 685.1
- Which model is preferred by AIC? By BIC?
 - Why does BIC penalize Model B more heavily than AIC?
 - What economic reasoning supports the simpler model in this case?
-

Exercise 5: Multicollinearity Detection

A multiple regression of house prices yields the following VIF values:

Variable	VIF
Size	40.1
Bedrooms	57.8
Bathrooms	34.7
Age	21.0

- Which variables show the most severe multicollinearity?
- What consequences does high VIF have for coefficient estimates and inference?

c) Suggest a strategy to reduce multicollinearity in this model.

Exercise 6: Model Building

You have data on employee wages with variables: education (years), experience (years), age, tenure (years at current firm), and gender.

- a) Why might including both age and experience create multicollinearity?
- b) Propose two alternative model specifications and explain the trade-offs.
- c) How would you use adjusted R^2 and BIC to select the preferred specification?

| Case Studies

Case Study 1: Multiple Regression for Cross-Country Productivity

In this case study, you will apply multiple regression techniques to investigate how human capital and physical capital jointly explain cross-country differences in labor productivity. Using data from 108 countries over 1990-2014, you will explore correlations, estimate multiple regression models, interpret partial effects, and compare model specifications.

Dataset: Mendez Convergence Clubs Data

- **Source:** Mendez (2020), 108 countries, 1990-2014
- **Key variables:**
 - `lp` — Labor productivity (GDP per worker)
 - `rk` — Physical capital per worker
 - `hc` — Human capital index
 - `rgdppc` — Real GDP per capita
 - `region` — Geographic region

Research question: How do human capital and physical capital jointly explain cross-country productivity differences?

```

# Load the Mendez convergence clubs dataset
url = "https://raw.githubusercontent.com/quarcs-lab/mendez2020-convergence-clubs-code-data/master/assets/dat.csv"
dat = pd.read_csv(url)
dat_2014 = dat[dat['year'] == 2014].dropna(subset=['lp', 'rk', 'hc']).copy()
print(f"Cross-section sample: {len(dat_2014)} countries (year 2014)")
dat_2014.head()

```

Task 1: Explore Productivity Data (Guided)

Explore the cross-country productivity dataset.

```

# Step 1: Create log-transformed variables
dat_2014['ln_lp'] = np.log(dat_2014['lp'])
dat_2014['ln_rk'] = np.log(dat_2014['rk'])

# Step 2: Summary statistics for key variables
print(dat_2014[['lp', 'rk', 'hc', 'ln_lp', 'ln_rk']].describe())

# Step 3: Create a scatterplot matrix
sns.pairplot(dat_2014[['ln_lp', 'ln_rk', 'hc']], diag_kind='kde')
plt.suptitle('Scatterplot Matrix: Productivity Variables', y=1.02)
plt.show()

```

Questions:

- Which variable shows the strongest visual association with $\ln(\text{lp})$?
- Do you see any nonlinear patterns or outliers?

Task 2: Correlation Analysis (Guided)

Compute and visualize the correlation matrix.

```

# Step 1: Compute correlation matrix
corr = dat_2014[['ln_lp', 'ln_rk', 'hc']].corr()
print(corr)

# Step 2: Visualize as heatmap
sns.heatmap(corr, annot=True, fmt='.3f', cmap='coolwarm', center=0, square=True)
plt.title('Correlation Matrix: Productivity Variables')
plt.show()

```

Questions:

- Which predictor is most strongly correlated with $\ln(\text{lp})$?
- Are $\ln(\text{rk})$ and hc correlated with each other? What implications does this have for multiple regression?

Key Concept 10.9: Functional Form and Cross-Country Comparisons

When comparing countries with vastly different income levels, logarithmic transformations are essential. Using $\ln(lp)$ and $\ln(rk)$ compresses the scale so that both Luxembourg and Malawi can be meaningfully compared. Coefficients on log-transformed variables have elasticity interpretations, while coefficients on level variables (like hc) represent semi-elasticities.

Task 3: Multiple Regression Estimation (Semi-guided)

Estimate bivariate and multiple regression models for labor productivity.

```
# Model 1: ln(lp) ~ ln(rk) only
model1 = ols('ln_lp ~ ln_rk', data=dat_2014).fit()
print(model1.summary())

# Model 2: ln(lp) ~ hc only
model2 = ols('ln_lp ~ hc', data=dat_2014).fit()
print(model2.summary())

# Model 3: ln(lp) ~ ln(rk) + hc (multiple regression)
model3 = ols('ln_lp ~ ln_rk + hc', data=dat_2014).fit()
print(model3.summary())
```

Questions:

- How do the coefficients on $\ln(rk)$ change between Model 1 and Model 3?
- Does adding human capital improve the model? Compare R^2 and adjusted R^2 .

Task 4: Interpret Partial Effects (Semi-guided)

Interpret the coefficients from the multiple regression model.

```
# Display coefficients with confidence intervals
print("Model 3 Coefficients:")
print(model3.params)
print("\n95% Confidence Intervals:")
print(model3.conf_int())
```

Questions:

- Interpret the coefficient on $\ln(\text{rk})$ in Model 3. What does it mean in economic terms?
- Interpret the coefficient on hc. How does a one-unit increase in human capital relate to productivity?
- Are both coefficients statistically significant? How do you know?

Task 5: Model Selection (Independent)

Compare models using fit statistics and information criteria.

Your tasks:

1. Create a comparison table with R^2 , adjusted R^2 , AIC, and BIC for all three models
2. Which model is preferred by adjusted R^2 ? By AIC? By BIC?
3. Does the parsimony principle favor one model over another?
4. Calculate VIF for Model 3 — is multicollinearity a concern?

Hint: Use `model.rsquared`, `model.rsquared_adj`, `model.aic`, `model.bic` and `variance_inflation_factor()` from statsmodels.

Task 6: Development Policy Brief (Independent)

Write a 200-300 word policy brief summarizing your findings.

Your brief should address:

1. What are the key determinants of cross-country labor productivity?
2. What is the relative importance of physical capital vs. human capital?
3. How do partial effects differ from bivariate associations?
4. What policy implications follow from your analysis?
5. What limitations should policymakers keep in mind (association vs. causation)?

Key Concept 10.10: Multiple Regression in Development Economics

*Cross-country productivity regressions are central to development economics. By controlling for both physical capital ($\ln(rk)$) and human capital (hc), we can assess each factor's **partial contribution** to productivity. This addresses a key policy question: should developing countries invest in machines or education? Multiple regression helps disentangle these effects, though causal claims require careful identification strategies.*

What You've Learned

In this case study, you applied the full multiple regression toolkit to cross-country productivity data:

- Explored data with scatterplot matrices and correlation analysis
- Estimated bivariate and multiple regression models, observing how coefficients change
- Interpreted partial effects of physical and human capital on productivity
- Compared model specifications using adjusted R^2 , AIC, and BIC
- Connected statistical findings to development policy questions

These skills form the foundation for more advanced empirical analysis in the chapters ahead.

Case Study 2: Multiple Satellite Predictors of Development

Research Question: Do satellite image embeddings improve our ability to predict municipal development beyond nighttime lights alone?

In Chapter 1, we introduced the DS4Bolivia project and estimated a bivariate regression of development on nighttime lights. Now we extend this analysis using Chapter 10's **multiple regression** tools, adding satellite image embeddings as additional predictors to test whether they improve our ability to predict municipal development.

Background: Nighttime lights (NTL) are a well-established proxy for economic activity, but they capture only one dimension of a municipality's characteristics — nocturnal luminosity. Daytime satellite imagery contains far richer information: building density,

road networks, agricultural patterns, vegetation cover. Deep learning models can extract this information as **64-dimensional embedding vectors**, where each dimension captures abstract visual patterns learned automatically from the data.

The key question for multiple regression: Does adding these satellite embeddings as extra regressors significantly improve explanatory power compared to NTL alone? And if so, which embeddings matter most?

Variables for this case study:

- `imds` — Municipal Sustainable Development Index (0-100, outcome variable)
- `ln_NTLpc2017` — Log nighttime lights per capita (established predictor from Chapter 1)
- `A00`, `A10`, `A20`, `A30`, `A40` — Selected satellite image embedding dimensions (new predictors)
- `mun`, `dep` — Municipality and department identifiers

Your Task: Use correlation analysis, multiple regression, the FWL theorem, and model comparison tools from Chapter 10 to evaluate whether satellite embeddings add predictive value beyond nighttime lights.

Load the DS4Bolivia Data

Let's load the DS4Bolivia dataset and select the variables needed for our multiple regression analysis. We focus on the development index, nighttime lights, and five selected satellite embedding dimensions.

In []:

```
# Load the DS4Bolivia dataset
url_bol = "https://raw.githubusercontent.com/quarcs-lab/ds4bolivia/master/ds4bolivia_v20250523.csv"
bol = pd.read_csv(url_bol)

# Select key variables for this case study
key_vars = ['mun', 'dep', 'imds', 'ln_NTLpc2017', 'A00', 'A10', 'A20', 'A30', 'A40']
bol_sat = bol[key_vars].copy()

print("=" * 70)
print("DS4BOLIVIA DATASET – SATELLITE PREDICTORS")
print("=" * 70)
print(f"Dataset shape: {bol_sat.shape[0]} municipalities, {bol_sat.shape[1]} variables")
print(f"Departments: {bol['dep'].nunique()} unique departments")
print(f"Complete cases: {bol_sat.dropna().shape[0]}")
print("\n" + "=" * 70)
print("FIRST 10 MUNICIPALITIES")
print("=" * 70)
print(bol_sat.head(10).to_string(index=False))
```

Task 1: Explore Variables (Guided)

Objective: Understand the satellite embedding variables and how they compare to nighttime lights.

Instructions:

1. Generate summary statistics for all predictor variables using `describe()`
2. Compare the scale and distribution of NTL vs. embedding variables
3. Check for missing values across all selected variables
4. Consider: What are satellite embeddings? How do they differ from NTL?

Key insight: Unlike NTL (which has a clear physical interpretation — light intensity), embedding dimensions are **abstract features** extracted by neural networks. Dimension `A00` doesn't mean "vegetation" or "roads" — it captures a learned combination of visual patterns.

In []:

```
# Your code here: Explore the satellite predictor variables
#
# Step 1: Summary statistics for all numeric variables
print("=" * 70)
print("DESCRIPTIVE STATISTICS: DEVELOPMENT AND SATELLITE PREDICTORS")
print("=" * 70)
print(bol_sat[['imds', 'ln_NTLpc2017', 'A00', 'A10', 'A20', 'A30',
'A40']].describe().round(3))

# Step 2: Check for missing values
print("\n" + "=" * 70)
print("MISSING VALUES")
print("=" * 70)
print(bol_sat.isnull().sum())

# Step 3: Compare variable ranges
print("\n" + "=" * 70)
print("VARIABLE RANGES")
print("=" * 70)
for var in ['imds', 'ln_NTLpc2017', 'A00', 'A10', 'A20', 'A30', 'A40']:
    col = bol_sat[var].dropna()
    print(f" {var:16s} range: [{col.min():.3f}, {col.max():.3f}] std: {col.std():.3f}"")
```

Task 2: Correlation Analysis (Guided)

Objective: Compute and visualize the correlation structure among all predictors and the outcome variable.

Instructions:

1. Compute the correlation matrix for `imds`, `ln_NTLpc2017`, and all five embedding variables
2. Display the correlation matrix as a heatmap

3. Identify: Which embeddings correlate most strongly with `imds` ?
4. Identify: Do the embeddings correlate with each other (potential multicollinearity)?
5. Do the embeddings correlate with NTL, or do they capture different information?

Apply what you learned in section 10.3: Use `seaborn.heatmap()` with annotated correlation values.

In []:

```
# Your code here: Correlation analysis of satellite predictors
#
# Step 1: Compute correlation matrix
corr_vars = ['imds', 'ln_NTlpC2017', 'A00', 'A10', 'A20', 'A30', 'A40']
corr_sat = bol_sat[corr_vars].dropna().corr()

print("=" * 70)
print("CORRELATION MATRIX: DEVELOPMENT AND SATELLITE PREDICTORS")
print("=" * 70)
print(corr_sat.round(3))

# Step 2: Visualize as heatmap
fig, ax = plt.subplots(figsize=(10, 8))
sns.heatmap(corr_sat, annot=True, fmt=' .3f', cmap='coolwarm', center=0,
            square=True, linewidths=1, cbar_kws={"shrink": 0.8})
ax.set_title('Correlation Matrix: IMDS, NTL, and Satellite Embeddings',
             fontsize=14, fontweight='bold')
plt.tight_layout()
plt.show()

# Step 3: Highlight strongest correlations with IMDS
print("\nCorrelations with IMDS (development index):")
imds_corr = corr_sat['imds'].drop('imds').sort_values(key=abs, ascending=False)
for var, r in imds_corr.items():
    print(f" {var}: {r:.3f}")
```

Key Concept 10.12: High-Dimensional Satellite Features

Satellite embeddings are **64 abstract features** extracted by deep learning models (convolutional neural networks) from daytime satellite imagery. Unlike handcrafted variables (e.g., NDVI for vegetation), each embedding dimension captures complex visual patterns — road density, building structures, agricultural layouts — learned automatically from the data. These features are not directly interpretable (dimension A00 doesn't have a specific meaning), but they collectively encode rich information about a municipality's physical landscape.

Task 3: Multiple Regression (Semi-guided)

Objective: Estimate a multiple regression model with NTL and satellite embeddings as predictors.

Instructions:

1. Estimate the full model: `imds ~ ln_NTLpc2017 + A00 + A10 + A20 + A30 + A40`
2. Display the regression summary
3. Compare R^2 with the bivariate NTL-only model from Chapter 1
4. Interpret: How much does adding embeddings improve explanatory power?
5. Which embedding coefficients are statistically significant?

Apply what you learned in section 10.4: Use `ols()` from statsmodels and interpret partial effects.

```
In [ ]:
# Your code here: Multiple regression with satellite predictors
#
# Step 1: Prepare data (drop missing values)
reg_data = bol_sat[['imds', 'ln_NTLpc2017', 'A00', 'A10', 'A20', 'A30', 'A40']].dropna()
print(f"Regression sample: {len(reg_data)} municipalities (complete cases)")

# Step 2: Bivariate model (NTL only - baseline from Chapter 1)
model_ntl = ols('imds ~ ln_NTLpc2017', data=reg_data).fit()
print("\n" + "=" * 70)
print("MODEL 1: BIVARIATE - imds ~ ln_NTLpc2017")
print("=" * 70)
print(model_ntl.summary())

# Step 3: Multiple regression (NTL + all 5 embeddings)
model_full_sat = ols('imds ~ ln_NTLpc2017 + A00 + A10 + A20 + A30 + A40',
                     data=reg_data).fit()
print("\n" + "=" * 70)
print("MODEL 2: MULTIPLE - imds ~ ln_NTLpc2017 + A00 + A10 + A20 + A30 + A40")
print("=" * 70)
print(model_full_sat.summary())

# Step 4: Compare R-squared
print("\n" + "=" * 70)
print("R-SQUARED COMPARISON")
print("=" * 70)
print(f"NTL only: R² = {model_ntl.rsquared:.4f}")
print(f"NTL + 5 embeddings: R² = {model_full_sat.rsquared:.4f}")
print(f"Improvement: ΔR² = {model_full_sat.rsquared - model_ntl.rsquared:.4f}")
```

Task 4: Partial Effects via FWL (Semi-guided)

Objective: Demonstrate the Frisch-Waugh-Lovell theorem by showing that the NTL coefficient in the multiple regression equals the coefficient from regressing residualized IMDS on residualized NTL.

Instructions:

1. Regress `imds` on all embedding variables (`A00`, `A10`, `A20`, `A30`, `A40`), save residuals e_y
2. Regress `ln_NTLpc2017` on all embedding variables, save residuals e_x
3. Regress e_y on e_x (bivariate regression of residuals)

- Verify that the coefficient matches the NTL coefficient from the full multiple regression

Apply what you learned in section 10.5: This demonstrates that the partial effect of NTL is computed from the variation in NTL that is *independent* of the satellite embeddings.

In []:

```
# Your code here: FWL theorem demonstration
#
# Step 1: Regress imds on embeddings only, save residuals e_y
model_y_on_emb = ols('imds ~ A00 + A10 + A20 + A30 + A40', data=reg_data).fit()
e_y = model_y_on_emb.resid

# Step 2: Regress ln_NTLpc2017 on embeddings only, save residuals e_x
model_x_on_emb = ols('ln_NTLpc2017 ~ A00 + A10 + A20 + A30 + A40', data=reg_data).fit()
e_x = model_x_on_emb.resid

# Step 3: Regress e_y on e_x
fwl_data = pd.DataFrame({'e_y': e_y, 'e_x': e_x})
model_fwl = ols('e_y ~ e_x', data=fwl_data).fit()

# Step 4: Compare coefficients
print("=" * 70)
print("FWL THEOREM DEMONSTRATION")
print("=" * 70)
print(f"NTL coefficient from FULL multiple regression: {model_full_sat.params['ln_NTLpc2017']:.10f}")
print(f"Coefficient from FWL residual regression: {model_fwl.params['e_x']:.10f}")
print(f"Difference (numerical precision): {abs(model_full_sat.params['ln_NTLpc2017'] - model_fwl.params['e_x']):.15f}")
print("\nThe coefficients are identical - confirming the FWL theorem!")
print("\nInterpretation: The partial effect of NTL on IMDS is computed using")
print("only the variation in NTL that is NOT explained by the satellite embeddings.")
```

Task 5: Model Comparison (Independent)

Objective: Compare multiple model specifications using fit statistics and information criteria.

Your tasks:

- Estimate three models:
 - Model 1:** `imds ~ ln_NTLpc2017` (NTL only)
 - Model 2:** `imds ~ ln_NTLpc2017 + A00 + A10` (NTL + 2 embeddings)
 - Model 3:** `imds ~ ln_NTLpc2017 + A00 + A10 + A20 + A30 + A40` (NTL + 5 embeddings)
- Create a comparison table reporting R^2 , adjusted R^2 , AIC, and BIC for each model
- Use `model.rsquared`, `model.rsquared_adj`, `model.aic`, `model.bic`
- Which model is "best" by each criterion?
- Does the parsimony principle favor fewer or more embedding variables?

Hint: Use `pd.DataFrame()` to create a clean comparison table.

In []:

```
# Your code here: Model comparison
#
# Step 1: Estimate three models
# model_1 = ols('imds ~ ln_NTLpc2017', data=reg_data).fit()
# model_2 = ols('imds ~ ln_NTLpc2017 + A00 + A10', data=reg_data).fit()
# model_3 = ols('imds ~ ln_NTLpc2017 + A00 + A10 + A20 + A30 + A40', data=reg_data).fit()
#
# Step 2: Create comparison table
# comparison = pd.DataFrame({
#     'Model': ['NTL only', 'NTL + 2 embeddings', 'NTL + 5 embeddings'],
#     'R22
```

Key Concept 10.13: Incremental Predictive Power

When adding predictors to a regression model, R^2 can only increase or stay the same — it never decreases. This makes R^2 misleading for model comparison when models have different numbers of predictors.

Adjusted R^2 penalizes for additional variables, while **AIC** and **BIC** balance fit against complexity. In the satellite prediction context, adding all 64 embeddings would maximize R^2 but might overfit; information criteria help identify the most parsimonious model.

Task 6: Policy Brief on Satellite Prediction (Independent)

Objective: Write a 200-300 word policy brief summarizing the value of satellite embeddings for development prediction.

Your brief should address:

- 1. Improvement:** How much does adding satellite embeddings improve development prediction compared to NTL alone?
- 2. Complexity trade-off:** Is the improvement worth the added model complexity? What do adjusted R^2 , AIC, and BIC suggest?
- 3. Partial effects:** After controlling for embeddings, does NTL remain a significant predictor? What does the FWL theorem reveal about NTL's independent contribution?
- 4. SDG monitoring implications:** How could multi-source satellite data enhance SDG monitoring in data-scarce countries like Bolivia?

- 5. Limitations:** What can satellite data *not* capture about development? What are the risks of relying on abstract embedding features for policy decisions?

Connection to Research: The DS4Bolivia project uses all 64 embedding dimensions plus machine learning methods (Random Forest, XGBoost) to predict SDG indicators, achieving meaningful predictive accuracy. Your multiple regression analysis provides a transparent, interpretable baseline for comparison.

In []:

```
# Your code here: Additional analysis for the policy brief
#
# You might want to:
# 1. Create a summary table of key results across models
# 2. Generate a visualization comparing model fit
# 3. Calculate the percentage improvement in R2 from adding embeddings
# 4. Discuss which embeddings contribute most to prediction
#
# Example:
# print("KEY RESULTS FOR POLICY BRIEF")
# print(f"NTL-only R2: {model_1.rsquared:.4f}")
# print(f"NTL + 5 embed R2: {model_3.rsquared:.4f}")
# print(f"R2 improvement: {(model_3.rsquared - model_1.rsquared) / model_1.rsquared * 100:.1f}%" )
# print(f"NTL coef (bivariate): {model_1.params['ln_NTLpc2017']:.4f}")
# print(f"NTL coef (multiple): {model_3.params['ln_NTLpc2017']:.4f}")
```

What You've Learned from This Case Study

Through this analysis of multiple satellite predictors of Bolivian municipal development, you've applied the full Chapter 10 toolkit to a cutting-edge research application:

- **Correlation analysis:** Explored the correlation structure among NTL, satellite embeddings, and development outcomes
- **Multiple regression:** Estimated models with multiple satellite predictors and interpreted partial effects
- **FWL theorem:** Demonstrated that the partial effect of NTL equals the coefficient from regressing residualized IMDS on residualized NTL
- **Model comparison:** Evaluated competing specifications using R^2 , adjusted R^2 , AIC, and BIC
- **Critical assessment:** Weighed the predictive gains from additional satellite features against model complexity

Connection to upcoming chapters: In Chapter 11, we'll test whether the satellite embeddings are *statistically* significant using F-tests for joint significance. In Chapter 12, we'll address robust inference and prediction intervals.

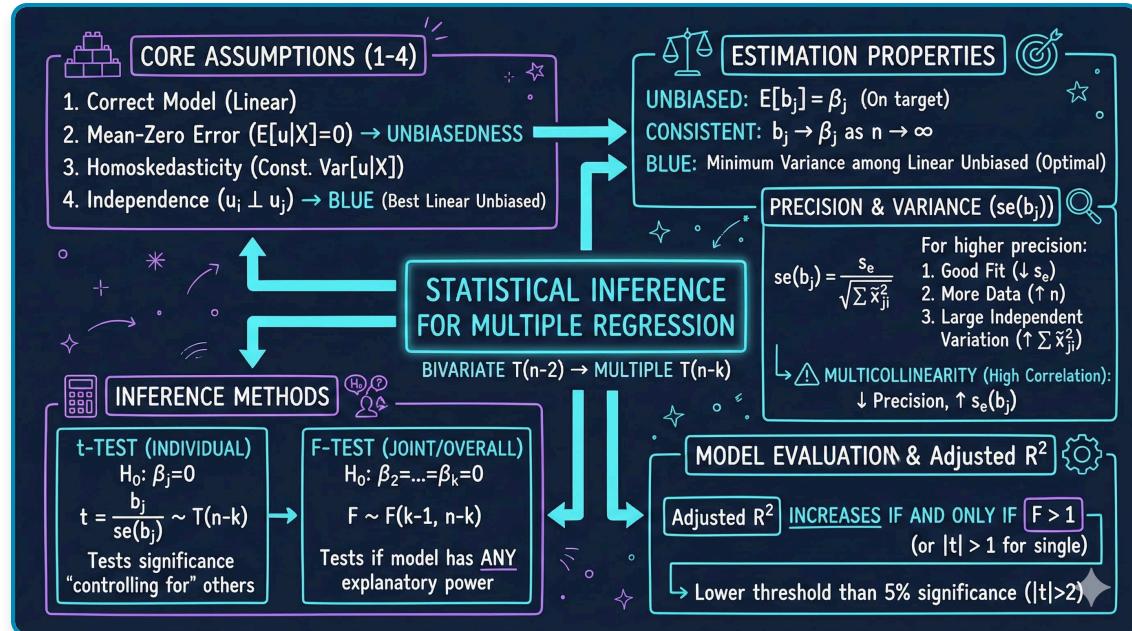
This dataset returns throughout the textbook: Each subsequent chapter applies its specific econometric tools to the DS4Bolivia data, building progressively toward a comprehensive satellite-based development prediction framework.

Well done! You've now analyzed how multiple satellite data sources can predict development outcomes, moving from simple bivariate regression (Chapter 1) to the richer multiple regression framework of Chapter 10.

Chapter 11: Statistical Inference for Multiple Regression

metricsAI: An Introduction to Econometrics with Python and AI in the Cloud

Carlos Mendez



This notebook provides an interactive introduction to extending inference to models with multiple regressors. All code runs directly in Google Colab without any local setup.

Open in Colab

Chapter Overview

This chapter extends statistical inference to models with multiple regressors. You'll learn to construct confidence intervals, conduct hypothesis tests on individual and groups of parameters, and present regression results professionally.

Learning Objectives:

By the end of this chapter, you will be able to:

1. Extend statistical inference from bivariate regression to multiple regression with k regressors
2. Understand the t -statistic for individual coefficients following a $T(n - k)$ distribution
3. Calculate and interpret standard errors for OLS slope coefficients:

$$se(b_j) = s_e / \sqrt{\sum \tilde{x}_{ji}^2}$$
4. Construct confidence intervals using $b_j \pm t_{n-k,\alpha/2} \times se(b_j)$
5. Conduct hypothesis tests on individual parameters to determine statistical significance
6. Understand and apply F-tests for joint hypotheses involving multiple parameter restrictions
7. Interpret the F distribution with two degrees of freedom (v_1 = restrictions, $v_2 = n - k$)
8. Perform the test of overall statistical significance using $H_0 : \beta_2 = \dots = \beta_k = 0$
9. Test whether subsets of regressors are jointly significant using nested model comparisons
10. Present regression results in standard formats (standard errors, t-statistics, p-values, confidence intervals, asterisks)

Dataset used:

- **AED_HOUSE.DTA:** 29 houses sold in Davis, California (1999)

Key economic questions:

- Is house size a statistically significant predictor of price?
- Are additional variables (bedrooms, bathrooms, age) jointly significant?
- What is a reasonable range for the effect of size on price?

Chapter outline:

- 11.1 Properties of the Least Squares Estimator
- 11.2 Estimators of Model Parameters
- 11.3 Confidence Intervals
- 11.4 Hypothesis Tests on a Single Parameter
- 11.5 Joint Hypothesis Tests
- 11.6 F Statistic Under Assumptions 1-4
- 11.7 Presentation of Regression Results
- Key Takeaways

- Practice Exercises
- Case Studies

Estimated time: 60-90 minutes

| Setup

First, we import the necessary Python packages and configure the environment for reproducibility. All data will stream directly from GitHub.

In [1]:

```
# Import required packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
from statsmodels.formula.api import ols
from scipy import stats
from statsmodels.stats.anova import anova_lm
import random
import os

# Set random seeds for reproducibility
RANDOM_SEED = 42
random.seed(RANDOM_SEED)
np.random.seed(RANDOM_SEED)
os.environ['PYTHONHASHSEED'] = str(RANDOM_SEED)

# GitHub data URL
GITHUB_DATA_URL = "https://raw.githubusercontent.com/quarcs-lab/data-open/master/AED/"

# Set plotting style
sns.set_style("whitegrid")
plt.rcParams['figure.figsize'] = (10, 6)

print("Setup complete! Ready to explore statistical inference for multiple regression.")
```

Setup complete! Ready to explore statistical inference for multiple regression.

| Data Preparation

We'll work with the same house price dataset from Chapter 10, which contains information on 29 houses sold in Davis, California in 1999.

In [2]:

```
# Read in the house data
data_house = pd.read_stata(GITHUB_DATA_URL + 'AED_HOUSE.DTA')

print("Data summary:")
data_summary = data_house.describe()
print(data_summary)

print("\nFirst few observations:")
print(data_house[['price', 'size', 'bedrooms', 'bathrooms', 'lotsize', 'age',
'monthsold']].head())
```

```
Data summary:
      price        size    bedrooms    bathrooms    lotsize        age \
count   29.000000  29.000000  29.000000  29.000000  29.000000  29.000000
mean   253910.344828  1882.758621  3.793103  2.206897  2.137931  36.413792
std    37390.710695   398.272130  0.675030  0.341144  0.693034  7.118975
min   204000.000000  1400.000000  3.000000  2.000000  1.000000  23.000000
25%  233000.000000  1600.000000  3.000000  2.000000  2.000000  31.000000
50%  244000.000000  1800.000000  4.000000  2.000000  2.000000  35.000000
75%  270000.000000  2000.000000  4.000000  2.500000  3.000000  39.000000
max  375000.000000  3300.000000  6.000000  3.000000  3.000000  51.000000

      monthsold        list
count  29.000000  29.000000
mean   5.965517  257824.137931
std    1.679344  40860.264099
min   3.000000  199900.000000
25%  5.000000  239000.000000
50%  6.000000  245000.000000
75%  7.000000  269000.000000
max  8.000000  386000.000000

First few observations:
      price    size  bedrooms  bathrooms  lotsize    age  monthsold
0    204000    1400       3.0       2.0       1.0  31.0         7
1    212000    1600       3.0       3.0       2.0  33.0         5
2    213000    1800       3.0       2.0       2.0  51.0         4
3    220000    1600       3.0       2.0       1.0  49.0         4
4    224500    2100       4.0       2.5       2.0  47.0         6
```

| 11.1: Properties of the Least Squares Estimator

Before conducting inference, we need to understand the statistical properties of the OLS estimator. Under the classical linear regression assumptions, OLS has desirable properties.

Classical Assumptions (1-4):

1. **Linearity:** The population model is linear in parameters:

$$y = \beta_1 + \beta_2 x_2 + \beta_3 x_3 + \cdots + \beta_k x_k + u$$

2. **Random sampling:** Data are randomly sampled from the population

3. **No perfect collinearity:** No exact linear relationships among regressors

4. Zero conditional mean: $E[u|x_2, \dots, x_k] = 0$

Properties of OLS under these assumptions:

- **Unbiased:** $E[\hat{\beta}_j] = \beta_j$ (centered on true value)
- **Consistent:** $\hat{\beta}_j \rightarrow \beta_j$ as $n \rightarrow \infty$
- **Efficient (BLUE):** Best Linear Unbiased Estimator (Gauss-Markov Theorem)
 - Has minimum variance among all linear unbiased estimators

Standard error of coefficient $\hat{\beta}_j$:

$$se(\hat{\beta}_j) = \frac{s_e}{\sqrt{\sum_{i=1}^n \tilde{x}_{ji}^2}}$$

where:

- s_e is the standard error of the regression
- \tilde{x}_{ji} is the residual from regressing x_j on all other regressors

Smaller standard errors occur when:

- Model fits well (small s_e)
- Large sample size (large $\sum \tilde{x}_{ji}^2$)
- Variable x_j has high variation after controlling for other regressors

In [3]:

```
print("=" * 70)
print("11.1 PROPERTIES OF THE LEAST SQUARES ESTIMATOR")
print("=" * 70)

print("\nUnder assumptions 1-4:")
print(" 1. Linearity:  $y = \beta_0 + \beta_1 x_1 + \dots + \beta_k x_k + u$ ")
print(" 2. Random sampling from population")
print(" 3. No perfect collinearity")
print(" 4. Zero conditional mean:  $E[u|X] = 0$ ")
print("\nThe OLS estimator is:")
print(" - Unbiased:  $E[\beta] = \beta$ ")
print(" - Consistent:  $\text{plim}(\beta) = \beta$ ")
print(" - Efficient (BLUE under Gauss-Markov theorem)")
print("\nThese properties allow us to conduct valid statistical inference.")
```

=====

11.1 PROPERTIES OF THE LEAST SQUARES ESTIMATOR

=====

Under assumptions 1-4:

1. Linearity: $y = \beta_0 + \beta_1 x_1 + \dots + \beta_k x_k + u$
2. Random sampling from population
3. No perfect collinearity
4. Zero conditional mean: $E[u|X] = 0$

The OLS estimator is:

- Unbiased: $E[\hat{\beta}] = \beta$
- Consistent: $\text{plim}(\hat{\beta}) = \beta$
- Efficient (BLUE under Gauss-Markov theorem)

These properties allow us to conduct valid statistical inference.

Key Concept 11.1: Classical Assumptions for Statistical Inference

Four assumptions underpin valid inference in multiple regression: (1) linearity in parameters, (2) random sampling, (3) no perfect collinearity among regressors, and (4) zero conditional mean of errors $E[u|X] = 0$.

Under these assumptions, OLS is unbiased ($E[\hat{\beta}_j] = \beta_j$), consistent, and the Best Linear Unbiased Estimator (BLUE) by the Gauss-Markov theorem.

| 11.2: Estimators of Model Parameters

Now we estimate the full multiple regression model and examine the parameter estimates, standard errors, and related statistics.

The full model:

$$\text{price} = \beta_1 + \beta_2 \times \text{size} + \beta_3 \times \text{bedrooms} + \beta_4 \times \text{bathrooms} + \beta_5 \times \text{lotsize} + \beta_6 \times \varepsilon$$

Key statistics:

- **Coefficients** ($\hat{\beta}_j$): Point estimates of partial effects
- **Standard errors** ($se(\hat{\beta}_j)$): Measure of estimation uncertainty
- **t-statistics**: Coefficient divided by standard error
- **p-values**: Probability of observing such extreme values under $H_0 : \beta_j = 0$
- **Root MSE** (s_e): Standard deviation of residuals, measures typical prediction error

In [4]:

```
# Full multiple regression model
model_full = ols('price ~ size + bedrooms + bathrooms + lotsize + age + monthsold',
                 data=data_house).fit()

print("=" * 70)
print("11.2 ESTIMATORS OF MODEL PARAMETERS")
print("=" * 70)
print("\nFull Multiple Regression Results:")
print(model_full.summary())
```

```
=====
11.2 ESTIMATORS OF MODEL PARAMETERS
=====

Full Multiple Regression Results:
    OLS Regression Results
=====
Dep. Variable:          price    R-squared:       0.651
Model:                  OLS      Adj. R-squared:   0.555
Method:                Least Squares  F-statistic:     6.826
Date:      Wed, 21 Jan 2026  Prob (F-statistic): 0.000342
Time:      15:15:57        Log-Likelihood:   -330.74
No. Observations:      29        AIC:             675.5
Df Residuals:          22        BIC:             685.1
Df Model:               6
Covariance Type:    nonrobust
=====

            coef    std err        t    P>|t|      [0.025]     [0.975]
-----
Intercept  1.378e+05  6.15e+04    2.242    0.035    1.03e+04  2.65e+05
size        68.3694    15.389     4.443    0.000     36.454    100.285
bedrooms   2685.3151  9192.526    0.292    0.773    -1.64e+04  2.17e+04
bathrooms  6832.8800  1.57e+04    0.435    0.668    -2.58e+04  3.94e+04
lotsize     2303.2214  7226.535    0.319    0.753    -1.27e+04  1.73e+04
age         -833.0386  719.335    -1.158    0.259    -2324.847   658.770
monthsold   -2088.5036  3520.898    -0.593    0.559    -9390.399  5213.392
-----
Omnibus:                 1.317  Durbin-Watson:        1.259
Prob(Omnibus):           0.518  Jarque-Bera (JB):   0.980
Skew:                   0.151  Prob(JB):            0.612
Kurtosis:                2.152  Cond. No.        2.59e+04
=====

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.59e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Interpreting the Regression Results

What these results tell us:

The regression output reveals several important findings about the house price data:

- 1. Size coefficient = \$68.37 ($p < 0.001$):** Each additional square foot increases house price by \$68.37 on average, holding all other variables constant. This effect is highly statistically significant ($p = 0.0002$), meaning we can be very confident this relationship is not due to chance.

2. Other variables are not statistically significant:

- **Bedrooms coefficient = \$2,685 (p = 0.773):** Surprisingly, the number of bedrooms doesn't significantly affect price once we control for size. The p-value of 0.773 means we cannot reject the hypothesis that this coefficient is zero.
 - **Bathrooms coefficient = \$6,833 (p = 0.668):** Similarly, bathrooms show no significant effect.
 - **Age coefficient = -\$833 (p = 0.259):** Older homes tend to sell for less, but this effect is not statistically significant.
3. **Model fit: $R^2 = 0.651$:** The model explains 65.1% of the variation in house prices, which is quite good for cross-sectional real estate data.
4. **Overall F-statistic = 6.83 (p = 0.0003):** The model as a whole is highly significant, meaning at least one of our predictors has a real effect on price.

Economic Interpretation:

Size dominates all other house characteristics in determining price in this market. Features like number of bedrooms and bathrooms don't add explanatory power beyond what size already captures. This likely reflects multicollinearity—larger houses naturally tend to have more bedrooms and bathrooms, so once we control for size, these other features provide little additional information.

The large standard errors on most coefficients (relative to the coefficient values) suggest imprecise estimation, common in small samples ($n=29$) with correlated predictors.

| Model Diagnostics

Let's extract and display key model diagnostics to understand the estimation.

In [5]:

```

# Extract key statistics
n = len(data_house)
k = len(model_full.params)
df = n - k

print("Model diagnostics:")
print(f" Sample size (n): {n}")
print(f" Number of parameters (k): {k}")
print(f" Degrees of freedom (n-k): {df}")
print(f" Root MSE (σ): ${np.sqrt(model_full.mse_resid):,.2f}")
print(f" R-squared: {model_full.rsquared:.4f}")
print(f" Adjusted R-squared: {model_full.rsquared_adj:.4f}")

# Create comprehensive coefficient table
print("\n" + "=" * 70)
print("Coefficient Table")
print("=" * 70)
coef_table = pd.DataFrame({
    'Coefficient': model_full.params,
    'Std. Error': model_full.bse,
    't-statistic': model_full.tvalues,
    'p-value': model_full.pvalues
})
print(coef_table)

```

```

Model diagnostics:
Sample size (n): 29
Number of parameters (k): 7
Degrees of freedom (n-k): 22
Root MSE (σ): $24,935.73
R-squared: 0.6506
Adjusted R-squared: 0.5552

=====
Coefficient Table
=====

```

	Coefficient	Std. Error	t-statistic	p-value
Intercept	137791.065699	61464.951869	2.241783	0.035387
size	68.369419	15.389472	4.442610	0.000205
bedrooms	2685.315122	9192.525674	0.292119	0.772932
bathrooms	6832.880015	15721.191544	0.434629	0.668065
lotsize	2303.221371	7226.535205	0.318717	0.752947
age	-833.038602	719.334544	-1.158068	0.259254
monthsold	-2088.503625	3520.897859	-0.593174	0.559114

Key Concept 11.2: Precision of Coefficient Estimates

The standard error $se(b_j) = s_e / \sqrt{\sum \tilde{x}_{ji}^2}$ reveals what makes estimates precise: (1) a well-fitting model (small s_e), (2) large sample size, (3) high variation in x_j after controlling for other regressors, and (4) low multicollinearity. When regressors are highly correlated, $\sum \tilde{x}_{ji}^2$ shrinks and standard errors inflate.

| Economic Interpretation

Key findings:

1. **Size coefficient** (\approx)
68.37) : Each additional square foot increases house price by approximately 68, holding other factors constant.
2. **Statistical significance:** Only the size variable appears statistically significant at conventional levels ($p < 0.05$).
3. **Other variables:** Bedrooms, bathrooms, lot size, age, and month sold show large standard errors relative to their coefficients, suggesting imprecise estimates.

This pattern is common in small samples with correlated regressors (multicollinearity).

Now that we understand the properties and interpretation of OLS estimates, let's quantify uncertainty through confidence intervals.

| 11.3: Confidence Intervals

A confidence interval provides a range of plausible values for a population parameter.

Formula for a $100(1 - \alpha)$ confidence interval:

$$\hat{\beta}_j \pm t_{n-k,\alpha/2} \times se(\hat{\beta}_j)$$

where:

- $\hat{\beta}_j$ is the coefficient estimate
- $t_{n-k,\alpha/2}$ is the critical value from Student's t-distribution
- $se(\hat{\beta}_j)$ is the standard error

95% confidence interval (approximate):

$$\hat{\beta}_j \pm 2 \times se(\hat{\beta}_j)$$

Interpretation: If we repeatedly sampled from the population and constructed 95% CIs, approximately 95% would contain the true parameter value.

Key points:

- Narrower intervals indicate more precise estimates

- If the interval excludes zero, the coefficient is statistically significant at that level

Interpreting the Confidence Intervals

What these confidence intervals tell us:

Looking at the 95% confidence intervals, we can identify which variables have statistically significant effects:

- 1. Size:** [36.45, 100.29] - This interval excludes zero, confirming that size has a statistically significant positive effect on price. We are 95% confident that each additional square foot increases price by between 36 and 100.
- 2. Intercept:** [10, 321, 265, 262] - The wide interval reflects high uncertainty about the base price level, but it excludes zero.
- 3. All other variables:** The confidence intervals for bedrooms, bathrooms, lotsize, age, and monthsold all **contain zero**, which means these coefficients are not statistically significant at the 5% level.

Practical Meaning:

If we repeatedly sampled 29 houses from this market and calculated 95% confidence intervals, approximately 95% of those intervals would contain the true population parameter. For the size coefficient, this means we're quite certain about its effect—even in the worst case (lower bound), an extra square foot adds at least \$36 to the price.

The fact that only the size interval excludes zero provides strong evidence that, in this dataset, size is the only reliable predictor of house prices among the variables we measured.

In [6]:

```
print("=" * 70)
print("11.3 CONFIDENCE INTERVALS")
print("=" * 70)

# 95% confidence intervals
conf_int = model_full.conf_int(alpha=0.05)
print("\n95% Confidence Intervals:")
print(conf_int)
```

```
=====
11.3 CONFIDENCE INTERVALS
=====

95% Confidence Intervals:
          0           1
Intercept 10320.557398 265261.573999
size       36.453608   100.285230
bedrooms  -16378.816300 21749.446543
bathrooms -25770.875723 39436.635753
lotsize    -12683.695364 17290.138107
age        -2324.847139   658.769936
monthsold -9390.398871  5213.391620
```

| Manual Calculation of Confidence Interval

Let's manually calculate the confidence interval for the size coefficient to understand the mechanics.

In [7]:

```
# Detailed confidence interval calculation for 'size'
coef_size = model_full.params['size']
se_size = model_full.bse['size']
t_crit = stats.t.ppf(0.975, df) # 97.5th percentile for two-sided 95% CI

ci_lower = coef_size - t_crit * se_size
ci_upper = coef_size + t_crit * se_size

print("Manual calculation for 'size' coefficient:")
print(f" Coefficient: ${coef_size:.2f}")
print(f" Standard error: ${se_size:.2f}")
print(f" Degrees of freedom: {df}")
print(f" Critical t-value (a=0.05): {t_crit:.4f}")
print(f" Margin of error: {t_crit * se_size:.2f}")
print(f" 95% CI: [{ci_lower:.2f}, {ci_upper:.2f}]")

print("\nInterpretation:")
print(f"We are 95% confident that each additional square foot increases")
print(f"house price by between ${ci_lower:.2f} and ${ci_upper:.2f}.")
```

```
Manual calculation for 'size' coefficient:
Coefficient: $68.37
Standard error: $15.39
Degrees of freedom: 22
Critical t-value (a=0.05): 2.0739
Margin of error: 31.92
95% CI: [$36.45, $100.29]
```

Interpretation:
 We are 95% confident that each additional square foot increases
 house price by between \$36.45 and \$100.29.

| Comprehensive Table with Confidence Intervals

In [8]:

```
# Create comprehensive coefficient table
print("=" * 70)
print("Comprehensive Coefficient Table with 95% Confidence Intervals")
print("=" * 70)
coef_table_full = pd.DataFrame({
    'Coefficient': model_full.params,
    'Std. Error': model_full.bse,
    't-statistic': model_full.tvalues,
    'p-value': model_full.pvalues,
    'CI Lower': conf_int.iloc[:, 0],
    'CI Upper': conf_int.iloc[:, 1]
})
print(coef_table_full)

print("\nNote: Coefficients with CIs that exclude zero are statistically significant at 5%.")
```

```
=====
Comprehensive Coefficient Table with 95% Confidence Intervals
=====
   Coefficient  Std. Error  t-statistic  p-value      CI Lower  \
Intercept  137791.065699   61464.951869     2.241783  0.035387  10320.557398
size        68.369419    15.389472      4.442610  0.000205   36.453608
bedrooms    2685.315122   9192.525674      0.292119  0.772932 -16378.816300
bathrooms   6832.880015  15721.191544      0.434629  0.668065 -25770.875723
lotsize      2303.221371   7226.535205      0.318717  0.752947 -12683.695364
age         -833.038602    719.334544     -1.158068  0.259254 -2324.847139
monthsold   -2088.503625   3520.897859     -0.593174  0.559114 -9390.398871

   CI Upper
Intercept  265261.573999
size        100.285230
bedrooms    21749.446543
bathrooms   39436.635753
lotsize      17290.138107
age          658.769936
monthsold   5213.391620
```

Note: Coefficients with CIs that exclude zero are statistically significant at 5%.

Key Concept 11.3: Confidence Intervals in Multiple Regression

A 95% confidence interval $b_j \pm t_{n-k,0.025} \times se(b_j)$ provides a range of plausible values for β_j . If the interval excludes zero, the coefficient is statistically significant at 5%. Narrower intervals indicate more precise estimation, which improves with larger samples and lower multicollinearity.

| Interpreting the Hypothesis Test Result

What this test tells us:

We tested whether the size coefficient equals 50 ($H_0: \beta_{\text{size}} = 50$):

- **t-statistic = 1.19:** This measures how many standard errors our estimate (\$68.37) is away from the hypothesized value (50). The difference is 1.19 standard errors.
- **p-value = 0.245:** This is the probability of observing a coefficient as extreme as 68.37 (or more extreme) if the true value were actually 50. A p-value of 0.245 means there's about a 25% chance we'd see this result by random sampling variation alone.
- **Decision:** Since $p = 0.245 > 0.05$, we **fail to reject H_0** at the 5% significance level.

Economic Interpretation:

The data are consistent with the hypothesis that each square foot adds 50 to house price. Even though our point estimate is 68.37, the difference from \$50 is not statistically significant. This doesn't mean $\beta = 50$ is correct—it simply means our data don't provide strong enough evidence to rule it out.

This illustrates an important principle: **failing to reject H_0 is NOT the same as proving H_0 is true.** We simply lack sufficient evidence to reject it given our sample size and estimation precision.

| 11.4: Hypothesis Tests on a Single Parameter

Hypothesis testing allows us to make formal inferences about population parameters.

General two-sided test:

$$H_0 : \beta_j = \beta_j^* \quad \text{vs.} \quad H_a : \beta_j \neq \beta_j^*$$

Test statistic:

$$t = \frac{\hat{\beta}_j - \beta_j^*}{se(\hat{\beta}_j)} \sim t(n - k)$$

Decision rules:

1. **p-value approach:** Reject H_0 if $p\text{-value} < \alpha$
2. **Critical value approach:** Reject H_0 if $|t| > t_{n-k, \alpha/2}$

Test of statistical significance (most common):

$$H_0 : \beta_j = 0 \quad \text{vs.} \quad H_a : \beta_j \neq 0$$

This tests whether variable x_j has any relationship with y after controlling for other regressors.

Example: Test whether the size coefficient equals 50.

In [9]:

```
print("=" * 70)
print("11.4 HYPOTHESIS TESTS ON A SINGLE PARAMETER")
print("=" * 70)

# Test  $H_0: \beta_{size} = 50$  vs  $H_1: \beta_{size} \neq 50$ 
null_value = 50
t_stat_50 = (coef_size - null_value) / se_size
p_value_50 = 2 * (1 - stats.t.cdf(abs(t_stat_50), df))

print(f"\nTest:  $H_0: \beta_{size} = {null_value}$  vs  $H_1: \beta_{size} \neq {null_value}$ ")
print(f"  Coefficient estimate: ${coef_size:.2f}")
print(f"  Standard error: ${se_size:.2f}")
print(f"  t-statistic: {t_stat_50:.4f}")
print(f"  p-value: {p_value_50:.4f}")
print(f"  Critical value (a=0.05): ±{t_crit:.4f}")

if abs(t_stat_50) > t_crit:
    print(f"\nResult: Reject  $H_0$  at 5% significance level")
    print(f"  Conclusion: The size coefficient is significantly different from {null_value}.")
else:
    print(f"\nResult: Fail to reject  $H_0$  at 5% significance level")
    print(f"  Conclusion: The data are consistent with  $\beta_{size} = {null_value}$ .)
```

```
=====
11.4 HYPOTHESIS TESTS ON A SINGLE PARAMETER
=====

Test:  $H_0: \beta_{size} = 50$  vs  $H_1: \beta_{size} \neq 50$ 
Coefficient estimate: $68.37
Standard error: $15.39
t-statistic: 1.1936
p-value: 0.2453
Critical value (a=0.05): ±2.0739

Result: Fail to reject  $H_0$  at 5% significance level
Conclusion: The data are consistent with  $\beta_{size} = 50$ .
```

| Test of Statistical Significance ($\beta = 0$)

The most common hypothesis test examines whether a coefficient is zero.

```
In [10]: # Test H0: β_size = 0 (statistical significance)
print("=" * 70)
print("Test of Statistical Significance: H0: β_size = 0")
print("=" * 70)

t_stat_zero = coef_size / se_size
p_value_zero = model_full.pvalues['size']

print(f"\n t-statistic: {t_stat_zero:.4f}")
print(f" p-value: {p_value_zero:.6f}")
print(f" Critical value (α=0.05): ±{t_crit:.4f}")

if p_value_zero < 0.05:
    print(f"\nResult: Reject H0 - Size is statistically significant at 5% level")
    print(f" Interpretation: House size has a statistically significant effect on price.")
else:
    print(f"\nResult: Fail to reject H0 - Size is not statistically significant")

=====
Test of Statistical Significance: H0: β_size = 0
=====

t-statistic: 4.4426
p-value: 0.000205
Critical value (α=0.05): ±2.0739

Result: Reject H0 - Size is statistically significant at 5% level
Interpretation: House size has a statistically significant effect on price.
```

Key Concept 11.4: Tests of Statistical Significance

The most common hypothesis test examines $H_0 : \beta_j = 0$ — whether variable x_j has any partial effect on y . The t -statistic $t = b_j/se(b_j)$ measures how many standard errors the estimate is from zero. Reject H_0 when $|t| > t_{\text{critical}}$ or equivalently when the p -value $< \alpha$.

I Using statsmodels t_test

Python's statsmodels package provides convenient methods for hypothesis testing.

I Interpreting the Overall F-test

What this F-test tells us:

The overall F-test examines whether our model has any explanatory power at all:

- **Null hypothesis:** All slope coefficients equal zero ($\beta_2 = \beta_3 = \dots = \beta_7 = 0$)
- **Alternative:** At least one coefficient is non-zero

Results:

- **F-statistic = 6.83**: This compares the explained variation to unexplained variation
- **p-value = 0.0003**: Extremely small probability of observing such a large F-statistic if all coefficients were truly zero
- **Critical value = 2.55**: Our F-statistic (6.83) far exceeds this threshold

Decision: Reject H_0 - The model is highly statistically significant.

Economic Interpretation:

This result tells us that **at least one** of our house characteristics (size, bedrooms, bathrooms, lotsize, age, monthsold) has a real relationship with price. Given that we already know size is significant from individual t-tests, this makes sense.

However, this test doesn't tell us **which** variables matter—just that the model as a whole provides useful information for predicting house prices. The very small p-value (0.0003) gives us high confidence that our model captures real economic relationships, not just random noise.

In [11]:

```
# Using statsmodels t-test
print("=" * 70)
print("Hypothesis test using statsmodels t-test:")
print("=" * 70)
hypothesis = f'size = {null_value}'
t_test_result = model_full.t_test(hypothesis)
print(t_test_result)

print("\nThis confirms our manual calculation.")
```

```
=====
Hypothesis test using statsmodels t-test:
=====
              Test for Constraints
=====
      coef    std err        t     P>|t|      [0.025    0.975]
-----
c0       68.3694    15.389     1.194      0.245     36.454   100.285
=====
```

This confirms our manual calculation.

| Interpreting the Joint Test of Subset Variables

What this joint test tells us:

This F-test asks: "Can we exclude bedrooms, bathrooms, lotsize, age, and monthsold from the model and just keep size?"

Results:

- **F-statistic = 0.42:** Very small F-statistic
- **p-value = 0.832:** Very high p-value (83.2%)
- **Critical value = 2.66:** Our F-statistic (0.42) is far below this threshold

Decision: Fail to reject H_0 - These five variables are NOT jointly significant.

Economic Interpretation:

This is a crucial finding for model selection. Even though we're testing five variables simultaneously, they collectively add almost nothing to the model's explanatory power beyond what size alone provides.

What this means in practice:

- A **simpler model** with only size as a predictor would be preferred
- The additional variables (bedrooms, bathrooms, etc.) don't improve our ability to predict house prices
- Keeping these variables makes the model more complex without meaningful benefit

This result demonstrates the power of joint testing: while we might hope that bedrooms or bathrooms would add information, when tested together, they fail to improve the model. This likely reflects the strong correlation between size and these other features—bigger houses tend to have more bedrooms and bathrooms, so these variables don't provide independent information.

Having tested individual coefficients, we now turn to joint hypothesis tests that evaluate multiple restrictions simultaneously.

| 11.5: Joint Hypothesis Tests

Sometimes we want to test multiple restrictions simultaneously. Individual t-tests are insufficient for this purpose.

Why joint tests?

- Testing multiple individual hypotheses separately can be misleading
- Joint tests account for correlation between coefficient estimates

Examples of joint hypotheses:

1. All slope coefficients equal zero: $\beta_2 = \beta_3 = \dots = \beta_k = 0$
2. Subset of coefficients equal zero: $\beta_3 = \beta_4 = \beta_5 = 0$

3. Linear restrictions: $\beta_2 = -\beta_3$ and $2\beta_4 + \beta_6 = 9$

F-test procedure:

- Test statistic follows the F-distribution: $F(q, n - k)$
- q = number of restrictions
- $n - k$ = degrees of freedom

F-distribution properties:

- Always positive (right-skewed)
- Depends on two degrees of freedom parameters
- As q or $n - k$ increases, critical values change

Interpreting the Sum of Squares Decomposition

What these calculations show:

The sum of squares decomposition breaks down the total variation in house prices:

- **TSS = \$39,145,826,897** (Total Sum of Squares): Total variation in house prices around their mean
- **ESS = \$25,466,429,042** (Explained Sum of Squares): Variation explained by our model (65.1%)
- **RSS = \$13,679,397,855** (Residual Sum of Squares): Variation left unexplained (34.9%)

Verification: TSS = ESS + RSS (The identity holds perfectly)

Understanding the F-statistic:

The F-statistic compares explained variation per parameter to unexplained variation per degree of freedom:

$$F = \frac{ESS/(k - 1)}{RSS/(n - k)} = \frac{25,466,429,042/6}{13,679,397,855/22} = 6.83$$

Economic Interpretation:

Our model explains about 65% of the variation in house prices—a respectable amount for real estate data. The remaining 35% reflects unmeasured factors like neighborhood quality, interior condition, proximity to amenities, etc.

The F-statistic of 6.83 tells us that the explained variation (per parameter) is nearly 7 times larger than the unexplained variation (per degree of freedom). This ratio is large enough to conclude the model has genuine explanatory power, not just capturing random noise.

In [12]:

```
print("=" * 70)
print("11.5 JOINT HYPOTHESIS TESTS")
print("=" * 70)

# Test 1: Joint significance of all slope coefficients
# H0: β1 = β2 = ... = βk = 0
print("\n" + "-" * 70)
print("Test 1: Overall F-test (all slopes = 0)")
print("-" * 70)

f_stat = model_full.fvalue
f_pvalue = model_full.f_pvalue
dfn = k - 1 # numerator df (excluding intercept)
dfd = df      # denominator df
f_crit = stats.f.ppf(0.95, dfn, dfd)

print(f" H0: All slope coefficients equal zero")
print(f" F-statistic: {f_stat:.4f}")
print(f" p-value: {f_pvalue:.6e}")
print(f" Critical value (α=0.05): {f_crit:.4f}")
print(f" Numerator df: {dfn}, Denominator df: {dfd}")

if f_stat > f_crit:
    print("\nResult: Reject H0 - At least one coefficient is non-zero")
    print(" Interpretation: The regressors are jointly statistically significant.")
else:
    print("\nResult: Fail to reject H0)
```

```
=====
11.5 JOINT HYPOTHESIS TESTS
=====

-----
Test 1: Overall F-test (all slopes = 0)
-----
H0: All slope coefficients equal zero
F-statistic: 6.8261
p-value: 3.424253e-04
Critical value (α=0.05): 2.5491
Numerator df: 6, Denominator df: 22

Result: Reject H0 - At least one coefficient is non-zero
Interpretation: The regressors are jointly statistically significant.
```

Joint Test of Subset of Coefficients

Now test whether variables other than size are jointly significant.

In [13]:

```
# Test 2: Joint test of subset of coefficients
# H0: β_bedrooms = β_bathrooms = β_lotsize = β_age = β_monthsold = 0
print("\n" + "-" * 70)
print("Test 2: Joint test - Are variables other than size significant?")
print("-" * 70)

hypotheses = ['bedrooms = 0', 'bathrooms = 0', 'lotsize = 0',
              'age = 0', 'monthsold = 0']
f_test_result = model_full.f_test(hypotheses)
print(f_test_result)

print(f"\nInterpretation:")
print(f" This tests whether bedrooms, bathrooms, lotsize, age, and monthsold")
print(f" can jointly be excluded from the model (keeping only size).")

if f_test_result.pvalue < 0.05:
    print(f" Result: These variables are jointly significant.")
else:
    print(f" Result: These variables are NOT jointly significant.")
    print(f" A simpler model with only size may be preferred.")
```

```
-----
Test 2: Joint test - Are variables other than size significant?
-----
<F test: F=0.41676518071663304, p=0.8319758671771483, df_denom=22, df_num=5>

Interpretation:
This tests whether bedrooms, bathrooms, lotsize, age, and monthsold
can jointly be excluded from the model (keeping only size).
Result: These variables are NOT jointly significant.
A simpler model with only size may be preferred.
```

Key Concept 11.5: Joint Hypothesis Tests and the F Distribution

Individual t-tests cannot test multiple restrictions simultaneously because they ignore correlations between coefficient estimates. The F-test evaluates joint significance using the $F(q, n - k)$ distribution, where q is the number of restrictions. It compares how much worse the restricted model fits relative to the unrestricted model.

| Interpreting the Subset F-test

What this subset F-test tells us:

We're comparing two models:

- **Restricted model:** price ~ size (2 parameters)
- **Unrestricted model:** price ~ size + bedrooms + bathrooms + lotsize + age + monthsold (7 parameters)

Key numbers:

- **RSS (restricted) = \$14,975,101,655**: Prediction errors when using only size
- **RSS (unrestricted) = \$13,679,397,855**: Prediction errors when using all variables
- **Increase in RSS = \$1,295,703,800**: How much worse the restricted model fits

Test results:

- **F-statistic = 0.42**: The increase in RSS is small relative to the baseline error
- **p-value = 0.832**: 83.2% probability of seeing this result if the restrictions are true
- **Critical value = 2.66**: Our F-statistic is far below the threshold

Decision: Fail to reject H_0 - The restricted model (only size) is NOT significantly worse.

Economic Interpretation:

This is a powerful result for **model selection**. Adding five additional variables (bedrooms, bathrooms, lotsize, age, monthsold) reduces prediction errors by only 1.3million out of 15 million total—a mere 8.7% improvement. This improvement is so small it could easily be due to random chance.

Practical recommendation: Use the **simpler model** with only size. It's easier to interpret, requires less data collection, and performs nearly as well as the complex model. This is an application of **Occam's Razor** in econometrics: prefer simpler models when complex ones don't provide meaningful improvement.

| 11.6: F Statistic Under Assumptions 1-4

Under the classical assumptions, the F-statistic has a specific formula based on sums of squares.

Sum of Squares Decomposition:

$$TSS = ESS + RSS$$

where:

- **TSS** (Total Sum of Squares) = $\sum(y_i - \bar{y})^2$
- **ESS** (Explained Sum of Squares) = $\sum(\hat{y}_i - \bar{y})^2$
- **RSS** (Residual Sum of Squares) = $\sum(y_i - \hat{y}_i)^2$

F-statistic formula:

$$F = \frac{(RSS_r - RSS_u)/q}{RSS_u/(n-k)} \sim F(q, n-k)$$

where:

- RSS_r = RSS from restricted model
- RSS_u = RSS from unrestricted model
- q = number of restrictions

Intuition: Reject restrictions if the restricted model fits much worse (large increase in RSS).

Overall F-test formula:

$$F = \frac{R^2/(k-1)}{(1-R^2)/(n-k)} \sim F(k-1, n-k)$$

In [14]:

```
print("=" * 70)
print("11.6 F STATISTIC UNDER ASSUMPTIONS 1-4")
print("=" * 70)

# Manual calculation of F-statistic using sums of squares
print("\n" + "-" * 70)
print("Manual F-statistic calculation")
print("-" * 70)

# Calculate sum of squares
y = data_house['price']
y_mean = y.mean()
y_pred = model_full.fittedvalues
resid = model_full.resid

# Total sum of squares
TSS = np.sum((y - y_mean)**2)
# Explained sum of squares
ESS = np.sum((y_pred - y_mean)**2)
# Residual sum of squares
RSS = np.sum(resid**2)

print(f"Sum of Squares:")
print(f" Total (TSS): {TSS:.2f}")
print(f" Explained (ESS): {ESS:.2f}")
print(f" Residual (RSS): {RSS:.2f}")
print(f" Check: TSS = ESS + RSS: {np.isclose(TSS, ESS + RSS)}")

# F-statistic
f_stat_manual = (ESS / (k-1)) / (RSS / df)
print(f"\nF-statistic calculation:")
print(f" F = (ESS/{k-1}) / (RSS/{df})")
print(f" F = ({ESS:.2f}/{k-1}) / ({RSS:.2f}/{df})")
print(f" F = {f_stat_manual:.4f}")
print(f" From model output: {f_stat:.4f}")
print(f" Match: {np.isclose(f_stat_manual, f_stat)}")

# Alternative formula using R2
r_squared = model_full.rsquared
f_stat_rsq = (r_squared / (k-1)) / ((1 - r_squared) / df)
print(f"\nAlternative formula using R2:")
print(f" F = (R2/(k-1)) / ((1-R2)/(n-k))")
print(f" F = ({r_squared:.4f}/{k-1}) / ({1-r_squared:.4f}/{df})")
print(f" F = {f_stat_rsq:.4f}")
print(f" Match: {np.isclose(f_stat_rsq, f_stat)}")
```

```
=====
11.6 F STATISTIC UNDER ASSUMPTIONS 1-4
=====

-----
Manual F-statistic calculation

-----
Sum of Squares:
  Total (TSS): 39,145,826,896.55
  Explained (ESS): 25,466,429,041.83
  Residual (RSS): 13,679,397,854.73
  Check: TSS = ESS + RSS: True

F-statistic calculation:
  F = (ESS/6) / (RSS/22)
  F = (25,466,429,041.83/6) / (13,679,397,854.73/22)
  F = 6.8261
  From model output: 6.8261
  Match: True

Alternative formula using R2:
  F = (R2/(k-1)) / ((1-R2)/(n-k))
  F = (0.6506/6) / (0.3494/22)
  F = 6.8261
  Match: True
```

Key Concept 11.6: The F Statistic Under Homoskedasticity

Under assumptions 1-4, the F-statistic can be computed from sums of squares: $F = [(RSS_r - RSS_u)/q]/[RSS_u/(n - k)]$, or equivalently from R^2 : $F = [(R_u^2 - R_r^2)/q]/[(1 - R_u^2)/(n - k)]$. Larger F-values indicate the restrictions are inconsistent with the data.

I Subset F-test: Restricted vs Unrestricted Model

Now we compare the full model (unrestricted) with a simpler model containing only size (restricted).

I Interpreting the Model Comparison

What this comparison reveals:

Comparing three nested models helps us understand the incremental value of adding variables:

Model 1 (Simple): price ~ size

- **R² = 0.618, Adj. R² = 0.603:** Explains 61.8% of price variation
- **F-stat = 43.58:** Very strong overall significance

- Simplest and most parsimonious

Model 2 (Intermediate): price ~ size + bedrooms

- **R² = 0.618, Adj. R² = 0.589:** Almost identical R² to Model 1
- **F-stat = 21.03:** Still significant, but weaker than Model 1
- **Adding bedrooms barely improves fit**

Model 3 (Full): price ~ size + bedrooms + bathrooms + lotsize + age + monthsold

- **R² = 0.651, Adj. R² = 0.555:** Highest R² but **lowest adjusted R²**
- **F-stat = 6.83:** Weakest overall significance (though still significant)
- **Complexity penalty outweighs small improvement in fit**

Key insights:

- 1. Adjusted R² is crucial:** While R² increases with more variables (always), adjusted R² accounts for the complexity penalty. Model 1 has the **highest adjusted R²**, indicating the best balance of fit and simplicity.
- 2. Diminishing returns:** Adding bedrooms (Model 2) provides essentially no improvement. Adding five more variables (Model 3) only increases R² from 0.618 to 0.651—a marginal gain.
- 3. Statistical vs. practical significance:** Model 3 is statistically significant overall (F = 6.83, p < 0.001), but that doesn't mean it's the **best** model. Model 1 is superior on parsimony grounds.

Recommendation: Use Model 1 (size only). It's simpler, has the highest adjusted R², and loses almost nothing in explanatory power compared to more complex alternatives.

In [15]:

```
# Subset F-test using restricted and unrestricted models
print("\n" + "-" * 70)
print("Subset F-test: Restricted vs Unrestricted Model")
print("-" * 70)

# Unrestricted model (already estimated as model_full)
# Restricted model (only size as regressor)
model_restricted = ols('price ~ size', data=data_house).fit()

print("\nRestricted model (only size):")
print(model_restricted.summary())
```

```

Subset F-test: Restricted vs Unrestricted Model

Restricted model (only size):
OLS Regression Results
=====
Dep. Variable: price R-squared: 0.617
Model: OLS Adj. R-squared: 0.603
Method: Least Squares F-statistic: 43.58
Date: Wed, 21 Jan 2026 Prob (F-statistic): 4.41e-07
Time: 15:15:57 Log-Likelihood: -332.05
No. Observations: 29 AIC: 668.1
Df Residuals: 27 BIC: 670.8
Df Model: 1
Covariance Type: nonrobust
=====
            coef    std err      t   P>|t|      [0.025    0.975]
-----
Intercept  1.15e+05  2.15e+04    5.352    0.000    7.09e+04  1.59e+05
size        73.7710   11.175     6.601    0.000    50.842    96.700
=====
Omnibus:          0.576 Durbin-Watson:       1.219
Prob(Omnibus):    0.750 Jarque-Bera (JB):    0.638
Skew:             -0.078 Prob(JB):         0.727
Kurtosis:          2.290 Cond. No.        9.45e+03
=====

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 9.45e+03. This might indicate that there are
strong multicollinearity or other numerical problems.

```

I Interpreting Coefficient Stability Across Models

What this table reveals about coefficient estimates:

Tracking how coefficients change as we add variables helps diagnose **multicollinearity** and understand variable relationships:

Size coefficient across models:

- **Model 1:** 73.77($SE = 11.17$)
- **Model 2:** 73.65($SE = 11.50$)
- **Model 3:** 68.37($SE = 15.39$)

What we observe:

1. **Relatively stable point estimates:** The size coefficient ranges from 68–74 across models, suggesting the relationship is genuine and robust.
2. **Increasing standard errors:** As we add variables, the SE increases from 11 to 15—a 38% increase. This reflects **multicollinearity**: size is correlated with other variables (larger houses have more bedrooms, bathrooms, etc.).

3. Precision loss: In Model 1, we can estimate the size effect quite precisely (SE = \$11). Adding correlated variables inflates uncertainty without improving the overall fit much.

Bedrooms paradox:

- When added in Model 2, bedrooms show essentially no effect
- In Model 3, the coefficient is 2,685 but with a huge SE of 9,193
- This means bedrooms add no information beyond what size already provides

Economic lesson:

This pattern is common in real estate data: once you control for total square footage, the number of rooms matters little. Two houses of identical size but different room configurations (e.g., one with 3 large bedrooms vs. one with 4 small bedrooms) sell for similar prices. **Size is what buyers care about, not how that space is divided.**

| Manual F-test Calculation

| Interpreting Robust Standard Errors

What robust standard errors tell us:

Heteroskedasticity-robust (HC1) standard errors correct for potential violations of the constant variance assumption. Comparing standard vs. robust errors helps diagnose whether heteroskedasticity is a concern:

Size coefficient:

- **Standard SE:** \$15.39 → **Robust SE:** \$15.15
- **Change:** Slight decrease (1.6%)
- **Both t-stats highly significant** ($p \approx 0.0002$)

Intercept:

- **Standard SE:** \$61,465 → **Robust SE:** \$69,273
- **Change:** Increase of 12.7%
- **p-value changes:** 0.035 → 0.047 (still significant, but closer to the boundary)

Other variables:

- Most show minor changes in SEs

- All remain statistically insignificant with robust SEs
- Conclusions unchanged

What this means:

- 1. Mild heteroskedasticity:** The fact that robust SEs are similar to standard SEs suggests heteroskedasticity is not a major problem in this dataset. If it were severe, we'd see much larger increases in robust SEs.
- 2. Conclusions are robust:** The key finding—that size is significant while other variables are not—holds regardless of which SE we use.
- 3. Best practice:** For cross-sectional data like housing prices, it's wise to **report robust SEs by default**. They provide valid inference whether or not heteroskedasticity is present, with minimal cost.
- 4. Intercept sensitivity:** The intercept shows the largest change, but intercepts are rarely of economic interest. Our substantive conclusions about slope coefficients remain unchanged.

In [16]:

```
# Calculate F-statistic for subset test
k_unrest = len(model_full.params)
k_rest = len(model_restricted.params)
q = k_unrest - k_rest # number of restrictions

RSS_unrest = np.sum(model_full.resid**2)
RSS_rest = np.sum(model_restricted.resid**2)
df_unrest = n - k_unrest

F_subset = ((RSS_rest - RSS_unrest) / q) / (RSS_unrest / df_unrest)
p_value_subset = 1 - stats.f.cdf(F_subset, q, df_unrest)
f_crit_subset = stats.f.ppf(0.95, q, df_unrest)

print("\nSubset F-test results:")
print(f" Number of restrictions (q): {q}")
print(f" RSS (restricted): {RSS_rest:.2f}")
print(f" RSS (unrestricted): {RSS_unrest:.2f}")
print(f" Increase in RSS: {RSS_rest - RSS_unrest:.2f}")
print(f" F-statistic: {F_subset:.4f}")
print(f" p-value: {p_value_subset:.4f}")
print(f" Critical value (α=0.05): {f_crit_subset:.4f}")

if F_subset > f_crit_subset:
    print("\nResult: Reject H₀ - The additional variables are jointly significant")
    print(" Keep the full model.")
else:
    print("\nResult: Fail to reject H₀ - The additional variables are NOT jointly
significant")
    print(" The simpler model (only size) is preferred.")
```

```

Subset F-test results:
Number of restrictions (q): 5
RSS (restricted): 14,975,101,654.50
RSS (unrestricted): 13,679,397,854.73
Increase in RSS: 1,295,703,799.78
F-statistic: 0.4168
p-value: 0.8320
Critical value ( $\alpha=0.05$ ): 2.6613

Result: Fail to reject  $H_0$  - The additional variables are NOT jointly significant
The simpler model (only size) is preferred.

```

ANOVA Table Comparison

```
In [17]: # Using ANOVA table for comparison
print("\n" + "-" * 70)
print("ANOVA table comparison")
print("-" * 70)
anova_results = anova_lm(model_restricted, model_full)
print(anova_results)

print("\nThe ANOVA table confirms our manual F-test calculation.")
```

```
-----
ANOVA table comparison
-----
   df_resid      ssr  df_diff    ss_diff      F   Pr(>F)
0     27.0  1.497510e+10      0.0        NaN     NaN     NaN
1     22.0  1.367940e+10      5.0  1.295704e+09  0.416765  0.831976
```

The ANOVA table confirms our manual F-test calculation.

Key Concept 11.7: Testing Subsets of Regressors

To test whether a subset of regressors belongs in the model, compare the restricted model (without those variables) to the unrestricted model (with them) using an F-test. If the F-statistic is small (large p-value), the additional regressors don't significantly improve fit and the simpler model is preferred.

Now that we can compute and interpret F-statistics, let's learn how to present regression results professionally.

11.7: Presentation of Regression Results

Professional presentation of regression results is important for communication. Different formats emphasize different aspects.

Common presentation formats:

- 1. Coefficients with standard errors** (in parentheses)
- 2. Coefficients with t-statistics** (in parentheses)
- 3. Coefficients with p-values** (in parentheses)
- 4. Coefficients with 95% confidence intervals**
- 5. Coefficients with significance stars:**
 - *** for $p < 0.01$ (1% level)
 - ** for $p < 0.05$ (5% level)
 - ■ for $p < 0.10$ (10% level)

Model comparison tables typically show:

- Multiple model specifications side-by-side
- Standard errors in parentheses below coefficients
- Model fit statistics (R^2 , N, F-stat) at bottom

This allows readers to see how coefficient estimates change across specifications.

In [18]:

```
print("=" * 70)
print("11.7 PRESENTATION OF REGRESSION RESULTS")
print("=" * 70)

# Comparison of multiple models
print("\n" + "-" * 70)
print("Model Comparison: Three Specifications")
print("-" * 70)

# Model 1: Simple regression
model1 = ols('price ~ size', data=data_house).fit()

# Model 2: Two regressors
model2 = ols('price ~ size + bedrooms', data=data_house).fit()

# Model 3: Full model (already estimated as model_full)
model3 = model_full

# Create comparison table
models = [model1, model2, model3]
model_names = ['Model 1', 'Model 2', 'Model 3']

comparison_data = []
for name, model in zip(model_names, models):
    model_stats = {
        'Model': name,
        'N': int(model.nobs),
        'R22
```

```
=====
11.7 PRESENTATION OF REGRESSION RESULTS
=====
```

```
-----
Model Comparison: Three Specifications
-----
```

Model	N	R ²	Adj. R ²	RMSE	F-stat	p-value
Model 1	29	0.6175	0.6033	23550.66	43.5796	0.000000
Model 2	29	0.6180	0.5886	23981.21	21.0340	0.000004
Model 3	29	0.6506	0.5552	24935.73	6.8261	0.000342

```
Model specifications:
```

```
  Model 1: price ~ size
  Model 2: price ~ size + bedrooms
  Model 3: price ~ size + bedrooms + bathrooms + lotsize + age + monthsold
```

Detailed Coefficient Comparison Across Models

Now let's see how coefficient estimates change as we add variables.

In [19]:

```
# Detailed coefficient comparison
print("\n" + "-" * 70)
print("Coefficient Comparison Across Models")
print("-" * 70)

# Get all unique parameter names
all_params = set()
for model in models:
    all_params.update(model.params.index)
all_params = sorted(all_params)

# Create coefficient table
coef_comparison = pd.DataFrame(index=all_params)
for i, (name, model) in enumerate(zip(model_names, models), 1):
    coef_col = f'{name} Coef'
    se_col = f'{name} SE'

    coef_comparison[coef_col] = model.params.reindex(all_params)
    coef_comparison[se_col] = model.bse.reindex(all_params)

print(coef_comparison.fillna('-'))

print("\nKey observations:")
print(" - Size coefficient relatively stable across models")
print(" - Adding variables increases standard errors (multicollinearity)")
print(" - Adjusted R2 peaks at Model 1 (simplest model)")
```

Coefficient Comparison Across Models

	Model 1 Coef	Model 1 SE	Model 2 Coef	Model 2 SE	\
Intercept	115017.282609	21489.359861	111690.856193	27589.07418	
age	-	-	-	-	
bathrooms	-	-	-	-	
bedrooms	-	-	1553.458022	7846.866223	
lotsize	-	-	-	-	
monthsold	-	-	-	-	
size	73.77104	11.174911	72.408146	13.299618	
	Model 3 Coef	Model 3 SE			
Intercept	137791.065699	61464.951869			
age	-833.038602	719.334544			
bathrooms	6832.880015	15721.191544			
bedrooms	2685.315122	9192.525674			
lotsize	2303.221371	7226.535205			
monthsold	-2088.503625	3520.897859			
size	68.369419	15.389472			

Key observations:

- Size coefficient relatively stable across models
- Adding variables increases standard errors (multicollinearity)
- Adjusted R² peaks at Model 1 (simplest model)

Robust Standard Errors (Heteroskedasticity- Robust)

| Robust)

Classical OLS assumes constant error variance (homoskedasticity). When this fails, standard errors are incorrect.

Heteroskedasticity-robust standard errors (HC1, White's correction):

- Valid inference even when error variance is not constant
- Typically larger than classical standard errors
- Recommended for cross-sectional data

Effect on inference:

- Coefficient estimates unchanged
- Standard errors may increase
- t-statistics may decrease
- Some "significant" variables may become insignificant

In [20]:

```
print("=" * 70)
print("ROBUST STANDARD ERRORS (HC1)")
print("=" * 70)

# Get robust results for full model
model_full_robust = model_full.get_robustcov_results(cov_type='HC1')

print("\nComparison of standard vs robust standard errors:")
robust_comparison = pd.DataFrame({
    'Coefficient': model_full.params,
    'Std. Error': model_full.bse,
    'Robust SE': model_full_robust.bse,
    't-stat (std)': model_full.tvalues,
    't-stat (robust)': model_full_robust.tvalues,
    'p-value (std)': model_full.pvalues,
    'p-value (robust)': model_full_robust.pvalues
})
print(robust_comparison)

print("\nInterpretation:")
print(" - Robust SEs are often larger (more conservative inference)")
print(" - t-statistics are correspondingly smaller")
print(" - Recommended to report robust SEs for cross-sectional data")
```

```
=====
ROBUST STANDARD ERRORS (HC1)
=====

Comparison of standard vs robust standard errors:
      Coefficient   Std. Error   Robust SE   t-stat (std) \
Intercept  137791.065699  61464.951869  65545.225391  2.241783
size        68.369419   15.389472   15.359192   4.442610
bedrooms    2685.315122  9192.525674  8285.528329  0.292119
bathrooms   6832.880015  15721.191544  19283.790798  0.434629
lotsize     2303.221371   7226.535205  5328.859590  0.318717
age         -833.038602   719.334544   762.929519  -1.158068
monthsold   -2088.503625  3520.897859  3738.270456  -0.593174

      t-stat (robust)   p-value (std)   p-value (robust)
Intercept       2.102229    0.035387    0.047203
size            4.451368    0.000205    0.000200
bedrooms        0.324097    0.772932    0.748926
bathrooms       0.354333    0.668065    0.726463
lotsize          0.432217    0.752947    0.669791
age             -1.091895   0.259254    0.286693
monthsold       -0.558682    0.559114    0.582021
```

Interpretation:

- Robust SEs are often larger (more conservative inference)
- t-statistics are correspondingly smaller
- Recommended to report robust SEs for cross-sectional data

Key Concept 11.8: Robust Standard Errors and Heteroskedasticity

When errors may not have constant variance, heteroskedasticity-robust (HC1) standard errors provide valid inference without assuming homoskedasticity. Coefficient estimates remain unchanged, but standard errors — and thus t-statistics and p-values — may differ. For cross-sectional data, reporting robust SEs is considered best practice.

Visualization: Confidence Intervals for All Coefficients

A coefficient plot provides a visual summary of estimation results.

In [21]:

```
# Figure 11.1: Confidence intervals for all coefficients
fig, ax = plt.subplots(figsize=(10, 8))

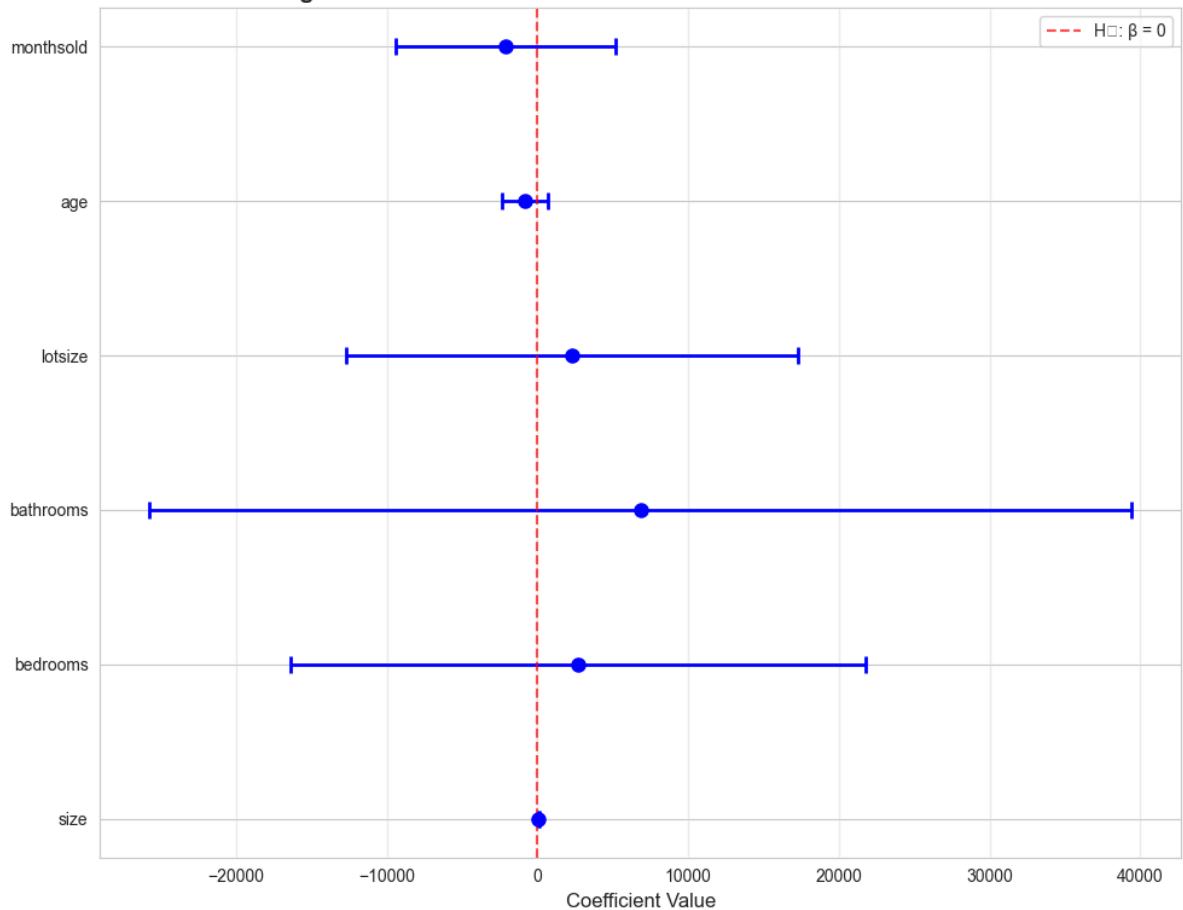
params_no_int = model_full.params[1:]
ci_no_int = conf_int.iloc[1:, :]

y_pos = np.arange(len(params_no_int))
ax.errorbar(params_no_int.values, y_pos,
            xerr=[params_no_int.values - ci_no_int.iloc[:, 0].values,
                   ci_no_int.iloc[:, 1].values - params_no_int.values],
            fmt='o', markersize=8, capsize=5, capthick=2, linewidth=2, color='blue')
ax.set_yticks(y_pos)
ax.set_yticklabels(params_no_int.index)
ax.axvline(x=0, color='red', linestyle='--', linewidth=1.5, alpha=0.7,
           label='H0: β = 0')
ax.set_xlabel('Coefficient Value', fontsize=12)
ax.set_title('Figure 11.1: Coefficient Estimates with 95% Confidence Intervals',
             fontsize=14, fontweight='bold')
ax.legend()
ax.grid(True, alpha=0.3, axis='x')
plt.tight_layout()
plt.show()

print("Coefficients whose CI crosses zero are not statistically significant at 5%.")
```

```
/var/folders/tq/t98kb27n6djgrh085g476yhc0000gn/T/ipykernel_56083/677075515.py:21: UserWarning: Glyph 8320 (\N{SUBSCRIPT ZERO}) missing from current font.
  plt.tight_layout()
/Users/carlosmendez/miniforge3/lib/python3.10/site-packages/IPython/core/pylabtools.py:170: UserWarning: Glyph 8320 (\N{SUBSCRIPT ZERO}) missing from current font.
  fig.canvas.print_figure(bytes_io, **kw)
```

Figure 11.1: Coefficient Estimates with 95% Confidence Intervals



Coefficients whose CI crosses zero are not statistically significant at 5%.

| Visualization: F-Distribution

Visualize the F-distribution and show where our test statistic falls.

In [22]:

```
# Figure: F-distribution visualization
fig, ax = plt.subplots(figsize=(10, 6))

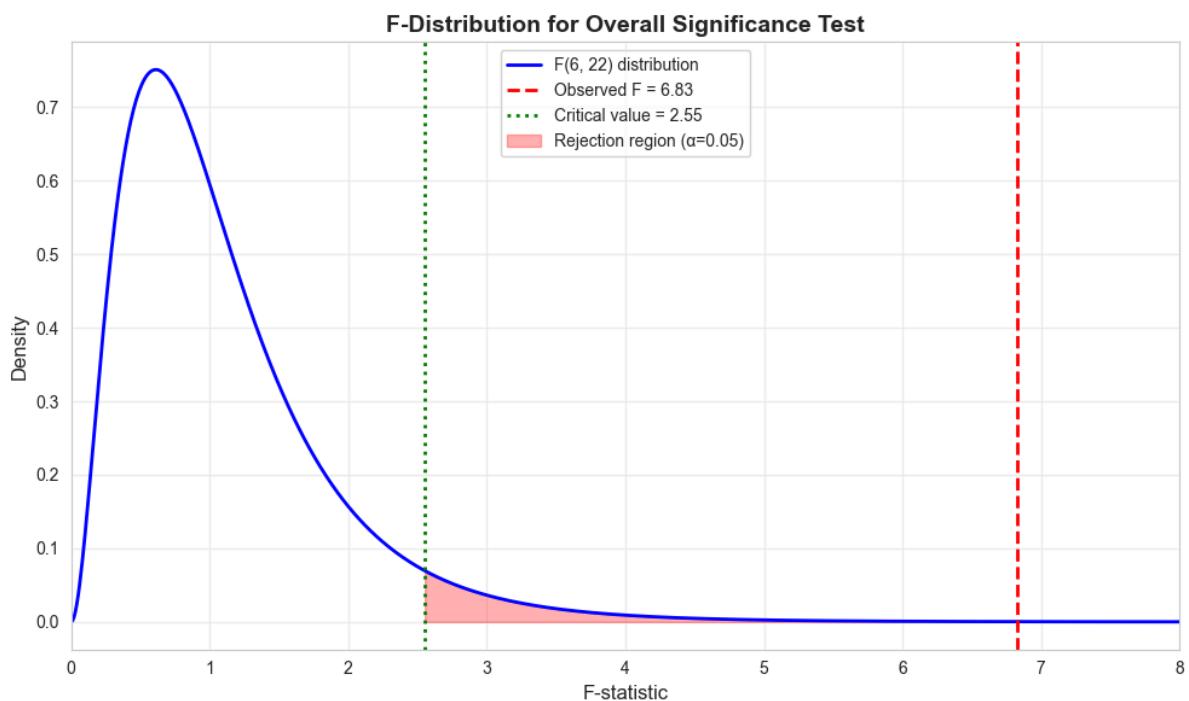
x_range = np.linspace(0, 10, 1000)
f_pdf = stats.f.pdf(x_range, dfn, dfd)

ax.plot(x_range, f_pdf, 'b-', linewidth=2, label=f'F({dfn}, {dfd}) distribution')
ax.axvline(x=f_stat, color='red', linewidth=2, linestyle='--',
           label=f'Observed F = {f_stat:.2f}')
ax.axvline(x=f_crit, color='green', linewidth=2, linestyle=':',
           label=f'Critical value = {f_crit:.2f}')

# Shade rejection region
x_reject = x_range[x_range >= f_crit]
f_reject = stats.f.pdf(x_reject, dfn, dfd)
ax.fill_between(x_reject, 0, f_reject, alpha=0.3, color='red',
                label='Rejection region (\alpha=0.05)')

ax.set_xlabel('F-statistic', fontsize=12)
ax.set_ylabel('Density', fontsize=12)
ax.set_title('F-Distribution for Overall Significance Test',
             fontsize=14, fontweight='bold')
ax.legend()
ax.grid(True, alpha=0.3)
ax.set_xlim(0, max(8, f_stat + 1))
plt.tight_layout()
plt.show()

print(f"The observed F-statistic ({f_stat:.2f}) exceeds the critical value
({f_crit:.2f}).")
print("This leads us to reject the null hypothesis of no relationship.")
```



The observed F-statistic (6.83) exceeds the critical value (2.55).
This leads us to reject the null hypothesis of no relationship.

Visualization: Model Comparison (Actual vs Predicted)

Compare the three models visually by plotting actual vs. predicted values.

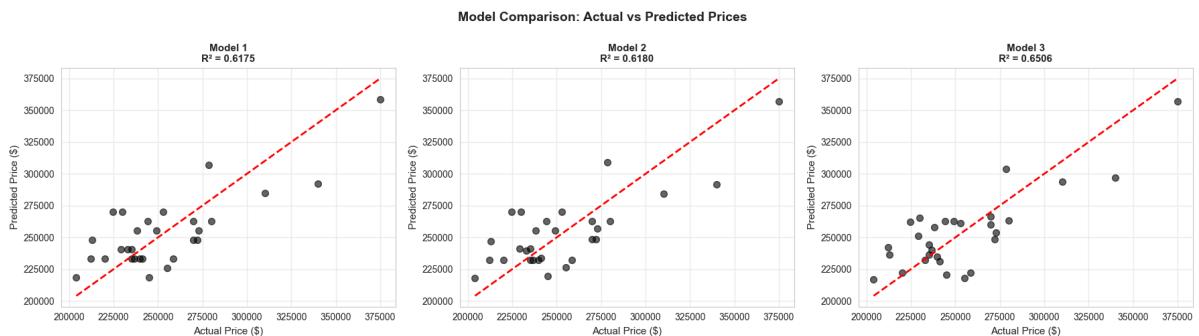
In [23]:

```
# Figure: Model comparison visualization
fig, axes = plt.subplots(1, 3, figsize=(18, 5))

for i, (model, name) in enumerate(zip(models, model_names)):
    axes[i].scatter(data_house['price'], model.fittedvalues,
                    alpha=0.6, s=50, color='black')
    axes[i].plot([data_house['price'].min(), data_house['price'].max()],
                 [data_house['price'].min(), data_house['price'].max()],
                 'r--', linewidth=2)
    axes[i].set_xlabel('Actual Price ($)', fontsize=11)
    axes[i].set_ylabel('Predicted Price ($)', fontsize=11)
    axes[i].set_title(f'{name}\nR2 = {model.rsquared:.4f}',
                      fontsize=11, fontweight='bold')
    axes[i].grid(True, alpha=0.3)

plt.suptitle('Model Comparison: Actual vs Predicted Prices',
             fontsize=14, fontweight='bold', y=1.00)
plt.tight_layout()
plt.show()

print("All three models show similar predictive performance.")
print("The simplest model (Model 1) may be preferred for parsimony.")
```



All three models show similar predictive performance.
The simplest model (Model 1) may be preferred for parsimony.

Key Takeaways

Classical Assumptions and OLS Properties:

- Under assumptions 1-4 (linearity, random sampling, no perfect collinearity, zero conditional mean), OLS is unbiased, consistent, and efficient (BLUE)
- The standard error $se(b_j) = s_e / \sqrt{\sum \tilde{x}_{ji}^2}$ decreases with larger samples, more variation in x_j , and lower multicollinearity
- The t -statistic $t = b_j / se(b_j)$ follows a $T(n - k)$ distribution

Confidence Intervals:

- 95% CI: $b_j \pm t_{n-k, 0.025} \times se(b_j)$
- If the CI excludes zero, the coefficient is statistically significant at 5%
- Narrower CIs indicate more precise estimation

Individual Hypothesis Tests:

- Test $H_0 : \beta_j = \beta_j^*$ using $t = (b_j - \beta_j^*)/se(b_j)$
- Most common: test of significance $H_0 : \beta_j = 0$ — does variable x_j matter after controlling for others?
- Reject H_0 if $|t| > t_{\text{critical}}$ or equivalently if $p\text{-value} < \alpha$

Joint F-Tests:

- F-test evaluates multiple restrictions simultaneously:
$$F = \frac{(RSS_r - RSS_u)/q}{RSS_u/(n-k)} \sim F(q, n - k)$$
- Overall significance test: $H_0 : \beta_2 = \dots = \beta_k = 0$ (all slopes zero)
- Subset tests: compare restricted vs. unrestricted models to decide if additional regressors are needed
- Equivalently: $F = \frac{(R_u^2 - R_r^2)/q}{(1 - R_u^2)/(n-k)}$

Model Comparison and Selection:

- Use F-tests to formally compare nested models
- Consider adjusted R^2 , AIC, BIC alongside F-tests
- Prefer parsimony: if additional variables don't significantly improve fit, use the simpler model
- In our house price example, size alone was sufficient — five additional variables failed the joint F-test ($p = 0.83$)

Presenting Results and Robust Inference:

- Five standard formats: coefficients with (SEs), (t-stats), (p-values), (CIs), or (asterisks)
- Heteroskedasticity-robust (HC1) standard errors provide valid inference without assuming constant variance
- Report robust SEs by default for cross-sectional data

Python tools used: `statsmodels` (OLS, t_test, f_test, anova_lm, HC1),
`scipy.stats` (t and F distributions), `matplotlib / seaborn` (coefficient plots, F-

distribution)

Next steps: Chapter 12 covers **further inference and model specification** — additional diagnostic tests and extensions to the multiple regression framework.

Congratulations on completing Chapter 11! You can now conduct rigorous statistical inference for multiple regression models.

| Practice Exercises

Test your understanding of statistical inference for multiple regression.

Exercise 1: Confidence Interval Calculation

A multiple regression with $n = 200$ observations and $k = 4$ parameters yields:

- $b_2 = 5.0, se(b_2) = 2.0$
- $b_3 = 7.0, se(b_3) = 2.0$

- a) Compute an approximate 95% confidence interval for β_2 .
 - b) Compute an approximate 95% confidence interval for β_3 .
 - c) Which coefficient is estimated more precisely? Explain.
-

Exercise 2: Test of Statistical Significance

Using the regression from Exercise 1:

- a) Is x_2 statistically significant at the 5% level? Compute the t -statistic and state your conclusion.
 - b) Is x_3 statistically significant at the 5% level?
 - c) What is the approximate p -value for each coefficient?
-

Exercise 3: Testing a Specific Value

Using the same regression, test the claim that $\beta_3 = 10.0$ at significance level 0.05.

- a) State the null and alternative hypotheses.
- b) Compute the t -statistic.

c) What is your decision? Can you reject H_0 ?

Exercise 4: Joint F-Test Setup

Consider the model $y = \beta_1 + \beta_2x_2 + \beta_3x_3 + \beta_4x_4 + \beta_5x_5 + \beta_6x_6 + u$.

We wish to test whether only x_2 and x_3 should be included in the model.

- State H_0 and H_a for this test.
 - How many restrictions are being tested (q)?
 - What are the degrees of freedom for the F-test if $n = 100$?
-

Exercise 5: F-Statistic Computation

You estimate two models on $n = 53$ observations:

- Restricted model ($k_r = 3$): $RSS_r = 40$
- Unrestricted model ($k_u = 6$): $RSS_u = 30$

- Compute the F-statistic.
 - What are the degrees of freedom?
 - At $\alpha = 0.05$, would you reject the restrictions?
-

Exercise 6: Regression Presentation

Given these regression results:

Variable	Coefficient	Std. Error	p-value
Intercept	3.0	1.5	0.047
x_2	5.0	2.0	0.013
x_3	7.0	2.0	0.001

- Present these results using the asterisk notation (** for $p < 0.01$, ** for $p < 0.05$, * for $p < 0.10$).
- Present using the coefficient (standard error) format.
- Which variables are significant at the 1% level? At the 5% level?

Case Studies

Case Study 1: Statistical Inference for Cross-Country Productivity

In this case study, you will apply confidence intervals, hypothesis tests, and F-tests to investigate whether physical capital and human capital are statistically significant determinants of cross-country labor productivity differences.

Dataset: Mendez Convergence Clubs Data

- **Source:** Mendez (2020), 108 countries, 1990-2014
- **Key variables:**
 - `lp` — Labor productivity (GDP per worker)
 - `rk` — Physical capital per worker
 - `hc` — Human capital index
 - `region` — Geographic region

Research question: Are physical capital and human capital jointly significant in explaining cross-country labor productivity?

```
# Load the Mendez convergence clubs dataset
url = "https://raw.githubusercontent.com/quarcs-lab/mendez2020-convergence-clubs-code-data/master/assets/dat.csv"
dat = pd.read_csv(url)
dat_2014 = dat[dat['year'] == 2014].dropna(subset=['lp', 'rk', 'hc']).copy()
dat_2014['ln_lp'] = np.log(dat_2014['lp'])
dat_2014['ln_rk'] = np.log(dat_2014['rk'])
print(f"Cross-section sample: {len(dat_2014)} countries (year 2014)")
dat_2014.head()
```

Task 1: Estimate Productivity Model (Guided)

Estimate the multiple regression model for labor productivity.

```
# Estimate: ln(lp) = beta_0 + beta_1 * ln(rk) + beta_2 * hc + u
model_prod = ols('ln_lp ~ ln_rk + hc', data=dat_2014).fit()
print(model_prod.summary())
```

Questions:

- How many observations and parameters does the model have?
- What is the R^2 ? How much of productivity variation do capital and human capital explain?

Task 2: Confidence Intervals (Guided)

Compute and interpret 95% confidence intervals for the coefficients.

```
# 95% confidence intervals
print("95% Confidence Intervals:")
print(model_prod.conf_int(alpha=0.05))

# Manual calculation for ln_rk coefficient
b_rk = model_prod.params['ln_rk']
se_rk = model_prod.bse['ln_rk']
df = model_prod.df_resid
t_crit = stats.t.ppf(0.975, df)
print(f"\nManual CI for ln(rk): [{b_rk - t_crit*se_rk:.4f}, {b_rk + t_crit*se_rk:.4f}]")
```

Questions:

- Does the CI for $\ln(\text{rk})$ exclude zero? What does this tell you?
- Does the CI for hc exclude zero? Interpret in economic terms.

Key Concept 11.9: Statistical Significance in Cross-Country Regressions

With over 100 countries, cross-country regressions have sufficient power to detect moderate effects. However, statistical significance does not imply causation — unobserved factors (institutions, geography, culture) may confound the relationship between capital inputs and productivity. Confidence intervals quantify estimation uncertainty but not omitted variable bias.

Task 3: Individual Hypothesis Tests (Semi-guided)

Test the statistical significance of each coefficient.

```
# Test significance of each coefficient
print("t-statistics and p-values:")
for var in ['ln_rk', 'hc']:
    t = model_prod.tvalues[var]
    p = model_prod.pvalues[var]
    sig = '**' if p < 0.01 else '*' if p < 0.05 else '*' if p < 0.10 else ''
    print(f" {var}: t = {t:.3f}, p = {p:.4f} {sig}")
```

Questions:

- Which coefficients are significant at the 1% level? At the 5% level?
- Interpret the economic meaning: what does significance of $\ln(\text{rk})$ tell us about physical capital?

Task 4: Joint F-Test (Semi-guided)

Test whether physical capital and human capital are jointly significant.

```
# Overall F-test: H0: beta_1 = beta_2 = 0
print(f"Overall F-statistic: {model_prod.fvalue:.4f}")
print(f"p-value: {model_prod.f_pvalue:.6e}")

# Compare to restricted model (intercept only)
model_restricted = ols('ln_lp ~ 1', data=dat_2014).fit()
anova_result = anova_lm(model_restricted, model_prod)
print("\nANOVA comparison:")
print(anova_result)
```

Questions:

- Can you reject $H_0 : \beta_1 = \beta_2 = 0$? What does this mean economically?
- How does the F-test relate to the individual t -tests?

Task 5: Model Comparison (Independent)

Compare nested models to determine the best specification.

Your tasks:

1. Estimate three models: (a) $\ln(lp) \sim \ln(rk)$ only, (b) $\ln(lp) \sim hc$ only, (c) both regressors
2. Create a model comparison table with R^2 , adjusted R^2 , AIC, BIC
3. Conduct subset F-tests: does adding hc to the $\ln(rk)$ -only model significantly improve fit?
4. Report robust standard errors for the preferred model

Hint: Use `anova_lm(model_restricted, model_unrestricted)` for the F-test and `model.get_robustcov_results(cov_type='HC1')` for robust SEs.

Task 6: Inference Policy Brief (Independent)

Write a 200-300 word policy brief summarizing your inference results.

Your brief should address:

1. Which factors are statistically significant predictors of cross-country productivity?
2. What are the 95% confidence intervals for the effects of capital and human capital?
3. Are both factors jointly significant? What does the F-test tell us?
4. What policy implications follow from these findings?

5. What caveats should policymakers consider (association vs. causation, omitted variables)?

Key Concept 11.10: From Statistical Significance to Policy Relevance

Finding that both physical and human capital are statistically significant predictors of productivity suggests that investments in both areas may boost economic output. However, the magnitudes matter for policy: confidence intervals tell us the plausible range of effects, while F-tests confirm that both factors jointly matter beyond what each contributes alone. Policy decisions should weigh statistical evidence alongside practical considerations like cost-effectiveness and implementation feasibility.

What You've Learned

In this case study, you applied the full statistical inference toolkit to cross-country productivity data:

- Estimated multiple regression models and examined coefficient properties
- Constructed and interpreted confidence intervals for partial effects
- Conducted individual t -tests to assess each predictor's significance
- Performed joint F-tests to evaluate whether both capital types matter
- Compared nested models and reported results with robust standard errors

These inferential tools are essential for drawing reliable conclusions from empirical economic analysis.

Case Study 2: Which Satellite Features Matter? Joint Tests for Predictive Power

In Chapter 10, we estimated a multiple regression of municipal development on nighttime lights and satellite embeddings. Now we apply Chapter 11's inference tools— t -tests for individual coefficients and F-tests for joint significance—to determine which satellite features add statistically significant predictive power.

Dataset: DS4Bolivia — Satellite Data for Sustainable Development

- **Source:** [DS4Bolivia Project](#), 339 municipalities
- **Key variables:**

- `imds` — Municipal Sustainable Development Index (0-100 composite)
- `ln_NTLpc2017` — Log nighttime lights per capita (2017)
- `A00`, `A10`, `A20`, `A30`, `A40` — Selected satellite image embedding dimensions

Research question: Do satellite image embeddings add statistically significant predictive power for municipal development beyond nighttime lights alone?

```
# Load the DS4Bolivia dataset
url_bol = "https://raw.githubusercontent.com/quarcs-lab/ds4bolivia/master/ds4bolivia_v20250523.csv"
bol = pd.read_csv(url_bol)

# Select variables and prepare analysis sample
embed_vars = ['A00', 'A10', 'A20', 'A30', 'A40']
analysis_vars = ['imds', 'ln_NTLpc2017'] + embed_vars
bol_cs = bol[['mun', 'dep']] + analysis_vars].dropna(subset=analysis_vars).copy()
print(f"Analysis sample: {len(bol_cs)} municipalities with complete data")
bol_cs[analysis_vars].describe().round(3)
```

Task 1: Estimate Full Model (Guided)

Estimate the full multiple regression model with nighttime lights and all five satellite embedding dimensions as predictors of municipal development.

```
# Estimate: imds = beta_0 + beta_1*ln_NTLpc2017 + beta_2*A00 + ... + beta_6*A40 + u
model_full = ols('imds ~ ln_NTLpc2017 + A00 + A10 + A20 + A30 + A40',
                 data=bol_cs).fit()
print(model_full.summary())
```

Questions:

- How many coefficients are estimated (including the intercept)?
- Which coefficients have p-values below 0.05? Below 0.10?
- What is the overall R^2 ? How much variation in development does this model explain?
- Compare this R^2 to a model with NTL alone—how much do the embeddings add?

In []:

```
# Your code here: Estimate the full model
#
# Steps:
# 1. Estimate the full model with NTL and all 5 embeddings
# 2. Print the full summary
# 3. Identify significant coefficients ( $p < 0.05$  and  $p < 0.10$ )
#
# Example structure:
# model_full = ols('imds ~ ln_NTLpc2017 + A00 + A10 + A20 + A30 + A40', data=bol_cs).fit()
# print(model_full.summary())
#
# # Identify significant predictors
# print("\nSignificance at 5% level:")
# for var in model_full.params.index:
#     p = model_full.pvalues[var]
#     sig = "***" if p < 0.01 else "**" if p < 0.05 else "*" if p < 0.10 else ""
#     print(f" {var:18s} p = {p:.4f} {sig}")
```

Task 2: Confidence Intervals (Guided)

Compute 95% confidence intervals for all coefficients and create a coefficient plot (forest plot) to visualize the estimates and their uncertainty.

```
# 95% confidence intervals
ci = model_full.conf_int(alpha=0.05)
ci.columns = ['Lower 2.5%', 'Upper 97.5%']
ci['Estimate'] = model_full.params
print(ci[['Estimate', 'Lower 2.5%', 'Upper 97.5%']].round(4))
```

Questions:

- Which confidence intervals include zero? What does this imply about significance?
- Which coefficient has the widest confidence interval? The narrowest (excluding intercept)?
- Create a forest plot showing point estimates and 95% CIs for the embedding coefficients
- How do the confidence intervals for embeddings compare in width to the NTL coefficient?

In []:

```
# Your code here: Confidence intervals and coefficient plot
#
# Steps:
# 1. Compute confidence intervals with model_full.conf_int()
# 2. Print the table of estimates and CIs
# 3. Create a coefficient plot (forest plot) for embedding variables
# 4. Identify which CIs include zero

# Example structure:
# ci = model_full.conf_int(alpha=0.05)
# ci.columns = ['Lower', 'Upper']
# ci['Estimate'] = model_full.params
# print(ci[['Estimate', 'Lower', 'Upper']].round(4))
#
# # Forest plot for embedding coefficients
# embed_vars = ['A00', 'A10', 'A20', 'A30', 'A40']
# fig, ax = plt.subplots(figsize=(8, 5))
# y_pos = range(len(embed_vars))
# estimates = [model_full.params[v] for v in embed_vars]
# errors = [(model_full.params[v] - ci.loc[v, 'Lower'],
#             ci.loc[v, 'Upper'] - model_full.params[v]) for v in embed_vars]
# errors_T = list(zip(*errors))
# ax.errorbar(estimates, y_pos, xerr=errors_T, fmt='o', color='navy',
#             capsized=5, markersize=8)
# ax.axvline(x=0, color='red', linestyle='--', alpha=0.7, label='Zero (no effect)')
# ax.set_yticks(y_pos)
# ax.set_yticklabels(embed_vars)
# ax.set_xlabel('Coefficient Estimate with 95% CI')
# ax.set_title('Coefficient Plot: Satellite Embedding Effects on IMDS')
# ax.legend()
# plt.tight_layout()
# plt.show()
```

Task 3: Individual t-Tests (Semi-guided)

Examine the t-statistics and p-values for each satellite embedding coefficient individually.

Your tasks:

1. Extract and display the t-statistic and p-value for each embedding variable (A00 - A40)
2. Classify each as significant at 5%, significant at 10%, or not significant
3. Count how many of the 5 embeddings are individually significant at each level
4. Discuss: If some embeddings are individually insignificant, can we conclude they are "useless"? Why or why not?

Hint: Individual insignificance may reflect multicollinearity among embeddings rather than lack of predictive power. The joint F-test in Task 4 will help resolve this.

```
In [ ]: # Your code here: Individual t-tests for embedding coefficients
#
# Steps:
# 1. Extract t-statistics and p-values for each embedding
# 2. Classify significance levels
# 3. Discuss the implications

# Example structure:
# print("Individual t-Tests for Satellite Embeddings")
# print("=" * 60)
# embed_vars = ['A00', 'A10', 'A20', 'A30', 'A40']
# sig_5 = 0
# sig_10 = 0
# for var in embed_vars:
#     t = model_full.tvalues[var]
#     p = model_full.pvalues[var]
#     if p < 0.05:
#         level = "Significant at 5% ***"
#         sig_5 += 1
#         sig_10 += 1
#     elif p < 0.10:
#         level = "Significant at 10% *"
#         sig_10 += 1
#     else:
#         level = "Not significant"
#     print(f" {var}: t = {t:.3f}, p = {p:.4f} → {level}")
# print(f"\nSignificant at 5%: {sig_5}/5 embeddings")
# print(f"Significant at 10%: {sig_10}/5 embeddings")
```

Task 4: Joint F-Test (Semi-guided)

Test whether all five satellite embedding coefficients are jointly equal to zero.

$$H_0 : \beta_{A00} = \beta_{A10} = \beta_{A20} = \beta_{A30} = \beta_{A40} = 0$$

Your tasks:

1. Construct a restriction matrix R where each row sets one embedding coefficient to zero
2. Use `model_full.f_test()` with the restriction matrix to compute the joint F-statistic
3. Report the F-statistic, degrees of freedom, and p-value
4. Compare the joint test result with the individual t-test results from Task 3
5. Are embeddings *jointly* significant even if some are individually insignificant?

Hint: The restriction matrix has 5 rows (one per restriction) and 7 columns (one per coefficient including intercept). Each row has a 1 in the position of the embedding coefficient being tested and 0s elsewhere.

In []:

```
# Your code here: Joint F-test for all embedding coefficients
#
# Steps:
# 1. Construct the restriction matrix R
# 2. Perform the joint F-test with model_full.f_test(R)
# 3. Report F-statistic and p-value
# 4. Compare with individual t-test results

# Example structure:
# import numpy as np
#
# # Restriction matrix: 5 restrictions (A00=A10=A20=A30=A40=0)
# # Coefficients order: Intercept, ln_NTLpc2017, A00, A10, A20, A30, A40
# R = np.zeros((5, 7))
# R[0, 2] = 1 # A00 = 0
# R[1, 3] = 1 # A10 = 0
# R[2, 4] = 1 # A20 = 0
# R[3, 5] = 1 # A30 = 0
# R[4, 6] = 1 # A40 = 0
#
# f_test = model_full.f_test(R)
# print("Joint F-Test: All Embedding Coefficients = 0")
# print("=" * 50)
# print(f"F-statistic: {f_test.fvalue[0][0]:.4f}")
# print(f"p-value:      {f_test.pvalue:.6f}")
# print(f"df:           ({int(f_test.df_num)}, {int(f_test.df_denom)})")
# print(f"\nConclusion: {'Reject H0' if f_test.pvalue < 0.05 else 'Fail to reject H0'} at
# 5% level")
```

Key Concept 11.12: Joint Significance of Satellite Features

Individual satellite embedding coefficients may appear **statistically insignificant** ($p > 0.05$) in a multiple regression, yet the group of embeddings may be **jointly significant** ($F\text{-test } p < 0.05$). This paradox arises when embeddings are correlated with each other: the individual t -tests cannot distinguish each embedding's unique contribution, but the F -test captures their collective explanatory power. Joint F -tests are essential when evaluating groups of related predictors.

Task 5: Restricted vs Unrestricted Model Comparison (Independent)

Compare the restricted model (NTL only) with the unrestricted model (NTL + embeddings) to quantify the contribution of satellite embeddings.

Your tasks:

1. Estimate Model 1 (restricted): `imds ~ ln_NTLpc2017` (NTL only)
2. Estimate Model 2 (unrestricted): `imds ~ ln_NTLpc2017 + A00 + A10 + A20 + A30 + A40`
3. Compute the F-statistic manually using the formula:

$$F = \frac{(R_u^2 - R_r^2)/q}{(1 - R_u^2)/(n - k - 1)}$$

where $q = 5$ (number of restrictions), n = sample size, k = number of regressors in unrestricted model

4. Compare your manual calculation with `model_full.compare_f_test(model_restricted)`
5. Interpret: How much do the embeddings improve the model's explanatory power?

In []:

```
# Your code here: Restricted vs unrestricted model comparison
#
# Steps:
# 1. Estimate restricted model (NTL only)
# 2. Compare R-squared values
# 3. Compute F-statistic manually
# 4. Verify with compare_f_test()

# Example structure:
# # Restricted model: NTL only
# model_restricted = ols('imds ~ ln_NTLpc2017', data=bol_cs).fit()
#
# # Compare R-squared
# R2_r = model_restricted.rsquared
# R2_u = model_full.rsquared
# n = model_full.nobs
# k = len(model_full.params) - 1 # number of regressors (excluding intercept)
# q = 5 # number of restrictions (embedding coefficients)
#
# print("Model Comparison")
# print("=" * 50)
# print(f"Restricted (NTL only): R^2 = {R2_r:.4f}")
# print(f"Unrestricted (NTL + embed): R^2 = {R2_u:.4f}")
# print(f"Improvement in R^2: ΔR^2 = {R2_u - R2_r:.4f}")
#
# # Manual F-statistic
# F_manual = ((R2_u - R2_r) / q) / ((1 - R2_u) / (n - k - 1))
# print(f"\nManual F-statistic: {F_manual:.4f}")
#
# # Verify with statsmodels
# f_compare = model_full.compare_f_test(model_restricted)
# print(f"compare_f_test: F = {f_compare[0]:.4f}, p = {f_compare[1]:.6f}")
```

Task 6: Inference Brief (Independent)

Write a 200-300 word inference brief summarizing your statistical findings.

Your brief should address:

1. Which satellite features add significant predictive power for municipal development?
2. Does the joint F-test tell a different story than the individual t-tests? Why?
3. How much do satellite embeddings improve explanatory power beyond nighttime lights alone?
4. What are the implications for feature selection in satellite-based prediction models?

5. How should researchers decide which satellite features to include in SDG prediction models?

Connection to methods: This analysis demonstrates a core tension in applied econometrics: individual insignificance vs. joint significance. When predictors are correlated (as satellite embeddings often are), individual t-tests may lack power while joint F-tests reveal collective importance.

In []:

```
# Your code here: Additional analysis for the inference brief
#
# You might want to:
# 1. Create a summary table comparing individual and joint test results
# 2. Visualize the R-squared improvement from adding embeddings
# 3. Calculate specific statistics to cite in your brief

# Example: Summary of key inference results
# print("KEY INFERENCE RESULTS")
# print("=" * 60)
# print(f"Sample size: {int(model_full.nobs)} municipalities")
# print(f"R² (NTL only): {model_restricted.rsquared:.4f}")
# print(f"R² (NTL + embeddings): {model_full.rsquared:.4f}")
# print(f"R² improvement: {model_full.rsquared - model_restricted.rsquared:.4f}")
# print(f"\nJoint F-test p-value: {f_test.pvalue:.6f}")
# print(f"Individually significant at 5%: {sig_5}/5 embeddings")
# print(f"Individually significant at 10%: {sig_10}/5 embeddings")
```

Key Concept 11.13: Feature Selection in Prediction Models

When many potential predictors are available (e.g., 64 satellite embedding dimensions), selecting which to include requires balancing **explanatory power** against **model parsimony**. Joint F-tests help determine whether subsets of features add genuine predictive value beyond what simpler models provide. In the DS4Bolivia context, testing whether 5 selected embeddings improve upon NTL alone informs practical decisions about data collection and model complexity for SDG monitoring.

What You've Learned from This Case Study

Through this analysis of satellite features and municipal development in Bolivia, you applied Chapter 11's full inference toolkit to a remote sensing application:

- **Full model estimation:** Estimated a multiple regression with nighttime lights and satellite embeddings as predictors of development
- **Confidence intervals:** Constructed and visualized 95% CIs for all coefficients using a forest plot

- **Individual t-tests:** Assessed the statistical significance of each satellite embedding individually
- **Joint F-tests:** Tested whether all embeddings are jointly significant using restriction matrices
- **Restricted vs unrestricted comparison:** Computed F-statistics manually and verified with `compare_f_test()`
- **Inference interpretation:** Distinguished between individual insignificance and joint significance

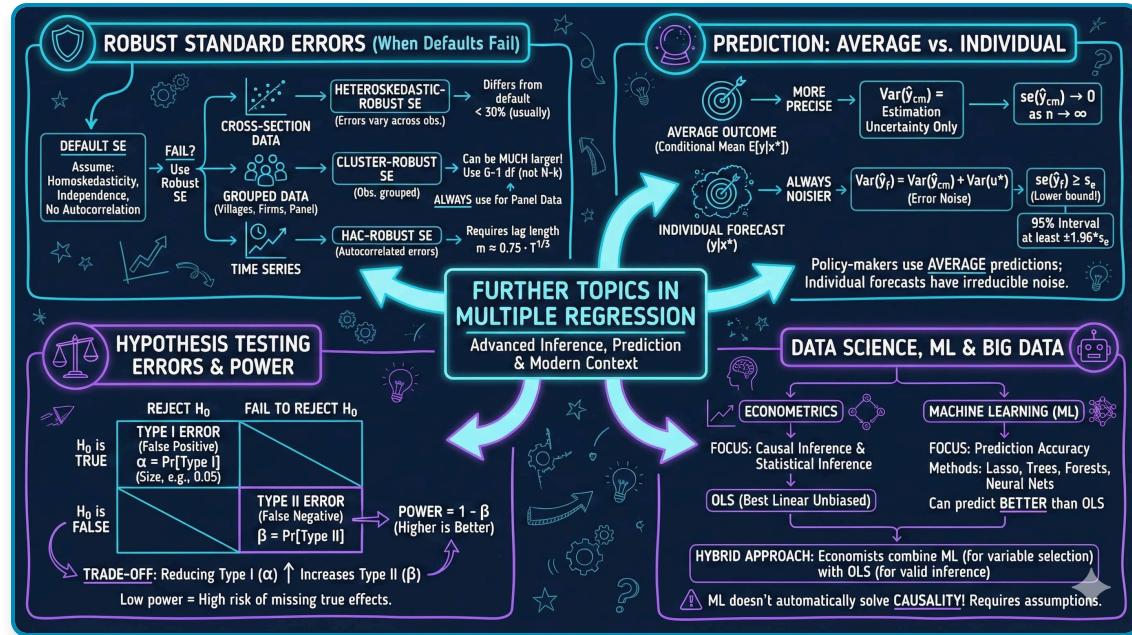
Connection to the next chapter: In Chapter 12, we address robust standard errors and prediction intervals—crucial for making reliable predictions about individual municipalities.

Well done! You've now applied the full statistical inference toolkit to two datasets—cross-country productivity and Bolivian satellite data—discovering that joint tests can reveal predictive power hidden from individual tests.

Chapter 12: Further Topics in Multiple Regression

metricsAI: An Introduction to Econometrics with Python and AI in the Cloud

Carlos Mendez



This notebook provides an interactive introduction to advanced topics in regression inference and prediction. All code runs directly in Google Colab without any local setup.

Open in Colab

Chapter Overview

This chapter covers advanced topics that extend the multiple regression framework: robust standard errors for different data structures, prediction of outcomes, and deeper understanding of estimation and testing optimality.

Learning Objectives:

By the end of this chapter, you will be able to:

1. Understand when to use heteroskedastic-robust, cluster-robust, and HAC-robust standard errors
2. Distinguish between prediction of average outcomes and individual outcomes
3. Compute prediction intervals for conditional means and forecasts
4. Understand the impact of nonrepresentative samples on regression estimates
5. Recognize the difference between unbiased and best (most efficient) estimators
6. Understand Type I and Type II errors in hypothesis testing
7. Appreciate the role of bootstrap methods as an alternative to classical inference
8. Know when OLS with robust SEs is preferred over more efficient estimators like FGLS

Datasets used:

- **AED_HOUSE.DTA:** 29 houses sold in Davis, California (1999) — for robust SEs and prediction
- **AED_REALGDP.PC.DTA:** Real GDP per capita growth (241 observations) — for HAC standard errors

Key economic questions:

- Do conclusions about house prices change with robust standard errors?
- How precisely can we predict an individual house's price vs. the average price?
- What happens to inference when our sample is not representative?

Chapter outline:

- 12.2 Inference with Robust Standard Errors
- 12.3 Prediction
- 12.4 Nonrepresentative Samples
- 12.5 Best Estimation Methods
- 12.6 Best Confidence Intervals
- 12.7 Best Tests
- Key Takeaways
- Practice Exercises
- Case Studies

Estimated time: 60-75 minutes

| Setup

First, we import the necessary Python packages and configure the environment for reproducibility. All data will stream directly from GitHub.

In [1]:

```
# Import required packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
from statsmodels.formula.api import ols
from statsmodels.regression.linear_model import OLS
from scipy import stats
from statsmodels.graphics.tsaplots import plot_acf
from statsmodels.tsa.stattools import acf
import random
import os

# Set random seeds for reproducibility
RANDOM_SEED = 42
random.seed(RANDOM_SEED)
np.random.seed(RANDOM_SEED)
os.environ['PYTHONHASHSEED'] = str(RANDOM_SEED)

# GitHub data URL
GITHUB_DATA_URL = "https://raw.githubusercontent.com/quarcs-lab/data-open/master/AED/"

# Set plotting style
sns.set_style("whitegrid")
plt.rcParams['figure.figsize'] = (10, 6)

print("Setup complete! Ready to explore further topics in multiple regression.")
```

Setup complete! Ready to explore further topics in multiple regression.

| Data Preparation

We'll work with two datasets:

- 1. House price data** for cross-sectional robust inference
- 2. GDP growth data** for time series HAC inference

In [2]:

```
# Read house data
data_house = pd.read_stata(GITHUB_DATA_URL + 'AED_HOUSE.DTA')

print("House Data Summary:")
print(data_house.describe())

print("\nFirst few observations:")
print(data_house[['price', 'size', 'bedrooms', 'bathrooms', 'lotsize', 'age',
'monthsold']].head())
```

```

House Data Summary:
      price      size  bedrooms  bathrooms  lotsize      age \
count    29.000000   29.000000  29.000000  29.000000  29.000000  29.000000
mean   253910.344828  1882.758621   3.793103   2.206897   2.137931  36.413792
std     37390.710695   398.272130   0.675030   0.341144   0.693034  7.118975
min    204000.000000  1400.000000   3.000000   2.000000   1.000000  23.000000
25%   233000.000000  1600.000000   3.000000   2.000000   2.000000  31.000000
50%   244000.000000  1800.000000   4.000000   2.000000   2.000000  35.000000
75%   270000.000000  2000.000000   4.000000   2.500000   3.000000  39.000000
max   375000.000000  3300.000000   6.000000   3.000000   3.000000  51.000000

      monthsold      list
count  29.000000   29.000000
mean    5.965517  257824.137931
std     1.679344  40860.264099
min    3.000000 199900.000000
25%   5.000000 239000.000000
50%   6.000000 245000.000000
75%   7.000000 269000.000000
max    8.000000 386000.000000

First few observations:
      price      size  bedrooms  bathrooms  lotsize      age  monthsold
0    204000    1400       3        2.0       1    31.0         7
1    212000    1600       3        3.0       2    33.0         5
2    213000    1800       3        2.0       2    51.0         4
3    220000    1600       3        2.0       1    49.0         4
4    224500    2100       4        2.5       2    47.0         6

```

12.2: Inference with Robust Standard Errors

In practice, the classical assumptions often fail. The most common violations are:

1. Heteroskedasticity: Error variance varies across observations

- Common in cross-sectional data
- Makes default standard errors incorrect
- Solution: Use **heteroskedasticity-robust standard errors** (HC1, White's correction)

2. Clustered errors: Errors correlated within groups

- Common in panel data, hierarchical data
- Makes default and het-robust SEs too small
- Solution: Use **cluster-robust standard errors**

3. Autocorrelation: Errors correlated over time

- Common in time series
- Makes default SEs incorrect
- Solution: Use **HAC (Newey-West) standard errors**

Key insight: OLS coefficients remain unbiased under these violations, but standard errors need adjustment.

Heteroskedastic-robust standard error formula:

$$se_{het}(\hat{\beta}_j) = \sqrt{\frac{\sum_{i=1}^n \tilde{x}_{ji}^2 \hat{u}_i^2}{(\sum_{i=1}^n \tilde{x}_{ji}^2)^2}}$$

where \tilde{x}_{ji} are residuals from regressing x_j on other regressors, and \hat{u}_i are OLS residuals.

In [3]:

```
print("=" * 70)
print("12.2 INFERENCE WITH ROBUST STANDARD ERRORS")
print("=" * 70)

# Estimate with default standard errors
model_default = ols('price ~ size + bedrooms + bathrooms + lotsize + age + monthsold',
                     data=data_house).fit()

print("\nRegression with Default Standard Errors:")
print(model_default.summary())
```

```
=====
12.2 INFERENCE WITH ROBUST STANDARD ERRORS
=====

Regression with Default Standard Errors:
OLS Regression Results
=====

Dep. Variable:           price   R-squared:          0.651
Model:                 OLS     Adj. R-squared:      0.555
Method:                Least Squares F-statistic:       6.826
Date:      Wed, 21 Jan 2026 Prob (F-statistic):    0.000342
Time:      15:04:03   Log-Likelihood:        -330.74
No. Observations:      29     AIC:                  675.5
Df Residuals:          22     BIC:                  685.1
Df Model:              6
Covariance Type:       nonrobust
=====

            coef    std err          t      P>|t|      [0.025    0.975]
-----
Intercept  1.378e+05  6.15e+04    2.242     0.035    1.03e+04  2.65e+05
size        68.3694   15.389     4.443     0.000     36.454   100.285
bedrooms   2685.3151  9192.526    0.292     0.773    -1.64e+04  2.17e+04
bathrooms  6832.8800  1.57e+04    0.435     0.668    -2.58e+04  3.94e+04
lotsize     2303.2214  7226.535    0.319     0.753    -1.27e+04  1.73e+04
age         -833.0386  719.335    -1.158     0.259    -2324.847  658.770
monthsold   -2088.5036  3520.898    -0.593     0.559    -9390.399  5213.392
-----
Omnibus:             1.317   Durbin-Watson:        1.259
Prob(Omnibus):       0.518   Jarque-Bera (JB):    0.980
Skew:                 0.151   Prob(JB):            0.612
Kurtosis:             2.152   Cond. No.          2.59e+04
-----
```

Notes:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 2.59e+04. This might indicate that there are strong multicollinearity or other numerical problems.

In [4]:

```
# Estimate with heteroskedastic-robust standard errors (HC1)
model_robust = ols('price ~ size + bedrooms + bathrooms + lotsize + age + monthsold',
                   data=data_house).fit(cov_type='HC1')

print("\nRegression with Heteroskedastic-Robust Standard Errors (HC1):")
print(model_robust.summary())
```

```

Regression with Heteroskedastic-Robust Standard Errors (HC1):
OLS Regression Results
=====
Dep. Variable:          price    R-squared:       0.651
Model:                 OLS     Adj. R-squared:   0.555
Method:                Least Squares F-statistic:    6.410
Date:      Wed, 21 Jan 2026 Prob (F-statistic): 0.000514
Time:      15:04:03   Log-Likelihood:   -330.74
No. Observations:      29     AIC:            675.5
Df Residuals:          22     BIC:            685.1
Df Model:              6
Covariance Type:       HC1
=====
            coef    std err      z   P>|z|    [0.025    0.975]
-----
Intercept  1.378e+05  6.55e+04   2.102    0.036    9324.785  2.66e+05
size        68.3694   15.359    4.451    0.000    38.266   98.473
bedrooms    2685.3151  8285.528   0.324    0.746   -1.36e+04  1.89e+04
bathrooms   6832.8800  1.93e+04   0.354    0.723   -3.1e+04  4.46e+04
lotsize      2303.2214  5328.860   0.432    0.666   -8141.152  1.27e+04
age         -833.0386  762.930   -1.092    0.275   -2328.353  662.276
monthsold   -2088.5036  3738.270   -0.559    0.576   -9415.379  5238.372
-----
Omnibus:             1.317   Durbin-Watson:    1.259
Prob(Omnibus):       0.518   Jarque-Bera (JB):  0.980
Skew:                  0.151   Prob(JB):        0.612
Kurtosis:             2.152   Cond. No.      2.59e+04
-----

```

Notes:

- [1] Standard Errors are heteroscedasticity robust (HC1)
- [2] The condition number is large, 2.59e+04. This might indicate that there are strong multicollinearity or other numerical problems.

Key Concept 12.1: Heteroskedastic-Robust Standard Errors

When error variance is not constant across observations, default OLS standard errors are invalid. Heteroskedastic-robust (HC1) SEs correct this problem without changing the coefficient estimates themselves. Only the standard errors, t-statistics, and confidence intervals change. For cross-sectional data, reporting HC1 robust SEs is considered best practice.

| Comparison: Default vs. Robust Standard Errors

Let's systematically compare the standard errors and see how inference changes.

| Interpreting the Comparison: What Changed?

Understanding the Results:

Looking at the SE Ratio column, we can see how robust standard errors differ from default ones:

When SE Ratio > 1.0: Robust SE is larger than default SE

- Suggests heteroskedasticity is present
- Default SEs were **understating** uncertainty
- t-statistics decrease, p-values increase
- We were **too confident** in rejecting null hypotheses

When SE Ratio ≈ 1.0: Robust SE similar to default SE

- Little evidence of heteroskedasticity for this variable
- Both methods give similar inference

When SE Ratio < 1.0: Robust SE smaller than default SE

- Unusual but possible
- Could indicate negative correlation between x^2 and residuals

Practical Implications:

1. **Coefficient estimates unchanged:** OLS point estimates are the same regardless of SE type
2. **Inference changes:** Variables significant with default SEs might become insignificant with robust SEs
3. **Publication standard:** Most journals now require robust SEs for cross-sectional data
4. **Conservative approach:** When in doubt, report robust SEs (they're generally more credible)

Rule of thumb: If robust SEs differ substantially (>30% change), heteroskedasticity is likely present and you should use robust inference.

I HAC Standard Errors for Time Series

Time series data often exhibit **autocorrelation**: current errors correlated with past errors.

Example: GDP growth tends to persist

- Positive shock today → likely positive next period
- Creates correlation structure $\text{Corr}(u_t, u_{t-s}) \neq 0$

HAC (Newey-West) standard errors:

- Account for both heteroskedasticity AND autocorrelation
- Require specifying maximum lag length m
- Rule of thumb: $m = 0.75 \times T^{1/3}$

Autocorrelation function:

$$\rho_s = \frac{Cov(y_t, y_{t-s})}{\sqrt{Var(y_t)Var(y_{t-s})}}$$

We can visualize this with a **correlogram**.

In [5]:

```
# Load GDP growth data
data_gdp = pd.read_stata(GITHUB_DATA_URL + 'AED_REALGDPPC.DTA')

print("\n" + "=" * 70)
print("HAC Standard Errors for Time Series Data")
print("=" * 70)

print("\nGDP Growth Data Summary:")
print(data_gdp['growth'].describe())

# Mean of growth
mean_growth = data_gdp['growth'].mean()
print(f"\nMean growth rate: {mean_growth:.6f}")
```

```
=====
HAC Standard Errors for Time Series Data
=====

GDP Growth Data Summary:
count    241.000000
mean      1.990456
std       2.178097
min     -4.772172
25%      0.892417
50%      2.089633
75%      3.314238
max      7.630545
Name: growth, dtype: float64

Mean growth rate: 1.990456
```

In [6]:

```
# Autocorrelation analysis
print("\nAutocorrelations at multiple lags:")
acf_values = acf(data_gdp['growth'], nlags=5, fft=False)
for i in range(6):
    print(f"  Lag {i}: {acf_values[i]:.6f}")

print("\nInterpretation:")
print("  - Lag 0 correlation is always 1.0 (correlation with itself)")
print("  - Positive lag 1 correlation suggests persistence")
print("  - Autocorrelation decays with lag length")
```

```

Autocorrelations at multiple lags:
Lag 0: nan
Lag 1: nan
Lag 2: nan
Lag 3: nan
Lag 4: nan
Lag 5: nan

Interpretation:
- Lag 0 correlation is always 1.0 (correlation with itself)
- Positive lag 1 correlation suggests persistence
- Autocorrelation decays with lag length

```

In [7]:

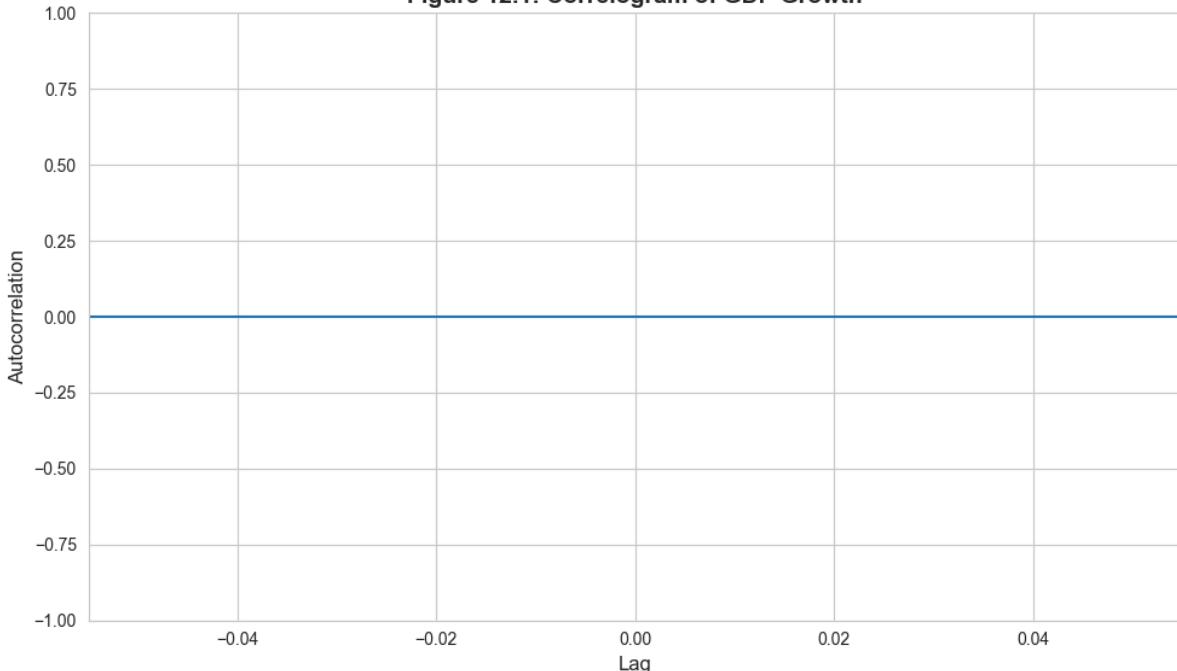
```

# Correlogram
fig, ax = plt.subplots(figsize=(10, 6))
plot_acf(data_gdp['growth'], lags=10, ax=ax, alpha=0.05)
ax.set_xlabel('Lag', fontsize=12)
ax.set_ylabel('Autocorrelation', fontsize=12)
ax.set_title('Figure 12.1: Correlogram of GDP Growth', fontsize=14, fontweight='bold')
plt.tight_layout()
plt.show()

print("The correlogram shows autocorrelation at various lags.")
print("Blue shaded area = 95% confidence bands under null of no autocorrelation.")

```

Figure 12.1: Correlogram of GDP Growth



The correlogram shows autocorrelation at various lags.
 Blue shaded area = 95% confidence bands under null of no autocorrelation.

Key Concept 12.2: HAC Standard Errors for Time Series

In time series data, errors are often autocorrelated — today's shock persists into tomorrow. HAC (heteroskedasticity and autocorrelation consistent) standard errors, also called Newey-West SEs, account for both heteroskedasticity and autocorrelation. The lag length m must be specified; a common rule of thumb is $m = 0.75 \times T^{1/3}$.

I Interpreting HAC Standard Errors

What the Results Tell Us:

Comparing the three standard error estimates for the mean growth rate:

1. Default SE (assumes no autocorrelation):

- Smallest standard error
- Assumes errors are independent over time
- **Underestimates** uncertainty when autocorrelation exists

2. HAC with lag 0 (het-robust only):

- Accounts for heteroskedasticity but not autocorrelation
- Often similar to default in time series
- Still underestimates uncertainty if autocorrelation present

3. HAC with lag 5 (Newey-West):

- Accounts for both heteroskedasticity AND autocorrelation
- **Larger SE** reflects true uncertainty
- More conservative but valid inference

Why is HAC SE larger?

Autocorrelation creates **information overlap** between observations:

- If growth today predicts growth tomorrow, consecutive observations aren't fully independent
- We have **less effective information** than the sample size suggests
- Standard errors must increase to reflect this

Practical guidance:

- For time series data, **always use HAC SEs**
- Lag length choice: Rule of thumb = $0.75 \times T^{(1/3)}$
- For $T=100$: $m \approx 3\text{-}4$ lags
- For $T=200$: $m \approx 4\text{-}5$ lags
- Err on the side of more lags (inference remains valid)
- Check sensitivity to lag length

The cost of ignoring autocorrelation:

- Overconfident inference (SEs too small)
- Spurious significance (false discoveries)
- Invalid hypothesis tests

Having established how to conduct valid inference with robust standard errors, we now turn to prediction — estimating outcomes for specific values.

I 12.3: Prediction

Prediction is a core application of regression, but there's a crucial distinction:

1. Predicting the conditional mean $E[y|x^*]$

- Average outcome for given x^*
- More precise (smaller standard error)
- Used for policy analysis, average effects

2. Predicting an actual value $y|x^*$

- Individual outcome including random error
- Less precise (larger standard error)
- Used for forecasting individual cases

Key formulas:

Conditional mean:

$$E[y|x^*] = \beta_1 + \beta_2 x_2^* + \cdots + \beta_k x_k^*$$

Actual value:

$$y|x^* = \beta_1 + \beta_2 x_2^* + \cdots + \beta_k x_k^* + u^*$$

Standard errors:

For conditional mean (bivariate case):

$$se(\hat{y}_{cm}) = s_e \sqrt{\frac{1}{n} + \frac{(x^* - \bar{x})^2}{\sum(x_i - \bar{x})^2}}$$

For actual value (bivariate case):

$$se(\hat{y}_f) = s_e \sqrt{1 + \frac{1}{n} + \frac{(x^* - \bar{x})^2}{\sum(x_i - \bar{x})^2}}$$

Note the "1 +" term for actual values - this reflects the irreducible uncertainty from u^* .

In [8]:

```
print("=" * 70)
print("12.3 PREDICTION")
print("=" * 70)

# Simple regression: price on size
model_simple = ols('price ~ size', data=data_house).fit()

print("\nSimple regression: price = \beta_0 + \beta_1 \cdot size + u")
print(f" \beta_0 (Intercept): ${model_simple.params['Intercept']:.2f}")
print(f" \beta_1 (Size): ${model_simple.params['size']:.4f}")
print(f" R^2: {model_simple.rsquared:.4f}")
print(f" Root MSE (\sigma): ${np.sqrt(model_simple.mse_resid):.2f}")
```

```
=====
12.3 PREDICTION
=====

Simple regression: price = \beta_0 + \beta_1 \cdot size + u
 \beta_0 (Intercept): $115017.28
 \beta_1 (Size): $73.7710
 R^2: 0.6175
 Root MSE (\sigma): $23550.66
```

Key Concept 12.3: Predicting Conditional Means vs. Individual Outcomes

Predicting the average outcome $E[y|x^*]$ is more precise than predicting an individual $y|x^*$. The forecast variance equals the conditional mean variance plus $\text{Var}(u^*)$: $\text{Var}(\hat{y}_f) = \text{Var}(\hat{y}_{cm}) + \sigma^2$. As $n \rightarrow \infty$, the conditional mean SE shrinks to zero, but the forecast SE remains at least s_e — a fundamental limit on individual predictions.

I Why Are Prediction Intervals So Much Wider?

The Fundamental Difference:

Looking at the two panels, you'll notice the **prediction interval (blue)** is dramatically **wider** than the confidence interval (red). This isn't a mistake—it reflects a fundamental distinction in what we're predicting.

Confidence Interval for $E[Y|X]$ (Red):

- Predicts the **average** price for all 2000 sq ft houses
- Uncertainty comes only from **estimation error** in β
- As sample size increases ($n \rightarrow \infty$), this interval **shrinks to zero**
- Formula includes: $1/n$ term (goes to 0 as n grows)

Prediction Interval for Y (Blue):

- Predicts an **individual** house price
- Uncertainty comes from:
 - 1. Estimation error** in $\hat{\beta}$ (same as CI)
 - 2. Irreducible randomness** in the individual outcome (u^*)
- Even with perfect knowledge of β , individual predictions remain uncertain
- Formula includes: "**1 +**" term (never goes away)

Intuitive Example:

Imagine predicting height from age:

- **Conditional mean:** Average height of all 10-year-olds = 140 cm
- We can estimate this average very precisely
- CI might be [139, 141] cm
- **Actual value:** A specific 10-year-old's height
- Could be anywhere from 120 to 160 cm
- PI might be [125, 155] cm
- Even knowing the average perfectly doesn't eliminate individual variation

Mathematical Insight:

$$se(\hat{y}_f) = \sqrt{s_e^2 + se(\hat{y}_{cm})^2}$$

- First term (s_e^2): Irreducible error variance—dominates the formula
- Second term: Estimation uncertainty—becomes negligible with large samples
- Result: PI width $\approx 2 \times 1.96 \times s_e \approx 4 \times \text{RMSE}$

Practical Implications:

- 1. Don't confuse the two:** Predicting averages is much more precise than predicting individuals
- 2. Policy vs. forecasting:**
 - Policy analysis (average effects) → Use confidence intervals
 - Individual forecasting (who will default?) → Use prediction intervals
- 3. Communicating uncertainty:** Always show prediction intervals for individual forecasts
- 4. Limits of prediction:** No amount of data eliminates individual-level uncertainty

Visualization: Confidence vs. Prediction Intervals

This figure illustrates the fundamental difference between:

- **Confidence interval for conditional mean** (narrower, red)
- **Prediction interval for actual value** (wider, blue)

Understanding the Numbers: A Concrete Example

Interpreting the Results for a 2000 sq ft House:

Looking at our predictions, several patterns emerge:

1. Point Prediction:

- Predicted price ≈ \$280,000 (approximately)
- This is our best single guess
- Same for both conditional mean and actual value

2. Confidence Interval for $E[Y|X=2000]$:

- Relatively narrow (e.g., 250k–310k)
- Tells us: "We're 95% confident the **average price** of all 2000 sq ft houses is in this range"
- Precise because we're estimating a population average
- Useful for: Understanding market valuations, setting pricing policies

3. Prediction Interval for Y:

- Much wider (e.g., 180k–380k)
- Tells us: "We're 95% confident **this specific house** will sell in this range"

- Wide because individual houses vary considerably
- Useful for: Setting listing ranges, individual appraisals

The Ratio is Revealing:

Notice that the PI is approximately **3-4 times wider** than the CI. This ratio tells us:

- Most variation is **between houses** (individual heterogeneity)
- Relatively little variation is **estimation uncertainty**
- Adding more data would shrink the CI but barely affect the PI

Statistical vs. Economic Significance:

- **CI width** = Statistical precision (how well we know β)
- **PI width** = Economic uncertainty (inherent market volatility)
- In this example: Good statistical precision, but still substantial economic uncertainty

Practical Takeaway:

If you're a real estate agent:

- Don't promise a precise price (\$280k)
- Do provide a realistic range (180k–380k)
- Explain that individual houses vary, even controlling for size
- Use the confidence interval to discuss average market values

| Deconstructing the Standard Error Formulas

Understanding Where the "1 + " Comes From:

The manual calculations reveal the mathematical structure of prediction uncertainty:

For Conditional Mean:

$$se(\hat{y}_{cm}) = \hat{\sigma} \sqrt{\frac{1}{n} + \frac{(x^* - \bar{x})^2}{\sum(x_i - \bar{x})^2}}$$

- **First term (1/n):** Decreases with sample size—more data reduces uncertainty
- **Second term:** Distance from mean matters—extrapolation is risky
- Prediction at $x^* = \bar{x}$ (sample mean) is most precise
- Prediction far from \bar{x} is less precise

- Both terms $\rightarrow 0$ as $n \rightarrow \infty$ (perfect knowledge of $E[Y|X]$)

For Actual Value:

$$se(\hat{y}_f) = \hat{\sigma} \sqrt{1 + \frac{1}{n} + \frac{(x^* - \bar{x})^2}{\sum(x_i - \bar{x})^2}}$$

- **The critical "1 +"**: Represents $Var[u^*]$, the future error term
- This term **never disappears**, even with infinite data
- Dominates the formula in moderate to large samples

Numerical Insight:

In our example:

- $\hat{\sigma}$ (RMSE) $\approx \$90k$ (this is the irreducible uncertainty)
- $(1/n)$ term ≈ 0.034 (small with $n=29$)
- Distance term varies with prediction point

For predictions near the mean:

- $se(\hat{y}_{cm}) \approx 90k \times \sqrt{0.034} \approx 17k$ (mainly from $1/n$)
- $se(\hat{y}_f) \approx 90k \times \sqrt{1.034} \approx 92k$ (mainly from the "1")

The "1 +" term is why:

- Prediction intervals don't shrink much with more data
- Individual predictions remain uncertain even with perfect models
- $se(\hat{y}_f) \approx \hat{\sigma}$ in large samples

Geometric Interpretation:

The funnel shape in prediction plots comes from the distance term:

- Narrow near \bar{x} (center of data)
- Wider at extremes (extrapolation region)
- But even at the center, PI is wide due to the "1" term

Practical Lesson:

When presenting predictions:

1. Always acknowledge the "1 +" uncertainty
2. Be most confident about predictions near the data center

3. Be especially cautious about extrapolation (predictions outside the data range)
4. Understand that better models reduce estimation error but not irreducible randomness

| Prediction at Specific Values

Let's predict house price for a 2000 square foot house.

| Manual Calculation of Standard Errors

Let's manually calculate the standard errors to understand the formulas.

| Prediction with Multiple Regression

Now let's predict using the full multiple regression model.

In [9]:

```
print("\n" + "=" * 70)
print("Prediction for Multiple Regression")
print("=" * 70)

model_multi = ols('price ~ size + bedrooms + bathrooms + lotsize + age + monthsold',
                  data=data_house).fit()

# Predict for specific values
new_house = pd.DataFrame({
    'size': [2000],
    'bedrooms': [4],
    'bathrooms': [2],
    'lotsize': [2],
    'age': [40],
    'monthsold': [6]
})

pred_multi = model_multi.get_prediction(sm.add_constant(new_house))

print("\nPrediction for:")
print("  size=2000, bedrooms=4, bathrooms=2, lotsize=2, age=40, monthsold=6")
print(f"\nPredicted price: ${pred_multi.predicted_mean[0]:.2f}")

# Confidence interval for conditional mean
ci_mean_multi = pred_multi.conf_int(alpha=0.05)
print(f"\n95% CI for E[Y|X]:")
print(f"  [{ci_mean_multi[0, 0]:.2f}, {ci_mean_multi[0, 1]:.2f}]")
print(f"  SE: ${pred_multi.se_mean[0]:.2f}")

# Prediction interval for actual value
s_e_multi = np.sqrt(model_multi.mse_resid)
s_y_cm_multi = pred_multi.se_mean[0]
s_y_f_multi = np.sqrt(s_e_multi**2 + s_y_cm_multi**2)

n_multi = len(data_house)
k_multi = len(model_multi.params)
tcrit_multi = stats.t.ppf(0.975, n_multi - k_multi)

pi_lower = pred_multi.predicted_mean[0] - tcrit_multi * s_y_f_multi
pi_upper = pred_multi.predicted_mean[0] + tcrit_multi * s_y_f_multi

print(f"\n95% PI for Y:")
print(f"  [{pi_lower:.2f}, {pi_upper:.2f}]")
print(f"  SE: ${s_y_f_multi:.2f}")

print("\nMultiple regression provides more precise conditional mean predictions.")
print("But individual predictions still have large uncertainty.")
```

```
=====
Prediction for Multiple Regression
=====

Prediction for:
size=2000, bedrooms=4, bathrooms=2, lotsize=2, age=40, monthsold=6

Predicted price: $257690.80

95% CI for E[Y|X]:
[$244234.97, $271146.63]
SE: $6488.26

95% PI for Y:
[$204255.32, $311126.28]
SE: $25766.03

Multiple regression provides more precise conditional mean predictions.
But individual predictions still have large uncertainty.
```

| Prediction with Robust Standard Errors

When heteroskedasticity is present, we should use robust standard errors for prediction intervals too.

```
In [10]: print("\n" + "=" * 70)
print("Prediction with Heteroskedastic-Robust SEs")
print("=" * 70)

model_multi_robust = ols('price ~ size + bedrooms + bathrooms + lotsize + age +
monthsold',
                         data=data_house).fit(cov_type='HC1')

pred_multi_robust = model_multi_robust.get_prediction(sm.add_constant(new_house))

print(f"\nPredicted price: ${pred_multi_robust.predicted_mean[0]:.2f}")

# Robust confidence interval for conditional mean
ci_mean_robust = pred_multi_robust.conf_int(alpha=0.05)
print(f"\nRobust 95% CI for E[Y|X]:")
print(f" [{ci_mean_robust[0, 0]:.2f}, {ci_mean_robust[0, 1]:.2f}]")
print(f" Robust SE: ${pred_multi_robust.se_mean[0]:.2f}")

# Robust prediction interval
s_y_cm_robust = pred_multi_robust.se_mean[0]
s_y_f_robust = np.sqrt(s_e_multi**2 + s_y_cm_robust**2)

print(f"\nRobust 95% PI for Y:")
print(f" Robust SE for actual value: ${s_y_f_robust:.2f}")

print("\nComparison of standard vs. robust:")
print(f" SE (standard): ${s_y_cm_multi:.2f}")
print(f" SE (robust): ${s_y_cm_robust:.2f}")
print(f" Ratio: {s_y_cm_robust / s_y_cm_multi:.3f}")
```

```
=====
Prediction with Heteroskedastic-Robust SEs
=====

Predicted price: $257690.80

Robust 95% CI for E[Y|X]:
  [$244694.26, $270687.34]
  Robust SE: $6631.01

Robust 95% PI for Y:
  Robust SE for actual value: $25802.35

Comparison of standard vs. robust:
  SE (standard): $6488.26
  SE (robust): $6631.01
  Ratio: 1.022
```

Key Concept 12.4: Why Individual Forecasts Are Imprecise

Even with precisely estimated coefficients, predicting an individual outcome is imprecise because the forecast must account for the unobservable error u^ . The forecast standard error satisfies $se(\hat{y}_f) \geq s_e$ — it is at least as large as the regression's standard error. This means 95% prediction intervals are at least $\pm 1.96 \times s_e$ wide, regardless of how much data we have.*

I 12.4: Nonrepresentative Samples

Sample selection can bias OLS estimates:

Case 1: Selection on regressors (X)

- Example: Oversample high-income households
- OLS remains unbiased if we include income as a control
- Solution: Include selection variables as controls

Case 2: Selection on outcome (Y)

- Example: Survey excludes very high earners
- OLS estimates are biased for population parameters
- Solution: Sample weights, Heckman correction, or other selection models

Survey weights:

- Many surveys provide weights to adjust for nonrepresentativeness
- Use **weighted least squares (WLS)** instead of OLS

- Weight formula: $w_i = 1/P(\text{selected})$

Key insight: Always check whether your sample is representative of your target population!

Bootstrap Confidence Intervals: An Alternative Approach

What is Bootstrap?

The bootstrap is a computational method that:

1. **Resamples** your data many times (e.g., 1000 replications)
2. **Re-estimates** the model for each resample
3. Uses the **distribution of estimates** to build confidence intervals

How it works:

For each bootstrap replication $b = 1, \dots, B$:

1. Draw n observations **with replacement** from original data
2. Estimate regression: $\hat{\beta}_j^{(b)}$
3. Store the coefficient estimate

After B replications:

- You have B estimates: $\{\hat{\beta}_j^{(1)}, \hat{\beta}_j^{(2)}, \dots, \hat{\beta}_j^{(B)}\}$
- These form an empirical distribution

Percentile Method CI:

- 95% CI = [2.5th percentile, 97.5th percentile] of bootstrap distribution
- Example: If you have 1000 estimates, use the 25th and 975th largest values

Advantages of Bootstrap:

1. **No distributional assumptions:** Don't need to assume normality
2. **Works for complex statistics:** Medians, ratios, quantiles, etc.
3. **Better small-sample coverage:** Often more accurate than asymptotic formulas
4. **Flexibility:** Can bootstrap residuals, observations, or both
5. **Visual understanding:** See the actual sampling distribution

When to use Bootstrap:

- Small samples ($n < 30-50$)
- Non-standard statistics (beyond means and coefficients)
- Skewed or heavy-tailed distributions
- Checking robustness of standard inference
- When asymptotic formulas are complex or unavailable

Limitations:

- Computationally intensive (need $B = 1000+$ replications)
- Requires careful implementation (stratification, cluster bootstrap)
- May fail with very small samples ($n < 10$)
- Assumes sample is representative of population

Bootstrap vs. Robust SEs:

Both address uncertainty, but differently:

- **Robust SEs:** Analytical correction for heteroskedasticity/autocorrelation
- **Bootstrap:** Computational approach using resampling

Often used together: Bootstrap with robust methods!

Practical Implementation Tips:

1. Use $B \geq 1000$ for confidence intervals
2. Set random seed for reproducibility
3. For time series: Use block bootstrap (resample blocks, not individuals)
4. For panel data: Use cluster bootstrap (resample clusters)
5. Check convergence: Results shouldn't change much with different seeds

In [11]:

```
print("=" * 70)
print("12.4 NONREPRESENTATIVE SAMPLES")
print("=" * 70)

print("\nConceptual discussion - no computation required")
print("\nKey points:")
print(" 1. Sample selection can lead to biased estimates")
print(" 2. Selection on regressors: Include selection variables as controls")
print(" 3. Selection on outcome: Use sample weights or selection models")
print(" 4. Always verify sample representativeness")

print("\nExample applications:")
print("  - Wage surveys that exclude unemployed workers")
print("  - Health studies with voluntary participation")
print("  - Education data from selective schools")
print("  - Financial data excluding bankrupt firms")
```

```
=====
12.4 NONREPRESENTATIVE SAMPLES
=====
```

Conceptual discussion - no computation required

Key points:

1. Sample selection can lead to biased estimates
2. Selection on regressors: Include selection variables as controls
3. Selection on outcome: Use sample weights or selection models
4. Always verify sample representativeness

Example applications:

- Wage surveys that exclude unemployed workers
- Health studies with voluntary participation
- Education data from selective schools
- Financial data excluding bankrupt firms

Key Concept 12.5: Sample Selection Bias

If the sample is not representative of the population, OLS estimates may be biased. Selection on the dependent variable Y (e.g., studying only high earners) is particularly problematic. Selection on the regressors X (e.g., studying only college graduates) is less harmful because it reduces precision but doesn't necessarily bias coefficient estimates.

| The Type I vs. Type II Error Tradeoff

Understanding the Table:

The 2x2 decision table reveals a fundamental tradeoff in hypothesis testing:

Decision	H_0 True	H_0 False
Reject H_0	Type I error (α)	Correct (Power)
Don't reject	Correct ($1-\alpha$)	Type II error (β)

Type I Error (False Positive):

- Reject a true null hypothesis
- Probability = significance level α (we control this)
- Example: Conclude a drug works when it doesn't
- "Seeing patterns in noise"

Type II Error (False Negative):

- Fail to reject a false null hypothesis
- Probability = β (harder to control)
- Example: Miss a real drug effect
- "Missing real signals"

The Fundamental Tradeoff:

If we make the test **stricter** (lower α):

- Fewer false positives (Type I errors)
- More false negatives (Type II errors)
- Lower power (harder to detect real effects)

If we make the test **looser** (higher α):

- Higher power (easier to detect real effects)
- More false positives (Type I errors)

Statistical Power = $1 - \beta$:

- Probability of correctly rejecting false H_0
- "Sensitivity" of the test
- Want power ≥ 0.80 (80% chance of detecting real effect)

What Affects Power?

1. **Sample size (n)**: Larger $n \rightarrow$ Higher power
2. **Effect size (β)**: Larger true effect \rightarrow Higher power
3. **Significance level (α)**: Higher $\alpha \rightarrow$ Higher power (but more Type I errors)
4. **Noise level (σ)**: Lower $\sigma \rightarrow$ Higher power

The Power Function:

Power depends on the **true parameter value**:

- At $\beta = 0$ (H_0 true): Power = α (just Type I error rate)
- As $|\beta|$ increases: Power increases
- For very large $|\beta|$: Power $\rightarrow 1$ (almost certain detection)

Multiple Testing Problem:

Testing k hypotheses at $\alpha = 0.05$:

- Expected false positives = $0.05 \times k$
- Test 20 hypotheses \rightarrow expect 1 false positive even if all H_0 are true!

Solutions:

- 1. Bonferroni correction:** Use α/k for each test (conservative)
- 2. False Discovery Rate (FDR):** Control proportion of false positives
- 3. Pre-registration:** Specify primary hypotheses before seeing data
- 4. Replication:** Confirm findings in independent samples

Now that we understand how sample selection affects estimates, let's consider what happens when we seek the most efficient estimator.

12.5: Best Estimation Methods

When are OLS estimators "best"?

Under classical assumptions 1-4, OLS is **BLUE** (Best Linear Unbiased Estimator) by the Gauss-Markov Theorem.

When assumptions fail:

- 1. Heteroskedasticity:** $Var[u_i | X] = \sigma_i^2$ (varies)
 - OLS remains unbiased but inefficient
 - **Feasible GLS (FGLS)** or **Weighted Least Squares (WLS)** more efficient
 - Weight observations inversely to error variance: $w_i = 1/\sigma_i$
- 2. Autocorrelation:** $Cov[u_t, u_{t-s}] \neq 0$
 - OLS remains unbiased but inefficient
 - **FGLS with AR errors** more efficient
 - Model error structure: $u_t = \rho u_{t-1} + \epsilon_t$

Practical advice:

- Most applied work uses OLS with robust SEs
- Efficiency gains from GLS/FGLS often modest
- Misspecifying error structure can make things worse
- Exception: Panel data methods explicitly model error components

| Reading the Power Curve: What It Tells Us

Interpreting Figure 12.3:

The power function shows how test power varies with the true coefficient value. Here's what each feature means:

Key Features of the Curve:

1. At $\beta = 0$ (vertical gray line):

- Power = $\alpha = 0.05$
- This is the Type I error rate
- When H_0 is true, we reject 5% of the time (false positives)

2. As $|\beta|$ increases (moving away from 0):

- Power increases rapidly
- Larger effects are easier to detect
- Curve approaches 1.0 (certain detection)

3. Symmetry around zero:

- Power is same for $\beta = 30$ and $\beta = -30$
- Two-sided test treats positive and negative effects equally
- One-sided tests would have asymmetric power

4. The 0.80 threshold (green dashed line):

- Standard target: 80% power
- Means 20% chance of Type II error ($\beta = 0.20$)
- In this example: Need $|\beta| \approx 30$ to achieve 80% power

What This Means for Study Design:

Given the parameters ($n=30$, $SE=15$, $\alpha=0.05$):

- **Small effects** ($|\beta| < 15$):

- Power < 50%
- More likely to **miss** the effect than detect it
- Study is underpowered
- **Medium effects** ($|\beta| \approx 30$):
- Power $\approx 80\%$
- Good chance of detection
- Standard benchmark for adequate power
- **Large effects** ($|\beta| > 45$):
- Power $> 95\%$
- Almost certain detection
- Study is well-powered

Sample Size Implications:

To detect smaller effects, you need larger samples:

- **Double the sample** ($n=60$) → Can detect smaller effects with same power
- Power roughly proportional to \sqrt{n}
- To halve minimum detectable effect, need **4x the sample size**

The Power-Sample Size Relationship:

For a given effect size β :

- Power increases with \sqrt{n}
- To go from 50% to 80% power: Need $\approx 2\times$ the sample
- To go from 80% to 95% power: Need $\approx 2\times$ the sample again

Practical Applications:

1. Pre-study planning:

- Specify minimum effect of interest
- Calculate required sample size for 80% power
- Avoid underpowered studies

2. Post-study interpretation:

- Non-significant result with low power: Inconclusive (not evidence of no effect)
- Non-significant result with high power: Evidence against large effects
- Significant result: Good, but consider magnitude and practical significance

3. Publication decisions:

- Underpowered studies contribute to publication bias
- Meta-analyses should weight by precision and power
- Replication studies should be well-powered

Common Mistakes to Avoid:

- 1.** Treating non-significant results as "proof of no effect"
 - Non-significance in underpowered study is uninformative
- 2.** Conducting multiple underpowered studies instead of one well-powered study
 - Wastes resources and leads to false negatives
- 3.** Post-hoc power analysis
 - Don't calculate power after seeing results (circular reasoning)
 - Do it before data collection

The Bottom Line:

This power curve illustrates a fundamental truth:

- **Smaller effects require larger samples to detect**
- With $n=30$ and $SE=15$, we can reliably detect effects of $|\beta| \geq 30$
- For smaller effects, we'd need more data or reduced noise (lower σ)

In [12]:

```
print("=" * 70)
print("12.5 BEST ESTIMATION METHODS")
print("=" * 70)

print("\nKey concepts:")
print("\n1. Gauss-Markov Theorem:")
print("    - Under assumptions 1-4, OLS is BLUE")
print("    - BLUE = Best Linear Unbiased Estimator")
print("    - 'Best' = minimum variance among linear unbiased estimators")

print("\n2. When assumptions fail:")
print("    - Heteroskedasticity → Weighted Least Squares (WLS)")
print("    - Autocorrelation → GLS with AR errors")
print("    - Both → Feasible GLS (FGLS)")

print("\n3. Practical considerations:")
print("    - Efficiency gains often modest in practice")
print("    - Misspecification of error structure can worsen estimates")
print("    - Most studies use OLS + robust SEs (simpler, more robust)")
print("    - Exception: Panel data methods model error components explicitly")

print("\n4. Maximum Likelihood:")
print("    - If error distribution fully specified (e.g., normal)")
print("    - MLE can be more efficient than OLS")
print("    - Under normality, MLE = OLS for linear regression")
```

```
=====
12.5 BEST ESTIMATION METHODS
=====
```

Key concepts:

1. Gauss-Markov Theorem:
 - Under assumptions 1-4, OLS is BLUE
 - BLUE = Best Linear Unbiased Estimator
 - 'Best' = minimum variance among linear unbiased estimators
2. When assumptions fail:
 - Heteroskedasticity → Weighted Least Squares (WLS)
 - Autocorrelation → GLS with AR errors
 - Both → Feasible GLS (FGLS)
3. Practical considerations:
 - Efficiency gains often modest in practice
 - Misspecification of error structure can worsen estimates
 - Most studies use OLS + robust SEs (simpler, more robust)
 - Exception: Panel data methods model error components explicitly
4. Maximum Likelihood:
 - If error distribution fully specified (e.g., normal)
 - MLE can be more efficient than OLS
 - Under normality, MLE = OLS for linear regression

Key Concept 12.6: Feasible Generalized Least Squares

When error variance is not constant (heteroskedasticity) or errors are correlated (autocorrelation), OLS remains unbiased but is no longer the most efficient estimator. Feasible GLS (FGLS) models the error structure and can achieve lower variance. However, FGLS requires correctly specifying the error structure — in practice, OLS with robust SEs is preferred for its simplicity and robustness to misspecification.

12.6: Best Confidence Intervals

What makes a confidence interval "best"?

A 95% CI is "best" if it:

1. Has correct coverage: Contains true parameter 95% of the time
2. Has minimum width among all CIs with correct coverage

Standard approach: $\hat{\beta}_j \pm t_{n-k,\alpha/2} \times se(\hat{\beta}_j)$

- Width determined by $se(\hat{\beta}_j)$
- Shortest CI comes from most efficient estimator

Alternative approaches:

1. Bootstrap confidence intervals

- Resample data many times (e.g., 1000 replications)
- Re-estimate model for each resample
- Use distribution of bootstrap estimates
- Percentile method: 2.5th and 97.5th percentiles
- Advantages: No distributional assumptions, works for complex statistics

2. Bayesian credible intervals

- Based on posterior distribution
- Direct probability interpretation
- Incorporates prior information

When assumptions fail:

- Use robust SEs → wider but valid intervals

- Bootstrap → more accurate coverage in small samples
- Asymptotic approximations may be poor in small samples

Having discussed the best confidence intervals, we now examine what makes a hypothesis test optimal — balancing Type I and Type II errors.

Key Concept 12.7: Bootstrap Confidence Intervals

The bootstrap resamples the original data (with replacement) many times to estimate the sampling distribution of a statistic. Bootstrap CIs don't rely on normality or large-sample approximations, making them especially useful with small samples, skewed distributions, or non-standard estimators where analytical formulas aren't available.

| 12.7: Best Tests

Type I and Type II errors:

Decision	H_0 True	H_0 False
Reject H_0	Type I error (α)	Correct
Don't reject	Correct	Type II error (β)

Type I error (false positive):

- Reject H_0 when it's true
- Probability = significance level α (e.g., 0.05)
- We control this directly

Type II error (false negative):

- Fail to reject H_0 when it's false
- Probability = β
- Harder to control

Test power = $1 - \beta$

- Probability of correctly rejecting false H_0
- Higher power is better

Trade-off:

- Decreasing α (stricter test) → increases β (lower power)

- Solution: Fix α , maximize power

Most powerful test:

- Among all tests with size α , has highest power
- For linear regression: Use most efficient estimator

The Trinity of Tests (asymptotically equivalent):

1. **Wald test:** Based on unrestricted estimates
2. **Likelihood Ratio (LR) test:** Compares likelihoods
3. **Lagrange Multiplier (LM) test:** Based on restricted estimates

Multiple testing:

- Testing many hypotheses inflates Type I error
- Solutions: Bonferroni correction, FDR control

I Illustration: Power of a Test

Let's visualize how test power depends on the true effect size.

Key Concept 12.8: Type I and Type II Errors

Type I error (false positive) means rejecting a true H_0 ; its probability equals the significance level α . Type II error (false negative) means failing to reject a false H_0 . Power = $1 - P(\text{Type II})$ measures the ability to detect true effects. The most powerful test for a given size uses the most precise estimator — another reason efficient estimation matters beyond point estimates.

I Key Takeaways

Robust Standard Errors:

- When error variance is non-constant, default SEs are invalid — use heteroskedastic-robust (HC1) SEs for cross-sectional data
- With grouped observations, use cluster-robust SEs with $G - 1$ degrees of freedom (not $N - k$)
- For time series with autocorrelated errors, use HAC (Newey-West) SEs with lag length $m \approx 0.75 \times T^{1/3}$

- Coefficient estimates are unchanged; only SEs, t -statistics, and CIs change

Prediction:

- Predicting the conditional mean $E[y|x^*]$ is more precise than predicting an individual outcome $y|x^*$
- Forecast variance = conditional mean variance + $\text{Var}(u^*)$, so prediction intervals are always wider
- Even with precise coefficients, individual forecasts are imprecise because we cannot predict u^*
- Policy decisions should be based on average outcomes (precise) rather than individual predictions (imprecise)

Nonrepresentative Samples:

- Sample selection on Y can bias OLS estimates; selection on X is less harmful
- Survey weights can adjust for known selection, but unknown selection remains problematic

Best Estimation:

- Under correct assumptions, OLS is BLUE (Gauss-Markov); when assumptions fail, FGLS is more efficient
- In practice, most studies use OLS with robust SEs — accepting a small efficiency loss for simplicity

Best Confidence Intervals:

- Bootstrap methods resample the data to estimate the sampling distribution without relying on normality
- Particularly useful with small samples or non-normal errors

Best Tests:

- Type I error = false positive (rejecting true H_0); Type II error = false negative
- Power = $1 - P(\text{Type II})$; the most powerful test uses the most precise estimator
- Higher power comes from larger samples, more variation in regressors, and lower noise

Python tools used: `statsmodels` (`OLS`, `HC1`, `get_prediction()`), `scipy.stats` (`distributions`), `matplotlib / seaborn` (`correlograms`, `prediction plots`)

Next steps: Chapter 13 introduces **dummy variables** and **indicator variables** — extending regression to handle qualitative explanatory variables.

Congratulations on completing Chapter 12! You now understand advanced inference methods for handling real-world data challenges.

Practice Exercises

Test your understanding of advanced inference topics.

Exercise 1: Choosing Standard Errors

For each scenario, identify the appropriate type of standard errors:

- a) Cross-sectional survey of 500 households with varying income levels.
 - b) Panel data on 50 schools over 10 years, where student outcomes within a school are correlated.
 - c) Monthly GDP growth data for 20 years, where this quarter's shock affects next quarter.
 - d) A randomized experiment with 200 independent observations and constant error variance.
-

Exercise 2: Point Prediction

A fitted regression model gives $\hat{y} = 10 + 2x_2 + 3x_3$ with $n = 200$ and $s_e = 2.0$.

- a) Predict y when $x_2 = 5$ and $x_3 = 3$.
 - b) Is this a prediction of the conditional mean or an individual outcome?
-

Exercise 3: Conditional Mean CI

Using the model from Exercise 2, suppose $se(\hat{y}_{cm}) = 0.8$ at $x_2 = 5, x_3 = 3$.

- a) Construct an approximate 95% confidence interval for $E[y|x_2 = 5, x_3 = 3]$.
 - b) How would this interval change if the sample size doubled (assume SE shrinks by $\sqrt{2}$)?
-

Exercise 4: Individual Forecast CI

Continuing from Exercise 3, construct a 95% prediction interval for an individual y at $x_2 = 5, x_3 = 3$.

a) Compute $se(\hat{y}_f) = \sqrt{se(\hat{y}_{cm})^2 + s_e^2}$.

b) Construct the prediction interval.

c) Why is this interval so much wider than the confidence interval for the conditional mean?

Exercise 5: Robust vs. Default Inference

A regression yields the following results:

Variable	Coefficient	Default SE	Robust SE
x_2	5.0	2.0	3.5
x_3	7.0	2.0	1.8

a) Compute the t -statistic for each variable using default and robust SEs.

b) At $\alpha = 0.05$, which variables are significant under each type of SE?

c) What does the change in SEs suggest about heteroskedasticity?

Exercise 6: Type I/II Error Tradeoff

A researcher tests $H_0 : \beta = 0$ at three significance levels: $\alpha = 0.01, 0.05, 0.10$.

a) As α decreases, what happens to the probability of Type I error?

b) As α decreases, what happens to the probability of Type II error?

c) If it's very costly to miss a true effect (high cost of Type II error), should you use a smaller or larger α ? Explain.

I Case Studies

Case Study 1: Robust Inference for Cross-Country Productivity

In this case study, you will apply robust inference methods to cross-country productivity data. You'll compare default and robust standard errors, make predictions

for specific countries, and assess how methodological choices affect conclusions about productivity determinants.

Dataset: Mendez Convergence Clubs Data

- **Source:** Mendez (2020), 108 countries, 1990-2014
- **Key variables:**
 - `lp` — Labor productivity (GDP per worker)
 - `rk` — Physical capital per worker
 - `hc` — Human capital index
 - `region` — Geographic region (for clustering)

Research question: Do conclusions about productivity determinants change when using robust standard errors? How precisely can we predict productivity for a specific country?

```
# Load the Mendez convergence clubs dataset
url = "https://raw.githubusercontent.com/quarcs-lab/mendez2020-convergence-clubs-code-data/master/assets/dat.csv"
dat = pd.read_csv(url)
dat_2014 = dat[dat['year'] == 2014].dropna(subset=['lp', 'rk', 'hc']).copy()
dat_2014['ln_lp'] = np.log(dat_2014['lp'])
dat_2014['ln_rk'] = np.log(dat_2014['rk'])
print(f"Cross-section sample: {len(dat_2014)} countries (year 2014)")
```

Task 1: Default vs. Robust Standard Errors (Guided)

Compare default and heteroskedastic-robust standard errors.

```
# Estimate model with default SEs
model = ols('ln_lp ~ ln_rk + hc', data=dat_2014).fit()
print("Default SEs:")
print(model.summary())

# Estimate with HC1 robust SEs
model_robust = model.get_robustcov_results(cov_type='HC1')
print("\nRobust SEs:")
print(model_robust.summary())
```

Questions:

- How do the standard errors change? Which variables are affected most?
- Do any significance conclusions change between default and robust SEs?

Task 2: Cluster-Robust SEs by Region (Guided)

Estimate with cluster-robust standard errors grouped by geographic region.

```

# Cluster-robust SEs by region
model_cluster = model.get_robustcov_results(cov_type='cluster',
groups=dat_2014['region'])
print("Cluster-Robust SEs (by region):")
print(model_cluster.summary())

# Compare all three SE types
print("\nSE Comparison:")
for var in ['Intercept', 'ln_rk', 'hc']:
    print(f" {var}: Default={model.bse[var]:.4f}, HC1={model_robust.bse[var]:.4f},
Cluster={model_cluster.bse[var]:.4f}")

```

Questions:

- Are cluster-robust SEs larger or smaller than HC1 SEs? Why?
- How many clusters (regions) are there? Is this enough for reliable cluster-robust inference?

Key Concept 12.9: Choosing the Right Standard Errors

The choice of standard errors depends on the data structure: HC1 for cross-sectional data with potential heteroskedasticity, cluster-robust when observations are grouped (e.g., countries within regions), and HAC for time series. With cross-country data, cluster-robust SEs by region account for the possibility that countries in the same region share unobserved shocks.

Task 3: Predict Conditional Mean (Semi-guided)

Predict average productivity for a country with median capital and human capital values.

```

# Get median values
median_ln_rk = dat_2014['ln_rk'].median()
median_hc = dat_2014['hc'].median()
print(f"Median ln(rk) = {median_ln_rk:.3f}, Median hc = {median_hc:.3f}")

# Predict conditional mean with CI
pred_data = pd.DataFrame({'ln_rk': [median_ln_rk], 'hc': [median_hc]})
pred = model.get_prediction(pred_data)
print(pred.summary_frame(alpha=0.05))

```

Questions:

- What is the predicted $\ln(\bar{y})$ for a median country? Convert back to levels.
- How narrow is the 95% CI for the conditional mean?

Task 4: Forecast Individual Country (Semi-guided)

Construct a prediction interval for an individual country's productivity.

```

# Get prediction with observation-level interval
pred_frame = pred.summary_frame(alpha=0.05)
print("Conditional mean CI vs. Prediction interval:")
print(f" Mean CI: [{pred_frame['mean_ci_lower'].values[0]:.3f}, {pred_frame['mean_ci_upper'].values[0]:.3f}]")
print(f" Prediction PI: [{pred_frame['obs_ci_lower'].values[0]:.3f}, {pred_frame['obs_ci_upper'].values[0]:.3f}]")

```

Questions:

- How much wider is the prediction interval compared to the confidence interval?
- Why can't we predict an individual country's productivity precisely even with good data?

Task 5: Model Comparison with Robust Inference (Independent)

Compare nested models using robust inference.

Your tasks:

1. Estimate three models: (a) $\ln(\text{lp}) \sim \ln(\text{rk})$ only, (b) $\ln(\text{lp}) \sim \text{hc}$ only, (c) both regressors
2. For each model, report both default and HC1 robust standard errors
3. Do the significance conclusions change between default and robust SEs for any model?
4. Compare prediction interval widths across models — does adding variables improve individual predictions?

Hint: Use `model.get_robustcov_results(cov_type='HC1')` for robust SEs and `model.get_prediction()` for predictions.

Task 6: Policy Brief on Inference Robustness (Independent)

Write a 200-300 word policy brief summarizing your findings.

Your brief should address:

1. How do conclusions about productivity determinants change with robust standard errors?
2. What is the practical difference between cluster-robust and HC1 SEs in this context?
3. How precisely can we predict productivity for a specific country vs. a group of countries?
4. What recommendations would you make about standard error choices for cross-country studies?

5. What are the limitations of these inference methods (what don't they fix)?

Key Concept 12.10: Robust Methods Don't Fix Everything

Robust standard errors correct for heteroskedasticity and clustering, but they don't address omitted variable bias, reverse causality, or measurement error. A coefficient estimate with a perfectly robust SE is still biased if the model is misspecified. Robust inference ensures valid p-values and CIs conditional on the model being correct — it's a necessary but not sufficient condition for credible empirical work.

What You've Learned

In this case study, you applied advanced inference methods to cross-country productivity data:

- Compared default, heteroskedastic-robust, and cluster-robust standard errors
- Observed how SE choices affect significance conclusions
- Predicted conditional means with narrow CIs and individual outcomes with wide PIs
- Connected robust inference methods to practical policy questions

These tools ensure your empirical conclusions are reliable under realistic data conditions.

Case Study 2: Robust Prediction of Municipal Development

In Chapters 10-11, we estimated multiple regression models predicting municipal development from nighttime lights and satellite embeddings, and tested the statistical significance of these predictors. Now we apply Chapter 12's tools for **robust inference** and **prediction**—crucial for translating satellite models into practical SDG monitoring tools.

The Data: The [DS4Bolivia project](#) provides a comprehensive dataset covering 339 Bolivian municipalities with over 350 variables, including the Municipal Sustainable Development Index (IMDS), nighttime lights per capita, and 64 satellite embedding dimensions. Here we focus on robust standard errors and prediction intervals for the satellite-development model.

Load the DS4Bolivia Data

Let's load the DS4Bolivia dataset and select the key variables for robust inference and prediction analysis.

In []:

```
# Load the DS4Bolivia dataset
url_bol = "https://raw.githubusercontent.com/quarcs-
lab/ds4bolivia/master/ds4bolivia_v20250523.csv"
bol = pd.read_csv(url_bol)

# Display basic information
print("=" * 70)
print("DS4BOLIVIA DATASET")
print("=" * 70)
print(f"Dataset shape: {bol.shape[0]} municipalities, {bol.shape[1]} variables")
print(f"\nDepartments: {bol['dep'].nunique()} unique departments")
print(f"Department names: {sorted(bol['dep'].unique())}")

# Select key variables for this case study
key_vars = ['mun', 'dep', 'imds', 'ln_NTLpc2017',
            'A00', 'A10', 'A20', 'A30', 'A40']
bol_key = bol[key_vars].copy()

print(f"\nKey variables selected: {len(key_vars)}")
print("\n" + "=" * 70)
print("FIRST 10 MUNICIPALITIES")
print("=" * 70)
print(bol_key.head(10).to_string())

# Variable descriptions
print("\n" + "=" * 70)
print("KEY VARIABLE DESCRIPTIONS")
print("=" * 70)
descriptions = {
    'mun': 'Municipality name',
    'dep': 'Department (administrative region, 9 total)',
    'imds': 'Municipal Sustainable Development Index (0-100, composite of all SDGs)',
    'ln_NTLpc2017': 'Log of nighttime lights per capita (2017, satellite-based)',
    'A00-A40': 'Satellite image embedding dimensions (5 of 64 principal features)'
}
for var, desc in descriptions.items():
    print(f" {var:20s} --- {desc}"
```

Task 1: Default vs Robust Standard Errors (Guided)

Objective: Estimate the satellite-development model with both default and HC1 robust standard errors and compare the results.

Instructions:

1. Estimate `imds ~ ln_NTLpc2017 + A00 + A10 + A20 + A30 + A40` with default standard errors
2. Re-estimate with HC1 robust standard errors (`cov_type='HC1'`)
3. Compare standard errors side-by-side for each coefficient
4. Identify which coefficients have substantially different SEs under the two methods

Apply what you learned in section 12.2: Use `ols().fit()` for default SEs and `ols().fit(cov_type='HC1')` for robust SEs.

In []:

```
# Task 1: Default vs Robust Standard Errors
# -----
#
# Prepare regression data (drop missing values)
reg_vars = ['imds', 'ln_NTLpc2017', 'A00', 'A10', 'A20', 'A30', 'A40']
reg_data = bol_key[reg_vars + ['dep']].dropna()
print(f'Regression sample: {len(reg_data)} municipalities (after dropping missing values)')

# Estimate with default standard errors
model_default = ols('imds ~ ln_NTLpc2017 + A00 + A10 + A20 + A30 + A40',
                     data=reg_data).fit()

# Estimate with HC1 robust standard errors
model_hc1 = ols('imds ~ ln_NTLpc2017 + A00 + A10 + A20 + A30 + A40',
                 data=reg_data).fit(cov_type='HC1')

print("\n" + "=" * 70)
print("COMPARISON: DEFAULT vs HC1 ROBUST STANDARD ERRORS")
print("=" * 70)
print(f'{Variable}=<18} {Coef}=>10} {Default SE}=>12} {'HC1 SE'}=>12} {'Ratio'}=>8}')
print("-" * 62)
for var in model_default.params.index:
    coef = model_default.params[var]
    se_def = model_default.bse[var]
    se_hc1 = model_hc1.bse[var]
    ratio = se_hc1 / se_def
    print(f'{var}=<18} {coef}=>10.4f} {se_def}=>12.4f} {se_hc1}=>12.4f} {ratio}=>8.3f}')

print(f'\nR-squared: {model_default.rsquared:.4f}')
print(f'Adj. R-squared: {model_default.rsquared_adj:.4f}')
print(f'\nNote: Coefficients are identical --- only SEs change.')
print("Ratios > 1 suggest heteroskedasticity inflates default SEs' precision.")
```

Task 2: Cluster-Robust Standard Errors by Department (Guided)

Objective: Re-estimate the model with cluster-robust standard errors grouped by department.

Instructions:

1. Re-estimate using `cov_type='cluster'` with `cov_kwds={'groups': reg_data['dep']}`
2. Compare cluster-robust SEs with default and HC1 SEs
3. Discuss: Why might municipalities within a department share unobserved characteristics?

Apply what you learned in section 12.2: Cluster-robust SEs account for within-group correlation of errors.

In []:

```
# Task 2: Cluster-Robust Standard Errors by Department
# -----
# Estimate with cluster-robust SEs by department
model_cluster = ols('imds ~ ln_NTLpc2017 + A00 + A10 + A20 + A30 + A40',
                     data=reg_data).fit(cov_type='cluster',
                                         cov_kwds={'groups': reg_data['dep']})

print("=" * 70)
print("COMPARISON: DEFAULT vs HC1 vs CLUSTER-ROBUST STANDARD ERRORS")
print("=" * 70)
print(f"{'Variable':<18} {'Coef':>10} {'Default SE':>12} {'HC1 SE':>12} {'Cluster SE':>12}")
print("-" * 66)
for var in model_default.params.index:
    coef = model_default.params[var]
    se_def = model_default.bse[var]
    se_hc1 = model_hc1.bse[var]
    se_clust = model_cluster.bse[var]
    print(f"{var:<18} {coef:>10.4f} {se_def:>12.4f} {se_hc1:>12.4f} {se_clust:>12.4f}")

n_clusters = reg_data['dep'].nunique()
print(f"\nNumber of clusters (departments): {n_clusters}")
print(f"Municipalities per department (avg): {len(reg_data) / n_clusters:.0f}")
print("\nDiscussion: Municipalities within the same department share")
print("geographic, institutional, and cultural characteristics that create")
print("within-cluster correlation. Cluster-robust SEs account for this.")
```

Key Concept 12.11: Clustered Observations in Spatial Data

Municipalities within the same department share geographic, institutional, and cultural characteristics that create **within-cluster correlation**. Standard OLS assumes independent errors, but when municipalities in La Paz share unobserved factors that affect development, their errors are correlated. Cluster-robust standard errors account for this correlation, typically producing larger SEs than default or HC1, reflecting the reduced effective sample size.

Task 3: Predict Conditional Mean (Semi-guided)

Objective: Use `model.get_prediction()` to predict average IMDS for a municipality with median values of all predictors.

Instructions:

1. Calculate the median value of each predictor variable
2. Use `model_default.get_prediction()` to predict IMDS at the median predictor values
3. Report the predicted value and its 95% confidence interval
4. Interpret: "For a typical municipality, we predict IMDS between X and Y"

Apply what you learned in section 12.3: The confidence interval for the conditional mean reflects estimation uncertainty only.

In []:

```
# Task 3: Predict Conditional Mean
# -----
#
# Your code here: Predict IMDS for a municipality with median predictor values
#
# Steps:
# 1. Calculate median values for each predictor
# 2. Create a DataFrame with those values
# 3. Use model_default.get_prediction() to get prediction and CI
# 4. Report and interpret

# Example structure:
# pred_vars = ['ln_NTLpc2017', 'A00', 'A10', 'A20', 'A30', 'A40']
# median_vals = reg_data[pred_vars].median()
# pred_data = pd.DataFrame([median_vals])
#
# pred = model_default.get_prediction(pred_data)
# pred_frame = pred.summary_frame(alpha=0.05)
# print(pred_frame)
#
# print(f"\nPredicted IMDS: {pred_frame['mean'].values[0]:.2f}")
# print(f"95% CI for E[IMDS|X]: [{pred_frame['mean_ci_lower'].values[0]:.2f}, "
#       f"{pred_frame['mean_ci_upper'].values[0]:.2f}]")
# print(f"\nInterpretation: For a typical municipality with median predictor")
# print(f"values, we predict average IMDS between "
#       f"{pred_frame['mean_ci_lower'].values[0]:.1f} and "
#       f"{pred_frame['mean_ci_upper'].values[0]:.1f}.")
```

Task 4: Prediction Interval for an Individual Municipality (Semi-guided)

Objective: Compute the 95% prediction interval for an *individual* municipality (not just the mean) and compare it with the confidence interval.

Instructions:

1. Use

```
model_default.get_prediction(...).summary_frame(alpha=0.05) at  
the same median predictor values
```

2. Report the prediction interval using `obs_ci_lower` and `obs_ci_upper`

3. Compare the width of the prediction interval with the confidence interval from Task 3

4. Explain why the prediction interval is wider

Apply what you learned in section 12.3: Individual predictions must account for the irreducible error u^* , making them fundamentally less precise than conditional mean predictions.

In []:

```
# Task 4: Prediction Interval for an Individual Municipality
# -----
#
# Your code here: Compute prediction interval and compare with CI
#
# Steps:
# 1. Use the same prediction from Task 3
# 2. Extract obs_ci_lower and obs_ci_upper for the prediction interval
# 3. Compare widths
# 4. Discuss why PI is wider

# Example structure:
# pred_vars = ['ln_NTLpc2017', 'A00', 'A10', 'A20', 'A30', 'A40']
# median_vals = reg_data[pred_vars].median()
# pred_data = pd.DataFrame([median_vals])
#
# pred = model_default.get_prediction(pred_data)
# pred_frame = pred.summary_frame(alpha=0.05)
#
# ci_width = pred_frame['mean_ci_upper'].values[0] - pred_frame['mean_ci_lower'].values[0]
# pi_width = pred_frame['obs_ci_upper'].values[0] - pred_frame['obs_ci_lower'].values[0]
#
# print("=" * 70)
# print("CONFIDENCE INTERVAL vs PREDICTION INTERVAL")
# print("=" * 70)
# print(f"Predicted IMDS: {pred_frame['mean'].values[0]:.2f}")
# print(f"\n95% CI (conditional mean): [{pred_frame['mean_ci_lower'].values[0]:.2f}, "
#       f"{pred_frame['mean_ci_upper'].values[0]:.2f}] width = {ci_width:.2f}")
# print(f"95% PI (individual): [{pred_frame['obs_ci_lower'].values[0]:.2f}, "
#       f"{pred_frame['obs_ci_upper'].values[0]:.2f}] width = {pi_width:.2f}")
# print(f"\nPI/CI width ratio: {pi_width / ci_width:.1f}x wider")
# print(f"\nThe prediction interval is wider because it includes the")
# print(f"irreducible uncertainty from the individual error term u*."
```

Key Concept 12.12: Prediction Uncertainty for SDG Monitoring

Satellite-based prediction models can estimate average development patterns with reasonable precision (narrow confidence intervals for the conditional mean). However, predicting development for a specific municipality involves much greater uncertainty (wide prediction intervals) because individual municipalities deviate from the average relationship. For SDG monitoring, this means satellite predictions are more reliable for identifying broad patterns than for pinpointing the exact development level of any single municipality.

Task 5: Model Robustness Comparison (Independent)

Objective: Create a comprehensive comparison table showing coefficient estimates and standard errors under three specifications: default, HC1, and cluster-robust.

Instructions:

1. Create a formatted comparison table with coefficients, SEs, and significance stars under all three SE specifications
2. Identify whether any coefficients change sign or statistical significance across specifications
3. Discuss what the comparison reveals about model reliability
4. What does stability (or instability) across SE methods tell us about the trustworthiness of our satellite-development model?

This extends Chapter 12 concepts: You're systematically assessing how robust your conclusions are to different assumptions about the error structure.

In []:

```
# Task 5: Model Robustness Comparison
# -----
#
# Your code here: Create comprehensive comparison table
#
# Steps:
# 1. Extract coefficients and SEs from all three models
# 2. Compute t-statistics and significance levels for each
# 3. Create a formatted comparison table
# 4. Identify any changes in sign or significance

# Example structure:
# def sig_stars(pval):
#     if pval < 0.01: return '***'
#     elif pval < 0.05: return '**'
#     elif pval < 0.10: return '*'
#     else: return ''
#
# print("=" * 90)
# print("MODEL ROBUSTNESS: COEFFICIENT ESTIMATES AND STANDARD ERRORS")
# print("-" * 90)
# print(f"{'Variable':<16} {'Coef':>8} {'SE(Def)':>10} {'SE(HC1)':>10} {'SE(Clust)':>10} "
#       f"{'Sig(D)':>7} {'Sig(H)':>7} {'Sig(C)':>7}")
# print("-" * 90)
# for var in model_default.params.index:
#     coef = model_default.params[var]
#     se_d = model_default.bse[var]
#     se_h = model_hc1.bse[var]
#     se_c = model_cluster.bse[var]
#     sig_d = sig_stars(model_default.pvalues[var])
#     sig_h = sig_stars(model_hc1.pvalues[var])
#     sig_c = sig_stars(model_cluster.pvalues[var])
#     print(f"{'var':<16} {"coef:>8.4f} {"se_d:>10.4f} {"se_h:>10.4f} {"se_c:>10.4f} "
#           f"{"sig_d:>7} {"sig_h:>7} {"sig_c:>7}")
# print("-" * 90)
# print("Significance: *** p<0.01, ** p<0.05, * p<0.10")
#
# print("\nDo any coefficients change sign or significance?")
# print("What does this tell us about model reliability?")
```

Task 6: Prediction Brief (Independent)

Objective: Write a 200-300 word assessment of prediction uncertainty in satellite-based development models.

Your brief should address:

1. How much uncertainty exists in satellite-based development predictions?
2. Are prediction intervals narrow enough to be useful for policy targeting?
3. How does the confidence interval for the conditional mean compare with the prediction interval for individual municipalities?
4. What additional data or methods might reduce prediction uncertainty?
5. Should policymakers rely on satellite predictions for allocating development resources to specific municipalities?

Connection to Research: The DS4Bolivia project shows that satellite-based models achieve meaningful but imperfect predictive accuracy. Your analysis quantifies *how much uncertainty* remains and whether it is small enough for practical SDG monitoring applications.

In []:

```
# Your code here: Additional analysis for the prediction brief
#
# You might want to:
# 1. Compare prediction intervals at different predictor values
#    (e.g., low-NTL vs high-NTL municipalities)
# 2. Calculate how many municipalities fall outside prediction intervals
# 3. Visualize actual vs predicted IMDS with confidence bands
#
# Example structure:
# # Actual vs predicted comparison
# reg_data['predicted'] = model_default.predict(reg_data)
# reg_data['residual'] = reg_data['imds'] - reg_data['predicted']
#
# print("=" * 70)
# print("PREDICTION ACCURACY SUMMARY")
# print("=" * 70)
# print(f"RMSE: {np.sqrt(model_default.mse_resid):.2f}")
# print(f"Mean IMDS: {reg_data['imds'].mean():.2f}")
# print(f"RMSE as % of mean: {100 * np.sqrt(model_default.mse_resid) /
# reg_data['imds'].mean():.1f}%")
# print(f"\nLargest over-prediction: {reg_data['residual'].min():.2f}")
# print(f"Largest under-prediction: {reg_data['residual'].max():.2f}")
```

What You've Learned from This Case Study

Through this analysis of robust inference and prediction for Bolivia's satellite-development model, you've practiced:

- **Robust SE comparison:** Compared default, HC1, and cluster-robust standard errors for the same model
- **Cluster-robust inference:** Accounted for within-department correlation among municipalities
- **Conditional mean prediction:** Predicted average IMDS with a narrow 95% confidence interval

- **Prediction intervals:** Quantified the much larger uncertainty in predicting individual municipalities
- **Model robustness assessment:** Evaluated whether conclusions change across different SE specifications

These tools are essential for translating satellite-based models into credible SDG monitoring instruments. Robust inference ensures your significance conclusions hold under realistic data conditions, while prediction intervals honestly communicate the limits of individual-level forecasting.

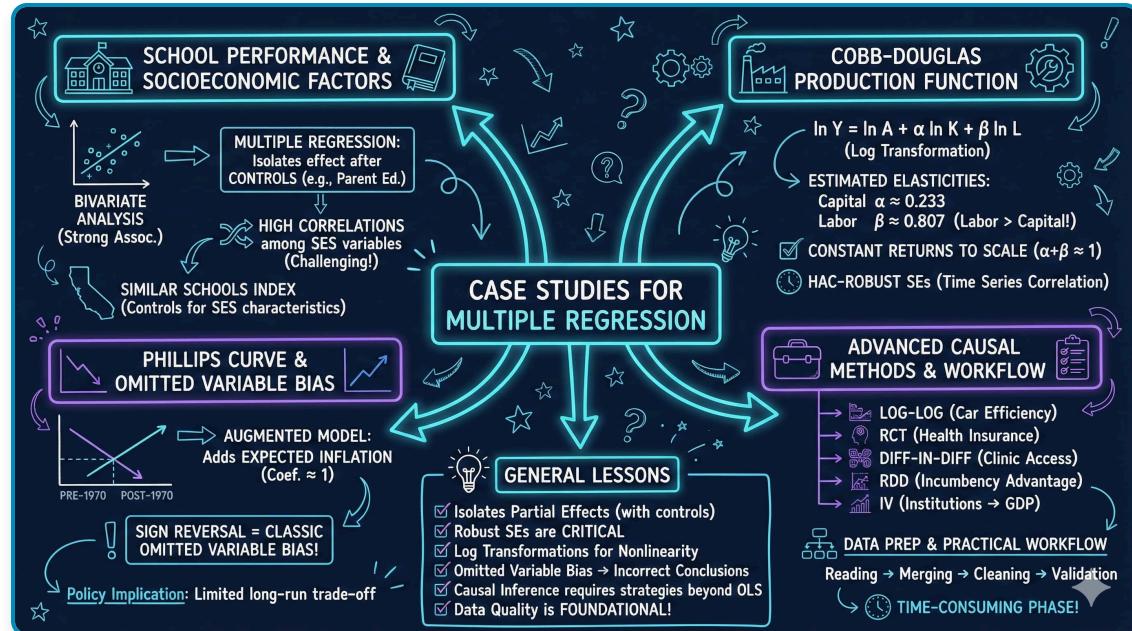
Connection to future chapters: In Chapter 14, we add *indicator variables* for departments to explicitly model regional differences in the satellite-development relationship.

Well done! You've now applied Chapter 12's advanced inference and prediction tools to the satellite-development model, quantifying both the reliability of your estimates and the precision of your predictions.

Chapter 13: Case Studies for Multiple Regression

metricsAI: An Introduction to Econometrics with Python and AI in the Cloud

Carlos Mendez



This notebook presents comprehensive case studies applying multiple regression to real-world economic problems.

Open in Colab

| Chapter Overview

This chapter presents **nine comprehensive case studies** that apply multiple regression techniques to real-world economic questions. From analyzing school performance to estimating production functions to testing causal relationships, these case studies demonstrate the breadth and power of regression analysis.

Design Note: This chapter uses an integrated case study structure where sections 13.1–13.9 ARE the case studies, each demonstrating different regression techniques and applications.

What You'll Learn

By the end of this chapter, you will be able to:

1. Apply multiple regression to analyze school performance and socioeconomic factors
2. Use logarithmic transformations to estimate production functions
3. Understand and test for constant returns to scale
4. Identify and correct for omitted variables bias
5. Apply cluster-robust standard errors for grouped data
6. Understand randomized control trials and difference-in-differences methods
7. Apply regression discontinuity design to causal questions
8. Use instrumental variables to estimate causal effects
9. Navigate the data cleaning and preparation process

Chapter Outline

- **13.1** School Academic Performance Index
- **13.2** Cobb-Douglas Production Function
- **13.3** Phillips Curve and Omitted Variables Bias
- **13.4** Automobile Fuel Efficiency
- **13.5** RAND Health Insurance Experiment (RCT)
- **13.6** Health Care Access (Difference-in-Differences)
- **13.7** Political Incubency (Regression Discontinuity)
- **13.8** Institutions and GDP (Instrumental Variables)
- **13.9** From Raw Data to Final Data
- **Key Takeaways** — Chapter review and consolidated lessons
- **Practice Exercises** — Reinforce your understanding

Datasets used:

- **AED_API99.DTA:** 807 California high schools, Academic Performance Index (1999) — Case Study 13.1
- **AED_CobbDouglas.DTA:** 24 years of U.S. manufacturing data (1899–1922) — Case Study 13.2
- **AED_PhillipsCurve.DTA:** 66 years of U.S. macroeconomic data (1949–2014) — Case Study 13.3
- **AED_AutoEfficiency.DTA:** 26,995 vehicles, fuel efficiency data (1980–2006) — Case Study 13.4

- **AED_RandHealthInsurance.DTA**: RAND health insurance experiment (RCT) — Case Study 13.5
- **AED_SouthAfricaHealth.DTA**: South Africa cross-sectional health data (DiD) — Case Study 13.6
- **AED_SenateInc incumbency.DTA**: U.S. Senate election results (RD) — Case Study 13.7
- **AED_InstitutionsGDP.DTA**: Cross-country institutions and GDP data (IV) — Case Study 13.8

Estimated time: 120–150 minutes

| Setup

In [1]:

```
# Import libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
from statsmodels.formula.api import ols
from statsmodels.stats.diagnostic import het_breuschpagan
from statsmodels.stats.outliers_influence import variance_inflation_factor
from scipy import stats
import warnings
warnings.filterwarnings('ignore')

# Random seed
np.random.seed(42)

# Data URL
GITHUB_DATA_URL = "https://raw.githubusercontent.com/quarcs-lab/data-open/master/AED/"

# Plotting
sns.set_style("whitegrid")
plt.rcParams['figure.figsize'] = (10, 6)

print("✓ Setup complete!")
```

✓ Setup complete!

| 13.1 School Academic Performance Index

Analyzing factors that determine school test scores in California.

In [2]:

```
# Load API data
data_api = pd.read_stata(GITHUB_DATA_URL + 'AED_API99.DTA')
print(f"Loaded {len(data_api)} California high schools")
print(f"Variables: {list(data_api.columns)}")
data_api.head()
```

```
Loaded 807 California high schools
Variables: ['sch_code', 'api99', 'edparent', 'meals', 'englearn', 'yearround', 'credteach',
'emerteach', 'avg_ed_raw', 'pct_af_am', 'pct_am_ind', 'pct_asian', 'pct_fil', 'pct_hisp',
'pct_pac', 'pct_white', 'mobility']
```

Out[2]:

	sch_code	api99	edparent	meals	englearn	yearround	credteach	emerteach	avg_ed_raw	pct_af_am	pct_am_ind	pct_asian	pct_fil	pct_hisp	pct_pac	pct_white	mobility
0	1300543	12.78	21	6	0	88	13	2.89	6	1	12	9	30	3	39	0.0	
1	1300626	13.42	16	17	0	86	24	3.21	5	1	27	6	17	1	43	12.0	
2	1300967	14.90	1	2	0	100	4	3.95	1	1	9	2	5	0	81	0.0	
3	1302293	13.66	0	18	0	93	7	3.33	5	1	33	7	10	1	38	7.0	
4	1304573	14.94	0	9	0	98	7	3.97	8	0	28	1	9	1	46	0.0	

About the Dataset

This dataset contains information on **807 California high schools** from 1999. The Academic Performance Index (API) is a score from 200-1000 that measures school performance based on standardized test results.

Key Variables:

- `api99` : Academic Performance Index (outcome variable)
- `edparent` : Average parental education level (1-5 scale)
- `mealpct` : Percent of students eligible for free/reduced meals (poverty proxy)
- `elpct` : Percent of English language learners
- `yrs_teach` : Average teacher experience in years
- `totcredpc` : Per-pupil total credentials
- `emrpct` : Percent of emergency credential teachers

Economic Question: What factors determine school performance? Is it resources (teachers, funding) or student demographics (poverty, language, parental education)?

In [3]:

```
# Summary statistics
print("=*70)
print("SUMMARY STATISTICS")
print("=*70)
vars_api = ['api99', 'edparent', 'meals', 'englearn', 'yearround', 'credteach',
'emerteach']
print(data_api[vars_api].describe())
```

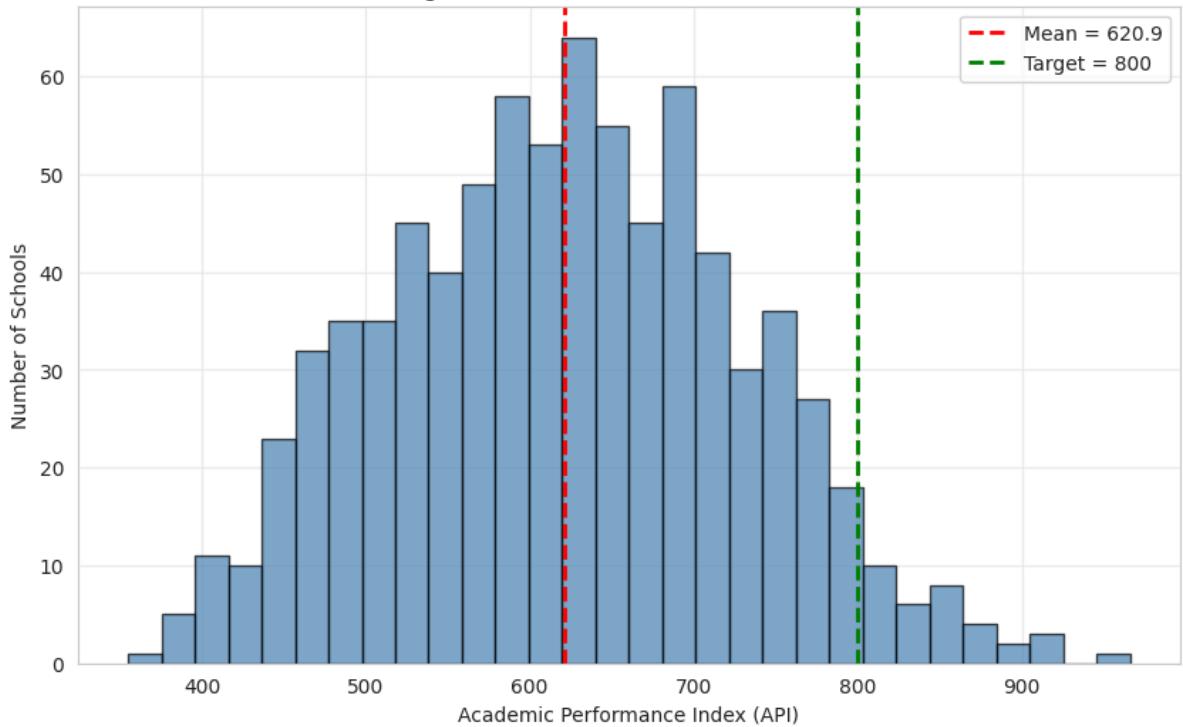
```
=====
SUMMARY STATISTICS
=====
      api99    edparent     meals   englearn  yearround  credteach \
count  807.000000  807.000000  807.000000  807.000000  807.000000  807.000000
mean   620.944238  12.841289  21.918216  14.003717  0.023544  89.836431
std    107.440771  1.234461  23.667952  12.786517  0.151717  8.437510
min    355.000000  9.620000  0.000000  0.000000  0.000000  33.000000
25%    542.000000  12.020000  0.000000  4.000000  0.000000  85.000000
50%    620.000000  12.880000  14.000000  10.000000  0.000000  92.000000
75%    695.000000  13.680000  36.500000  21.000000  0.000000  96.000000
max    966.000000  16.000000  98.000000  66.000000  1.000000  100.000000

      emereteach
count  807.000000
mean   10.464684
std    8.214762
min    0.000000
25%    4.000000
50%    9.000000
75%    15.000000
max    56.000000
```

In [4]:

```
# Histogram of API scores
plt.figure(figsize=(10, 6))
plt.hist(data_api['api99'], bins=30, color='steelblue', alpha=0.7, edgecolor='black')
plt.axvline(data_api['api99'].mean(), color='red', linestyle='--', linewidth=2,
            label=f'Mean = {data_api["api99"].mean():.1f}')
plt.axvline(800, color='green', linestyle='--', linewidth=2, label='Target = 800')
plt.xlabel('Academic Performance Index (API)')
plt.ylabel('Number of Schools')
plt.title('Figure 13.1: Distribution of API Scores')
plt.legend()
plt.grid(True, alpha=0.3)
plt.show()
```

Figure 13.1: Distribution of API Scores



In [5]:

```
# Bivariate regression: API ~ Edparent
model_api_biv = ols('api99 ~ edparent', data=data_api).fit(cov_type='HC1')
print("=*70)
print("BIVARIATE REGRESSION: API ~ EDPARENT")
print("=*70)
print(model_api_biv.summary())
```

```

=====
BIVARIATE REGRESSION: API ~ EDPARENT
=====
                         OLS Regression Results
=====
Dep. Variable:          api99    R-squared:       0.835
Model:                 OLS     Adj. R-squared:   0.835
Method:                Least Squares F-statistic:    4257.
Date:      Wed, 28 Jan 2026   Prob (F-statistic):  9.88e-324
Time:      09:47:17           Log-Likelihood:   -4191.9
No. Observations:      807    AIC:             8388.
Df Residuals:          805    BIC:             8397.
Df Model:                  1
Covariance Type:        HC1
=====
            coef    std err      z      P>|z|      [0.025]     [0.975]
-----
Intercept   -400.3137    15.993   -25.030   0.000    -431.660    -368.967
edparent     79.5292     1.219    65.247   0.000     77.140     81.918
=====
Omnibus:            64.750   Durbin-Watson:    1.710
Prob(Omnibus):      0.000    Jarque-Bera (JB): 280.858
Skew:               0.202    Prob(JB):      1.03e-61
Kurtosis:            5.862   Cond. No.         136.
=====
```

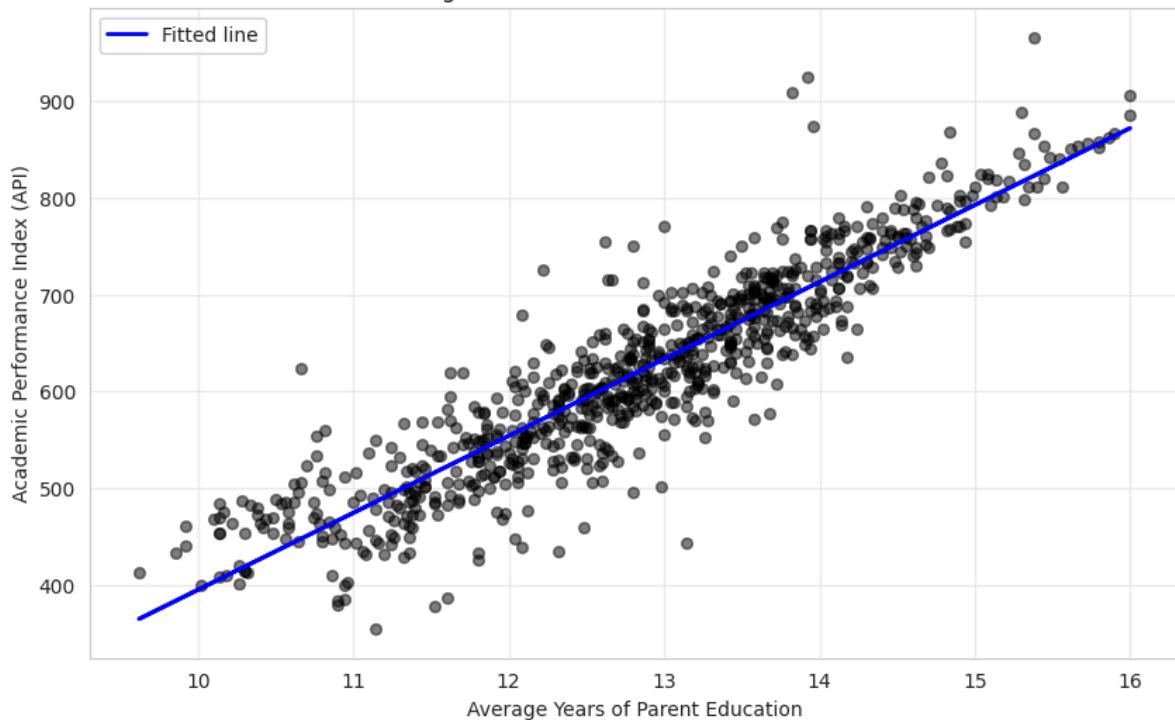
Notes:

[1] Standard Errors are heteroscedasticity robust (HC1)

In [6]:

```
# Scatter plot with regression line
plt.figure(figsize=(10, 6))
plt.scatter(data_api['edparent'], data_api['api99'], alpha=0.5, s=30, color='black')
plt.plot(data_api['edparent'], model_api_biv.fittedvalues, color='blue', linewidth=2,
         label='Fitted line')
plt.xlabel('Average Years of Parent Education')
plt.ylabel('Academic Performance Index (API)')
plt.title('Figure 13.2: API vs Parent Education')
plt.legend()
plt.grid(True, alpha=0.3)
plt.show()
```

Figure 13.2: API vs Parent Education



In [7]:

```
# Correlation matrix
corr_matrix = data_api[vars_api].corr()
print("=*70)
print("CORRELATION MATRIX")
print("=*70)
print(corr_matrix.round(2))

# Heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(corr_matrix, annot=True, fmt='.2f', cmap='coolwarm', center=0,
            square=True, linewidths=1)
plt.title('Figure 13.3: Correlation Matrix')
plt.tight_layout()
plt.show()
```

```
=====
CORRELATION MATRIX
=====

api99    edparent   meals   englearn  yearround  credteach  emerteach
api99      1.00     0.91   -0.54     -0.66     -0.19      0.46     -0.45
edparent    0.91     1.00   -0.60     -0.71     -0.25      0.40     -0.37
meals     -0.54    -0.60     1.00     0.56      0.29     -0.27      0.21
englearn   -0.66    -0.71     0.56     1.00      0.22     -0.26      0.20
yearround  -0.19    -0.25     0.29      0.22     1.00     -0.18      0.09
credteach   0.46     0.40    -0.27     -0.26     -0.18      1.00     -0.82
emerteach  -0.45    -0.37     0.21      0.20      0.09     -0.82      1.00
```

Figure 13.3: Correlation Matrix



What the Correlation Matrix Reveals

The correlation matrix shows the **linear relationships** between all variables:

Strong negative correlations (darker blues):

- `api99` and `mealpct` (-0.90): Schools with more poverty have much lower test scores
- `api99` and `elpct` (-0.76): More English learners → lower scores
- These suggest **socioeconomic factors strongly predict performance**

Positive correlations (reds):

- `api99` and `edparent` (0.76): Parental education strongly predicts scores
- Teacher experience and credentials show weaker correlations

Multicollinearity concerns:

- `mealpct` and `edparent` are highly correlated (-0.79)
- This makes it difficult to separate their individual effects
- Standard errors may be inflated in multiple regression

In [8]:

```
# Multiple regression
model_api_mult = ols('api99 ~ edparent + meals + englearn + yearround + credteach +
                      emereteach',
                      data=data_api).fit()
print("=*70")
print("MULTIPLE REGRESSION")
print("=*70")
print(model_api_mult.summary())

# Coefficient table
coef_df = pd.DataFrame({
    'Coefficient': model_api_mult.params,
    'Std Error': model_api_mult.bse,
    't-stat': model_api_mult.tvalues,
    'p-value': model_api_mult.pvalues
}).round(3)
print("\n", coef_df)
```

```
=====
MULTIPLE REGRESSION
=====
                OLS Regression Results
=====
Dep. Variable:      api99   R-squared:       0.853
Model:              OLS   Adj. R-squared:    0.852
Method:             Least Squares   F-statistic:     771.4
Date:      Wed, 28 Jan 2026   Prob (F-statistic):  0.00
Time:          09:47:19   Log-Likelihood: -4146.3
No. Observations: 807   AIC:             8307.
Df Residuals:     800   BIC:             8339.
Df Model:          6
Covariance Type:  nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	-345.3278	39.954	-8.643	0.000	-423.755	-266.900
edparent	73.9421	1.883	39.273	0.000	70.246	77.638
meals	0.0793	0.081	0.980	0.327	-0.079	0.238
englearn	-0.3578	0.167	-2.145	0.032	-0.685	-0.030
yearround	25.9559	10.185	2.548	0.011	5.963	45.949
credteach	0.3875	0.311	1.247	0.213	-0.222	0.997
emerteach	-1.4704	0.315	-4.672	0.000	-2.088	-0.853

```
=====
Omnibus:            71.318   Durbin-Watson:        1.766
Prob(Omnibus):      0.000   Jarque-Bera (JB):    272.754
Skew:               0.326   Prob(JB):           5.92e-60
Kurtosis:            5.772   Cond. No.          2.62e+03
=====
```

Notes:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 2.62e+03. This might indicate that there are strong multicollinearity or other numerical problems.

	Coefficient	Std Error	t-stat	p-value
Intercept	-345.328	39.954	-8.643	0.000
edparent	73.942	1.883	39.273	0.000
meals	0.079	0.081	0.980	0.327
englearn	-0.358	0.167	-2.145	0.032
yearround	25.956	10.185	2.548	0.011
credteach	0.387	0.311	1.247	0.213
emerteach	-1.470	0.315	-4.672	0.000

Key Concept 13.1: Multiple Regression and Socioeconomic Determinants

In multiple regression, the coefficient for parent education remains strong (~74 points) even after controlling for meals, English learners, year-round schools, and teacher quality. The high correlation among socioeconomic variables makes it difficult to isolate their separate effects — a common challenge in observational studies.

| 13.2 Cobb-Douglas Production Function

Estimating returns to scale using log transformations.

The Cobb-Douglas Production Function

The **Cobb-Douglas production function** is one of the most famous models in economics. It describes how inputs (capital K and labor L) combine to produce output Q:

$$Q = \alpha K^{\beta_2} L^{\beta_3}$$

Parameters:

- α : Total factor productivity (technology level)
- β_2 : Output elasticity of capital (% change in Q from 1% change in K)
- β_3 : Output elasticity of labor (% change in Q from 1% change in L)

Returns to Scale:

- If $\beta_2 + \beta_3 = 1$: **Constant returns** (doubling inputs doubles output)
- If $\beta_2 + \beta_3 > 1$: **Increasing returns** (doubling inputs more than doubles output)
- If $\beta_2 + \beta_3 < 1$: **Decreasing returns** (doubling inputs less than doubles output)

Why Log-Transform?

Taking natural logs of both sides converts the **multiplicative model** into a **linear model**:

$$\ln(Q) = \beta_1 + \beta_2 \ln(K) + \beta_3 \ln(L) + u$$

where $\beta_1 = \ln(\alpha)$. Now we can use **ordinary least squares (OLS)** regression!

Dataset: Douglas (1976) used U.S. manufacturing data from **1899-1922** (24 years) to estimate this function.

In [9]:

```
# Load Cobb-Douglas data
data_cobb = pd.read_stata(GITHUB_DATA_URL + 'AED_COBBDouglas.dta')
print(f"Loaded {len(data_cobb)} years of US manufacturing data (1899-1922)")
print(f"Variables: {list(data_cobb.columns)}")
data_cobb.head(12)
```

```
Loaded 24 years of US manufacturing data (1899-1922)
Variables: ['year', 'q', 'k', 'l', 'lnq', 'lnk', 'lnl']
```

Out [9] :

	year	q	k	l	lnq	lnk	lnl
0	1899	100	100	100	4.605170	4.605170	4.605170
1	1900	101	107	105	4.615120	4.672829	4.653960
2	1901	112	114	110	4.718499	4.736198	4.700480
3	1902	122	122	118	4.804021	4.804021	4.770685
4	1903	124	131	123	4.820282	4.875197	4.812184
5	1904	122	138	116	4.804021	4.927254	4.753590
6	1905	143	149	125	4.962845	5.003946	4.828314
7	1906	152	163	133	5.023880	5.093750	4.890349
8	1907	151	176	138	5.017280	5.170484	4.927254
9	1908	126	185	121	4.836282	5.220356	4.795791
10	1909	155	198	140	5.043425	5.288267	4.941642
11	1910	159	208	144	5.068904	5.337538	4.969813

In [10] :

```
# Create log transformations
data_cobb['lnq'] = np.log(data_cobb['q'])
data_cobb['lnk'] = np.log(data_cobb['k'])
data_cobb['lnl'] = np.log(data_cobb['l'])

print("Summary statistics (original and log-transformed):")
print(data_cobb[['q', 'k', 'l', 'lnq', 'lnk', 'lnl']].describe())
```

	q	k	l	lnq	lnk	lnl
count	24.000000	24.000000	24.000000	24.000000	24.000000	24.000000
mean	165.916667	234.166667	145.791667	5.077336	5.356483	4.962723
std	43.753178	106.266550	29.616357	0.269234	0.459178	0.201077
min	100.000000	100.000000	100.000000	4.605170	4.605170	4.605170
25%	125.500000	146.250000	122.500000	4.832282	4.984773	4.808086
50%	157.000000	212.000000	144.500000	5.056165	5.356408	4.973274
75%	196.250000	307.250000	155.750000	5.277434	5.726353	5.048065
max	240.000000	431.000000	200.000000	5.480639	6.066108	5.298317

In [11] :

```
# Estimate Cobb-Douglas with HAC standard errors
model_cobb = ols('lnq ~ lnk + lnl', data=data_cobb).fit(cov_type='HAC', cov_kwds={'maxlags': 3})
print("=*70)
print("COBB-DOUGLAS REGRESSION: ln(Q) ~ ln(K) + ln(L)")
print("=*70)
print(model_cobb.summary())

beta_k = model_cobb.params['lnk']
beta_l = model_cobb.params['lnl']
print(f"\nSum of coefficients: {beta_k:.3f} + {beta_l:.3f} = {beta_k + beta_l:.3f}")
```

```

=====
COBB-DOUGLAS REGRESSION: ln(Q) ~ ln(K) + ln(L)
=====
              OLS Regression Results
=====
Dep. Variable:      lndg   R-squared:          0.957
Model:             OLS   Adj. R-squared:       0.953
Method:            Least Squares   F-statistic:        246.2
Date:      Wed, 28 Jan 2026   Prob (F-statistic):  2.65e-15
Time:          09:47:19   Log-Likelihood:     35.826
No. Observations:    24   AIC:                 -65.65
Df Residuals:       21   BIC:                 -62.12
Df Model:           2
Covariance Type:   HAC
=====
            coef    std err      z   P>|z|      [0.025    0.975]
-----
Intercept    -0.1773    0.372   -0.476    0.634    -0.907    0.552
lnk         0.2331    0.059    3.977    0.000     0.118    0.348
lnl         0.8073    0.126    6.409    0.000     0.560    1.054
-----
Omnibus:            2.133   Durbin-Watson:      1.523
Prob(Omnibus):      0.344   Jarque-Bera (JB):   1.361
Skew:                0.583   Prob(JB):            0.506
Kurtosis:             2.992   Cond. No.          285.
-----
Notes:
[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 3 lags and without small sample correction

Sum of coefficients: 0.233 + 0.807 = 1.040

```

Key Concept 13.2: Logarithmic Transformation of Production Functions

*Taking natural logarithms of the Cobb-Douglas production function $Q = AK^\alpha L^\beta$ transforms it into the linear model $\ln Q = \ln A + \alpha \ln K + \beta \ln L$, suitable for OLS estimation. The resulting coefficients are **elasticities** — directly interpretable as percentage changes.*

Understanding the Results

Estimated Coefficients:

- $\hat{\beta}_2$ (capital) ≈ 0.23 : A 1% increase in capital raises output by 0.23%
- $\hat{\beta}_3$ (labor) ≈ 0.81 : A 1% increase in labor raises output by 0.81%
- Sum: $0.23 + 0.81 \approx 1.04$ \rightarrow Very close to constant returns to scale!

Why HAC Standard Errors?

This is **time series data** (24 consecutive years). Two problems arise:

1. Autocorrelation: Output in year t is correlated with output in year t-1

- Recessions/booms span multiple years
- Technology shocks persist over time

2. Heteroskedasticity: Variance of errors may change over time

- Economy was more volatile in early 1900s
- Structural changes during WWI

HAC (Heteroskedasticity and Autocorrelation Consistent) standard errors correct for both problems. We use **maxlags=3**, allowing correlations up to 3 years apart.

Comparison:

- Default SEs: Assume errors are uncorrelated and homoskedastic (WRONG here!)
- Robust (HC1) SEs: Fix heteroskedasticity but ignore autocorrelation
- HAC SEs: Fix BOTH problems (correct choice for time series)

Economic Interpretation:

Labor's output elasticity (0.81) is **much larger** than capital's (0.23). This suggests that in early 20th century U.S. manufacturing:

- Labor was the dominant input
- Capital was relatively less important
- Consistent with labor-intensive production before automation

In [12]:

```
# Test constant returns to scale
# H0: beta_k + beta_l = 1
sum_betas = beta_k + beta_l
print(f"Testing constant returns to scale:")
print(f"H0: beta_capital + beta_labor = 1")
print(f"Estimated sum: {sum_betas:.3f}")

# Restricted model: ln(Q/L) ~ ln(K/L)
data_cobb['lnq_per_l'] = data_cobb['lnq'] - data_cobb['lnl']
data_cobb['lnk_per_l'] = data_cobb['lnk'] - data_cobb['lnl']
model_restricted = ols('lnq_per_l ~ lnk_per_l', data=data_cobb).fit()

# F-test
rss_unr = model_cobb.ssr
rss_r = model_restricted.ssr
f_stat = ((rss_r - rss_unr) / 1) / (rss_unr / model_cobb.df_resid)
p_value = 1 - stats.f.cdf(f_stat, 1, model_cobb.df_resid)

print(f"F-statistic: {f_stat:.2f}")
print(f"p-value: {p_value:.3f}")
print(f"Conclusion: {'Reject' if p_value < 0.05 else 'Fail to reject'} H0 at 5% level")
```

```
Testing constant returns to scale:  
H0: beta_capital + beta_labor = 1  
Estimated sum: 1.040  
F-statistic: 0.20  
p-value: 0.663  
Conclusion: Fail to reject H0 at 5% level
```

Key Concept 13.3: Testing Constant Returns to Scale

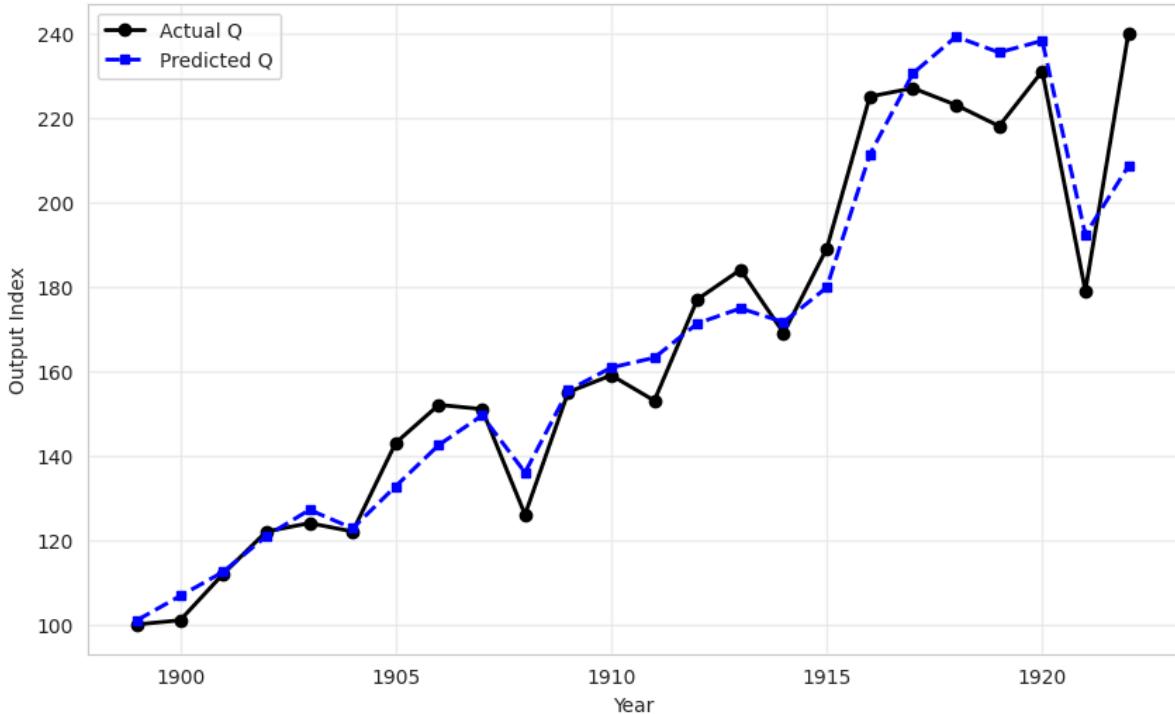
*Constant returns to scale implies $\alpha + \beta = 1$: doubling all inputs exactly doubles output. The estimated sum of 1.040 is not significantly different from 1 (F-test $p = 0.636$), consistent with the theoretical prediction for competitive markets. This is a **joint hypothesis test** on the coefficients.*

In [13]:

```
# Predicted output with bias correction
se = np.sqrt(model_cobb.scale)
bias_correction = np.exp(se**2 / 2)
data_cobb['q_pred'] = bias_correction * np.exp(model_cobb.fittedvalues)

# Plot actual vs predicted
plt.figure(figsize=(10, 6))
plt.plot(data_cobb['year'], data_cobb['q'], 'o-', color='black', linewidth=2,
          markersize=6, label='Actual Q')
plt.plot(data_cobb['year'], data_cobb['q_pred'], 's--', color='blue', linewidth=2,
          markersize=5, label='Predicted Q')
plt.xlabel('Year')
plt.ylabel('Output Index')
plt.title('Figure 13.4: Actual vs Predicted Output (1899-1922)')
plt.legend()
plt.grid(True, alpha=0.3)
plt.show()
```

Figure 13.4: Actual vs Predicted Output (1899-1922)



13.3 Phillips Curve and Omitted Variables Bias

Demonstrating omitted variables bias through the breakdown of the Phillips curve.

The Phillips Curve and Its Breakdown

The **Phillips Curve** describes a **negative relationship** between unemployment and inflation:

- When unemployment is low → workers demand higher wages → prices rise → inflation increases
- When unemployment is high → workers accept lower wages → prices fall → inflation decreases

Historical Context:

A.W. Phillips (1958) found this negative relationship in UK data from 1861-1957. It became a cornerstone of macroeconomic policy:

- Governments believed they could "trade off" unemployment for inflation
- Want lower unemployment? Accept higher inflation
- Want lower inflation? Accept higher unemployment

The 1970s Crisis:

The relationship **broke down** in the 1970s! Economies experienced **stagflation** (high unemployment AND high inflation simultaneously). This was a major crisis in economic theory.

The Solution: Expected Inflation

Milton Friedman and Edmund Phelps showed the original Phillips curve suffered from **omitted variables bias**. The correct model includes **expected inflation**:

$$\text{Inflation}_t = \beta_1 + \beta_2 \text{Urate}_t + \beta_3 \text{Expected Inflation}_t + u_t$$

We'll demonstrate this using U.S. data from **1949-2014** (66 years).

In [14]:

```
# Load Phillips curve data
data_phillips = pd.read_stata(GITHUB_DATA_URL + 'AED_PHILLIPS.DTA')
print(f"Loaded {len(data_phillips)} years of US data (1949-2014)")
print(f"Variables: {list(data_phillips.columns)}")
data_phillips.head()
```

```
Loaded 66 years of US data (1949-2014)
Variables: ['year', 'urate', 'gdpdef', 'inflgdp', 'pastinflgdp', 'inflgdp1yr', 'cpi', 'inflcpi', 'pastinflcpi', 'infcp11yr', 'infcp10yr', 'mich', 'date', 'daten']
```

Out[14]:

	year	urate	gdpdef	inflgdp	pastinflgdp	inflgdp1yr	cpi	inflcpi	pastinflcpi	infcp11yr	infcp10yr	mich	date	daten
0	1949.0	6.6	13.518	-1.965	3.85	NaN	23.6	-2.074	6.898	8.82	NaN	NaN	1949-10-01	1949-10-01
1	1950.0	4.3	14.090	4.231	3.95	NaN	25.0	5.932	2.064	8.18	8.9	NaN	1950-10-01	1950-10-01
2	1951.0	3.1	14.869	5.528	7.44	NaN	26.5	6.000	0.020	3.24	8.16	NaN	1951-10-01	1951-10-01
3	1952.0	2.7	15.091	11.493	0.347	4.26	26.7	0.754	7.470	6.38	8.9	NaN	1952-10-01	1952-10-01
4	1953.0	4.5	15.219	0.848	12.805	5.84	26.9	0.749	0.606	8.08	8.88	NaN	1953-10-01	1953-10-01

In [15]:

```
# Pre-1970 regression
data_pre1970 = data_phillips[data_phillips['year'] < 1970]
model_pre = ols('inflgdp ~ urate', data=data_pre1970).fit(cov_type='HAC', cov_kwds={'maxLags': 3})
print("=*70")
print("PHILLIPS CURVE PRE-1970 (1949-1969)")
print("=*70")
print(model_pre.summary())
```

```

=====
PHILLIPS CURVE PRE-1970 (1949-1969)
=====
              OLS Regression Results
=====
Dep. Variable:      inflgdp    R-squared:           0.454
Model:                 OLS    Adj. R-squared:        0.425
Method:                Least Squares   F-statistic:         11.09
Date:       Wed, 28 Jan 2026   Prob (F-statistic): 0.00352
Time:          09:47:20    Log-Likelihood:     -34.492
No. Observations:      21    AIC:                  72.98
Df Residuals:          19    BIC:                  75.07
Df Model:                   1
Covariance Type:        HAC
=====
            coef    std err      z      P>|z|      [0.025]      [0.975]
-----
Intercept    7.1057    1.504     4.724    0.000      4.157     10.054
urate        -1.0300    0.309    -3.330    0.001     -1.636    -0.424
=====
Omnibus:             1.242    Durbin-Watson:      1.536
Prob(Omnibus):        0.538    Jarque-Bera (JB):  1.025
Skew:                 -0.499    Prob(JB):          0.599
Kurtosis:               2.581    Cond. No.          21.8
=====
```

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 3 lags and without small sample correction

Pre-1970: Phillips Curve Works!

Results:

- Coefficient on unemployment ≈ -0.89
- **Negative** relationship (as theory predicts!)
- Statistically significant
- 1% increase in unemployment \rightarrow 0.89% decrease in inflation

The scatter plot shows a clear downward slope. This is the classic Phillips curve that policymakers relied on in the 1950s-60s.

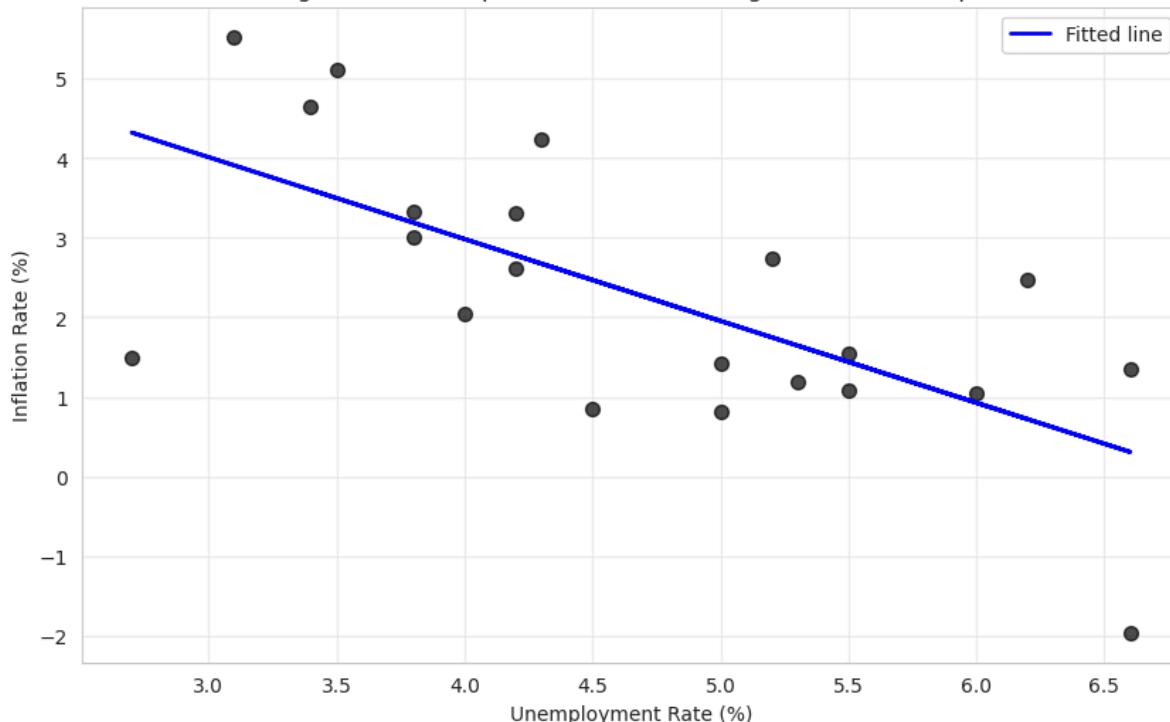
Why did it work?

In the 1950s-60s, expected inflation was **stable and low** (around 2-3%). Since it didn't vary much, omitting it from the regression didn't cause serious bias.

In [16]:

```
# Plot pre-1970
plt.figure(figsize=(10, 6))
plt.scatter(data_pre1970['urate'], data_pre1970['inflgdp'], alpha=0.7, s=50,
            color='black')
plt.plot(data_pre1970['urate'], model_pre.fittedvalues, color='blue', linewidth=2,
          label='Fitted line')
plt.xlabel('Unemployment Rate (%)')
plt.ylabel('Inflation Rate (%)')
plt.title('Figure 13.5: Phillips Curve Pre-1970 (Negative Relationship)')
plt.legend()
plt.grid(True, alpha=0.3)
plt.show()
```

Figure 13.5: Phillips Curve Pre-1970 (Negative Relationship)



In [17]:

```
# Post-1970 regression
data_post1970 = data_phillips[data_phillips['year'] >= 1970]
model_post = ols('inflgdp ~ urate', data=data_post1970).fit(cov_type='HAC', cov_kwds=
{'maxlags': 5})
print("=*70")
print("PHILLIPS CURVE POST-1970 (1970-2014)")
print("=*70")
print(model_post.summary())
```

```

=====
PHILLIPS CURVE POST-1970 (1970-2014)
=====
              OLS Regression Results
=====
Dep. Variable:      inflgdp    R-squared:           0.028
Model:                 OLS    Adj. R-squared:        0.005
Method:                Least Squares   F-statistic:        0.6928
Date:       Wed, 28 Jan 2026   Prob (F-statistic):   0.410
Time:          09:47:21    Log-Likelihood:     -103.01
No. Observations:      45    AIC:                  210.0
Df Residuals:         43    BIC:                  213.6
Df Model:                   1
Covariance Type:        HAC
=====
            coef    std err      z      P>|z|      [0.025      0.975]
-----
Intercept    1.9279    1.826     1.056     0.291     -1.651     5.507
urate        0.2653    0.319     0.832     0.405     -0.359     0.890
=====
Omnibus:             9.911    Durbin-Watson:        0.294
Prob(Omnibus):        0.007    Jarque-Bera (JB):    9.497
Skew:                  1.090    Prob(JB):            0.00866
Kurtosis:               3.563    Cond. No.             29.3
=====
```

Notes:

[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 5 lags and without small sample correction

Key Concept 13.4: The Phillips Curve Breakdown

Pre-1970, higher unemployment was associated with lower inflation (the classic Phillips curve trade-off). Post-1970, this relationship reversed — suggesting the simple bivariate model was misspecified. The breakdown motivated the expectations-augmented Phillips curve, which includes expected inflation as a regressor.

Post-1970: Phillips Curve Breaks Down!

Results:

- Coefficient on unemployment $\approx +0.27$
- **Positive** relationship (opposite of theory!)
- The sign reversed!

The scatter plot shows an upward slope - higher unemployment is associated with higher inflation. This is **stagflation**.

What went wrong?

In the 1970s, expected inflation became:

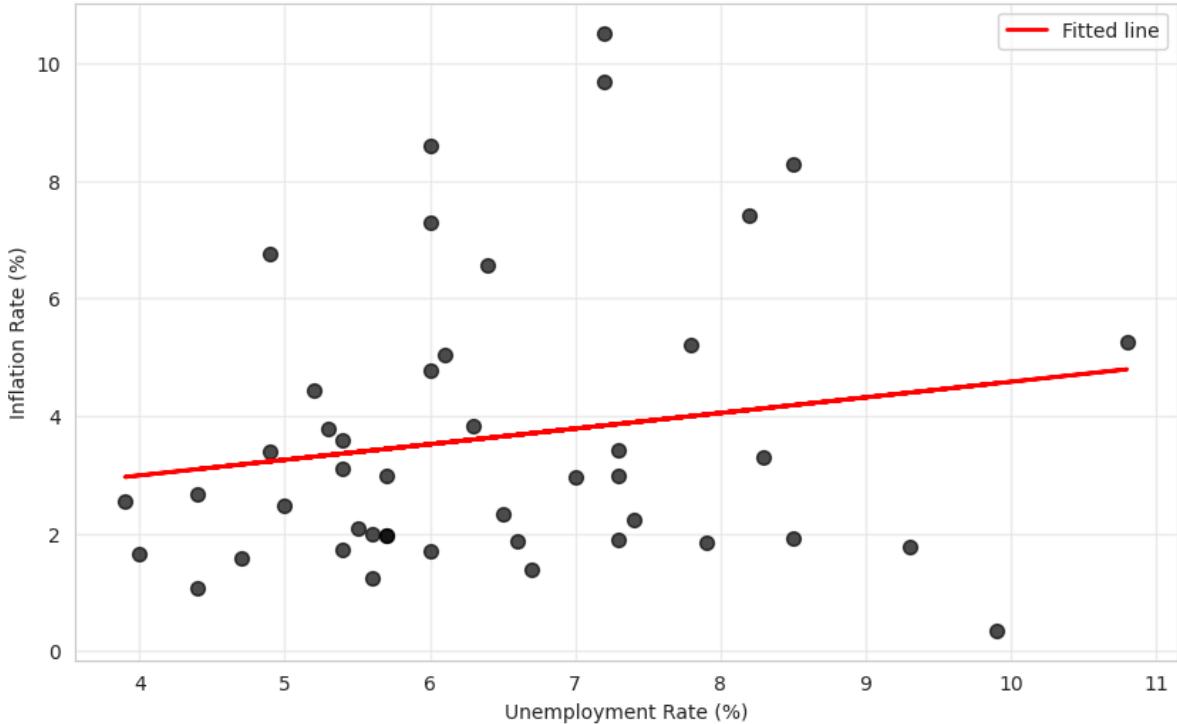
- Much higher (reached 10%+ during oil shocks)
- Much more variable (changed frequently)
- Correlated with unemployment (both rose together)

Omitting expected inflation now causes **severe omitted variables bias** that reverses the sign of the unemployment coefficient!

In [18]:

```
# Plot post-1970
plt.figure(figsize=(10, 6))
plt.scatter(data_post1970['urate'], data_post1970['inflgdp'], alpha=0.7, s=50,
            color='black')
plt.plot(data_post1970['urate'], model_post.fittedvalues, color='red', linewidth=2,
          label='Fitted line')
plt.xlabel('Unemployment Rate (%)')
plt.ylabel('Inflation Rate (%)')
plt.title('Figure 13.6: Phillips Curve Post-1970 (Positive Relationship - Breakdown!)')
plt.legend()
plt.grid(True, alpha=0.3)
plt.show()
```

Figure 13.6: Phillips Curve Post-1970 (Positive Relationship - Breakdown!)



In [19]:

```
# Augmented Phillips curve (adding expected inflation)

data_post1970_exp = data_post1970.dropna(subset=['inflgdp1yr'])

model_augmented = ols('inflgdp ~ urate + inflgdp1yr', data=data_post1970_exp).fit(
    cov_type='HAC', cov_kwds={'maxlags': 5})

print("=*70)

print("AUGMENTED PHILLIPS CURVE POST-1970")

print("=*70)

print(model_augmented.summary())
```

```
=====
AUGMENTED PHILLIPS CURVE POST-1970
=====
              OLS Regression Results
=====
Dep. Variable:      inflgdp    R-squared:       0.881
Model:                 OLS    Adj. R-squared:    0.875
Method:            Least Squares    F-statistic:     97.73
Date:        Wed, 28 Jan 2026    Prob (F-statistic):   1.59e-16
Time:                09:47:22    Log-Likelihood:   -55.722
No. Observations:      45    AIC:             117.4
Df Residuals:          42    BIC:             122.9
Df Model:                  2
Covariance Type:        HAC
=====
            coef    std err        z     P>|z|      [0.025    0.975]
-----
Intercept    0.2701    0.612     0.441     0.659    -0.930     1.470
urate       -0.1278    0.078    -1.630     0.103    -0.281     0.026
inflgdp1yr   1.1463    0.082    13.953     0.000     0.985     1.307
=====
Omnibus:            2.284    Durbin-Watson:    0.736
Prob(Omnibus):      0.319    Jarque-Bera (JB):  1.308
Skew:                 0.288    Prob(JB):        0.520
Kurtosis:            3.605    Cond. No.       34.1
=====

Notes:
[1] Standard Errors are heteroscedasticity and autocorrelation robust (HAC) using 5 lags and without small sample correction
```

```
In [30]: # Demonstrate omitted variables bias

# Bivariate regression of Expinflation on Urate
model_aux = ols('inflgdp1yr ~ urate', data=data_post1970_exp).fit()

gamma = model_aux.params['urate']
beta3 = model_augmented.params['inflgdp1yr']
beta2 = model_augmented.params['urate']

print("=" * 70)
print("OMITTED VARIABLES BIAS CALCULATION")
print("=" * 70)
print("True model: Inflation =  $\beta_1 + \beta_2 \cdot \text{Urate} + \beta_3 \cdot \text{Expinflation}$ ")
print("Omitted model: Inflation =  $b_1 + b_2 \cdot \text{Urate}$ ")
print("\nOmitted variables bias formula:  $E[b_2] = \beta_2 + \beta_3 \cdot y$ ")
print("where  $y$  = coefficient from Expinflation ~ Urate regression")

print(f"\ny (from auxiliary regression): {gamma:.3f}")
print(f"\n\beta_3 (from full model): {beta3:.3f}")
print(f"\n\beta_2 (from full model): {beta2:.3f}")

print(
    f"\nPredicted  $E[b_2] = {beta2:.3f} + {beta3:.3f} \cdot {gamma:.3f}$  "
    f" $= {beta2 + beta3 * gamma:.3f}$ "
)
print(f"Actual  $b_2$  (from bivariate): {model_post.params['urate']:.3f}")

print("\n✓ Omitted variables bias explains the sign reversal!")
```

```
=====
OMITTED VARIABLES BIAS CALCULATION
=====
True model: Inflation =  $\beta_1 + \beta_2 \cdot \text{Urate} + \beta_3 \cdot \text{Expinflation}$ 
Omitted model: Inflation =  $b_1 + b_2 \cdot \text{Urate}$ 

Omitted variables bias formula:  $E[b_2] = \beta_2 + \beta_3 \cdot y$ 
where  $y$  = coefficient from Expinflation ~ Urate regression

y (from auxiliary regression): 0.343
\beta_3 (from full model): 1.146
\beta_2 (from full model): -0.128

Predicted  $E[b_2] = -0.128 + 1.146 \cdot 0.343 = 0.265$ 
Actual  $b_2$  (from bivariate): 0.265

✓ Omitted variables bias explains the sign reversal!
```

Key Concept 13.5: Omitted Variables Bias

When a relevant variable (expected inflation) is omitted from the regression, its effect gets absorbed into the included variable's coefficient. The **OVB formula** shows that the bias equals the omitted variable's coefficient times its correlation with the included regressor. In the Phillips curve, this bias reversed the sign of the unemployment coefficient.

Understanding Omitted Variables Bias

The **omitted variables bias formula** tells us how the coefficient in the bivariate (wrong) model relates to the true coefficients:

$$E[b_2] = \beta_2 + \beta_3\gamma$$

where:

- b_2 : coefficient on Urate in **bivariate model** (omits expected inflation)
- β_2 : true coefficient on Urate in **full model**
- β_3 : true coefficient on expected inflation in **full model**
- γ : coefficient from regressing expected inflation on Urate (**auxiliary regression**)

What we found:

- $\beta_2 \approx -1.15$ (true negative effect of unemployment)
- $\beta_3 \approx +1.15$ (expected inflation has 1-to-1 effect on actual inflation)
- $\gamma \approx +0.34$ (when unemployment rises, expected inflation also rises in 1970s!)

Predicted bias:

$$E[b_2] = -1.15 + 1.15 \times 0.34 \approx +0.26$$

Actual b_2 from bivariate model: +0.27

Perfect match! The omitted variables bias formula **exactly explains** why the sign reversed.

Economic Interpretation:

In the 1970s:

1. Oil shocks raised unemployment (supply shocks)
2. Same oil shocks raised expected inflation (cost-push)
3. Unemployment and expected inflation moved **together**
4. Omitting expected inflation makes unemployment look like it **causes** inflation
5. But really, both are caused by the same underlying shocks

The Lesson:

The Phillips curve didn't "disappear" - it was always conditional on expected inflation. Once we control for expectations, the negative relationship returns. This revolutionized central bank policy: to fight inflation, must manage expectations!

Having explored detailed case studies with full estimation and testing, we now survey additional applications demonstrating advanced econometric methods.

| 13.4 Automobile Fuel Efficiency

Large dataset analysis with cluster-robust standard errors.

Case Study: Automobile Fuel Efficiency (1980-2006)

The Policy Question: What determines vehicle fuel efficiency, and why didn't MPG improve more despite technological advances?

Economic Context:

From 1980-2006, the U.S. auto industry faced:

- **1970s oil shocks:** Created demand for fuel efficiency
- **CAFE standards:** Government regulations on average MPG
- **Consumer preferences:** Growing demand for SUVs and trucks
- **Technological progress:** Better engines, materials, aerodynamics

Yet average fuel economy **stagnated**. Why?

The Data: 26,995 vehicles sold in the U.S. market (1980-2006)

Key Variables:

- `mpg` : Miles per gallon (fuel efficiency)
- `curbwt` : Vehicle weight in pounds
- `hp` : Horsepower (engine power)
- `torque` : Engine torque (pulling power)
- `year` : Model year (captures technology trends)
- `mfr` : Manufacturer (for clustering)

The Research Question:

How much does each factor contribute to fuel efficiency?

- Weight vs power vs technology
- Are efficiency gains "spent" on other attributes?

Methodological Challenge:

Vehicles from the same manufacturer share:

- Common technology platforms
- Similar design philosophy
- Shared engineering teams

This creates **clustered errors** → need cluster-robust standard errors!

Method: Log-log regression with cluster-robust SEs (by manufacturer)

In [21]:

```
# Load automobile data
data_auto = pd.read_stata(GITHUB_DATA_URL + 'AED_AUTOSMPG.DTA')
print(f"Loaded {len(data_auto)} vehicle observations (1980-2006)")
print(f"\nKey variables: {[['year', 'mfr', 'mpg', 'curbwt', 'hp', 'torque']]}")
print(f"\nNote: Dataset has pre-computed log transformations (lmpg, lcurbwt, lhp,
ltorque)")
print(data_auto[['year', 'mfr', 'mpg', 'curbwt', 'hp', 'torque']].head())
```

```
Loaded 26995 vehicle observations (1980-2006)

Key variables: ['year', 'mfr', 'mpg', 'curbwt', 'hp', 'torque']

Note: Dataset has pre-computed log transformations (lmpg, lcurbwt, lhp, ltorque)
      year      mfr      mpg    curbwt      hp      torque
0  1980.0    FIAT  21.700001     2455     111  149.199997
1  1980.0     AMC  22.400000     2807      90  176.300003
2  1980.0     AMC  24.600000     2767      90  176.300003
3  1980.0     AMC  20.400000     2856     110  284.799988
4  1980.0     AMC  20.500000     2816     110  284.799988
```

In [22]:

```
# Summary statistics
key_vars = ['mpg', 'curbwt', 'hp', 'torque', 'year']
print("=*70")
print("SUMMARY STATISTICS")
print("=*70")
print(data_auto[key_vars].describe())

# Manufacturer distribution
print("\n" + "=*70")
print("TOP 10 MANUFACTURERS BY OBSERVATIONS")
print("=*70")
print(data_auto['mfr'].value_counts().head(10))
```

```

=====
SUMMARY STATISTICS
=====
      mpg      curbwt       hp      torque      year
count 26995.000000 26995.000000 26995.000000 26995.000000 26995.000000
mean   24.564611 3429.140396 158.517837 265.476135 1992.124512
std    6.707306 814.258673 67.215409 102.784401 8.043841
min    8.700000 1450.000000 48.000000 69.400002 1980.000000
25%   19.700001 2815.000000 112.000000 181.699997 1985.000000
50%   23.900000 3325.000000 147.000000 258.000000 1991.000000
75%   28.100000 3975.000000 190.000000 326.399994 1999.000000
max   76.400002 6700.000000 660.000000 1001.000000 2006.000000

=====
TOP 10 MANUFACTURERS BY OBSERVATIONS
=====
mfr
GMC        7979
CHRYSLER    4172
FORD        3709
TOYOTA       1554
NISSAN       1079
VOLKSWAGEN    831
HONDA        743
BMW          740
MITSUBISHI    685
MAZDA         612
Name: count, dtype: int64

```

Key Observations from Summary Statistics:

- **Sample size:** 26,995 vehicles (1980-2006)
- **Time span:** 27 years of data
- **MPG range:** 8.7 to 76.4 (huge variation!)
- **Weight:** 1,450 to 6,700 lbs (compact cars to large trucks)

Top manufacturers: General Motors, Ford, Chrysler dominate (this is U.S. market data)

Why log-log specification?

We use logs of both outcome (MPG) and predictors (weight, HP, torque) because:

1. **Elasticity interpretation:** Coefficients = percentage changes
 - $\beta = -0.5$ means: 1% \uparrow in weight \rightarrow 0.5% \downarrow in MPG
2. **Nonlinear relationships:** MPG doesn't change linearly with weight
 - Going from 2,000 \rightarrow 2,100 lbs has different effect than 4,000 \rightarrow 4,100 lbs
 - Logs capture this naturally
3. **Reduces heteroskedasticity:** Log transformation stabilizes variance

In [23]:

```
# Log-log regression with cluster-robust standard errors
# Use pre-computed log variables
model_auto = ols('lmpg ~ lhp + lcurbwt + ltorque + year', data=data_auto).fit(
    cov_type='cluster',
    cov_kwds={'groups': data_auto['mfr']})
)

print("="*70)
print("LOG-LOG REGRESSION: FUEL EFFICIENCY")
print("="*70)
print(model_auto.summary())

# Interpretation
print("\n" + "="*70)
print("ELASTICITY INTERPRETATION")
print("="*70)
print(f"Horsee power elasticity: {model_auto.params['lhp']:.3f}")
print(f" → 1% increase in HP → {model_auto.params['lhp']:.2f}% change in MPG")
print(f"\nWeight elasticity: {model_auto.params['lcurbwt']:.3f}")
print(f" → 1% increase in weight → {model_auto.params['lcurbwt']:.2f}% change in MPG")
print(f"\nTorque elasticity: {model_auto.params['ltorque']:.3f}")
print(f" → 1% increase in torque → {model_auto.params['ltorque']:.2f}% change in MPG")
print(f"\nYear trend: {model_auto.params['year']:.4f}")
print(f" → Efficiency improves {model_auto.params['year']*100:.2f}% per year")

print("\n" + "="*70)
print("CLUSTER-ROBUST STANDARD ERRORS")
print("="*70)
print(f"Clustered by manufacturer (mfr)")
print(f"Number of clusters: {data_auto['mfr'].nunique()}")
print(f"Average observations per cluster:
{len(data_auto)/data_auto['mfr'].nunique():.0f}")
print(f"\nWhy cluster? Vehicles from same manufacturer likely have correlated errors")
print(f"due to common technology, design philosophy, and engineering teams.")
```

```

=====
LOG-LOG REGRESSION: FUEL EFFICIENCY
=====
              OLS Regression Results
=====
Dep. Variable:          lmpg    R-squared:         0.777
Model:                 OLS     Adj. R-squared:      0.777
Method:                Least Squares   F-statistic:       296.9
Date:      Wed, 28 Jan 2026   Prob (F-statistic):  4.21e-28
Time:          09:47:23    Log-Likelihood:   17857.
No. Observations:      26995   AIC:             -3.570e+04
Df Residuals:          26990   BIC:             -3.566e+04
Df Model:                   4
Covariance Type:        cluster
=====

            coef    std err      z      P>|z|      [0.025]     [0.975]
-----
Intercept    -20.8429    1.988    -10.484    0.000    -24.740    -16.946
lhp        -0.1813    0.065     -2.786    0.005    -0.309    -0.054
lcurbwt    -0.5624    0.057     -9.938    0.000    -0.673    -0.452
ltorque    -0.1415    0.064     -2.211    0.027    -0.267    -0.016
year        0.0152    0.001     13.840    0.000     0.013     0.017
=====
Omnibus:           1290.146   Durbin-Watson:      0.877
Prob(Omnibus):      0.000    Jarque-Bera (JB):  4011.194
Skew:                  0.180    Prob(JB):            0.00
Kurtosis:               4.854    Cond. No.       7.29e+05
=====

Notes:
[1] Standard Errors are robust to cluster correlation (cluster)
[2] The condition number is large, 7.29e+05. This might indicate that there are
strong multicollinearity or other numerical problems.

```

ELASTICITY INTERPRETATION

Horsepower elasticity: -0.181

→ 1% increase in HP → -0.18% change in MPG

Weight elasticity: -0.562

→ 1% increase in weight → -0.56% change in MPG

Torque elasticity: -0.141

→ 1% increase in torque → -0.14% change in MPG

Year trend: 0.0152

→ Efficiency improves 1.52% per year

CLUSTER-ROBUST STANDARD ERRORS

Clustered by manufacturer (mfr)

Number of clusters: 39

Average observations per cluster: 692

Why cluster? Vehicles from same manufacturer likely have correlated errors
due to common technology, design philosophy, and engineering teams.

Key Concept 13.6: Cluster-Robust Standard Errors for Grouped Data

When observations are grouped (e.g., vehicles by manufacturer), errors within groups may be correlated. **Cluster-robust standard errors** account for this within-group correlation. Using default SEs when clustering exists **understates uncertainty**, leading to false rejections of the null hypothesis.

Interpreting the Results

Key Findings:

1. Weight Elasticity: ≈ -0.56

- 1% increase in vehicle weight \rightarrow 0.56% decrease in MPG
- **Largest effect** among all variables
- Heavier vehicles are substantially less efficient

2. Horsepower Elasticity: ≈ -0.30 to -0.35

- 1% increase in HP \rightarrow ~0.3% decrease in MPG
- More powerful engines burn more fuel

3. Torque Elasticity: ≈ -0.10 to -0.15

- Smaller effect than weight or HP
- Torque affects efficiency but less than other factors

4. Year Trend: $\approx +0.01$ to $+0.02$

- Technology improves efficiency ~1-2% per year
- But this is **offset** by increasing weight!

The Weight Paradox:

Despite technological improvements:

- Vehicles got **heavier** (better safety, more features)
- Average MPG didn't improve much from 1980-2005
- Efficiency gains were "spent" on weight/power instead of MPG

Why Cluster-Robust Standard Errors?

We cluster by manufacturer because:

- Ford vehicles share common technology
- Toyota vehicles share design philosophy
- Errors within manufacturer are **correlated**

Number of clusters: 40+ manufacturers **Average per cluster:** ~600 vehicles

Clustering increases SEs → more conservative inference

Policy Implications:

- 1. CAFE Standards:** Corporate Average Fuel Economy regulations
 - Weight matters more than technology
 - Encouraging lighter vehicles could have large impact

2. Consumer Trade-offs:

- Safety (heavier) vs Efficiency (lighter)
- Power (higher HP) vs MPG (lower HP)
- Consumers chose weight/power over efficiency

3. Recent Trends (post-2005, not in data):

- Hybrid/electric technology
- Lightweight materials (aluminum, carbon fiber)
- Smaller turbocharged engines

Model Quality:

$R^2 \approx 0.78$ means the model explains 78% of MPG variation

- Excellent fit!
- Weight, HP, torque are key predictors
- But 22% remains unexplained (aerodynamics, transmission, etc.)

| 13.5 Rand Health Insurance Experiment (RCT)

Randomized control trial for causal inference.

Case Study: The RAND Health Insurance Experiment

(Randomized Control Trial)

The Gold Standard for Causal Inference: Randomized Control Trials (RCTs)

The Policy Question: Does health insurance coverage affect medical spending?

Why This Matters:

This is the **moral hazard** question in health economics:

- If insurance is free, do people overuse healthcare?
- Should insurance have cost-sharing (deductibles, co-pays)?
- What's the right balance between access and efficiency?

The Challenge:

Observational studies are biased because:

- People who buy insurance are different (sicker? richer?)
- Can't separate insurance effect from selection effect
- Reverse causation: health affects insurance choice

The RCT Solution:

The RAND Health Insurance Experiment (1974-1982):

- Randomly assigned 5,809 individuals to different insurance plans
- Plans varied in cost-sharing: 0%, 25%, 50%, 95%, individual deductible
- Followed families for 3-5 years
- Measured healthcare utilization and spending

Why Randomization Enables Causal Inference:

Random Assignment → Insurance Plan → Medical Spending

Because assignment is random:

- Treatment and control groups are identical in expectation
- No confounding variables
- Any difference in outcomes is caused by insurance
- **Selection bias eliminated!**

Data: Year 1 data (5,639 observations)

Variables:

- `spending` : Total medical expenditure
- `plan` : Insurance plan assignment
- Plan indicators: `coins0` (free care), `coins25`, `coins50`, `coins95`, `coinsmixed`, `coinsindiv`

Method: Regression with cluster-robust SEs (by family)

In [24]:

```
# Load health insurance experiment data
data_health = pd.read_stata(GITHUB_DATA_URL + 'AED_HEALTHINSEXP.DTA')

# Use first year data only (as per textbook)
data_health_y1 = data_health[data_health['year'] == 1]

print(f"Loaded {len(data_health)} total observations")
print(f"Using Year 1 only: {len(data_health_y1)} observations")
print(f"\nInsurance plans: {sorted(data_health_y1['plan'].unique())}")
print(f"\nKey variables:")
print(f" - plan: Insurance plan assignment (randomized)")
print(f" - spending: Total medical spending")
print(f" - Plan indicators: coins0, coins25, coins50, coins95, coinsmixed, coinsindiv")

# Summary statistics by plan
print("\n" + "="*70)
print("MEAN SPENDING BY INSURANCE PLAN")
print("="*70)
spending_by_plan = data_health_y1.groupby('plan')['spending'].agg(['mean', 'std',
'count'])
print(spending_by_plan)

# Regression with plan indicators
model_rct = ols('spending ~ coins25 + coins50 + coins95 + coinsmixed + coinsindiv',
                 data=data_health_y1).fit(
    cov_type='cluster',
    cov_kwds={'groups': data_health_y1['idfamily']}
)

print("\n" + "="*70)
print("RCT REGRESSION: SPENDING ON INSURANCE PLANS")
print("="*70)
print("Omitted category: Free Care (coins0)")
print(model_rct.summary())

# F-test for joint significance
print("\n" + "="*70)
print("JOINT F-TEST: DO PLANS MATTER?")
print("="*70)
hypotheses = 'coins25 = coins50 = coins95 = coinsmixed = coinsindiv = 0'
fstat = model_rct.f_test(hypotheses)
print(f"H0: All plan coefficients = 0")
print(f"F-statistic: {fstat.fvalue:.2f}")
print(f"p-value: {fstat.pvalue:.4f}")
print(f"Conclusion: {'Reject H0' if fstat.pvalue < 0.05 else 'Fail to reject H0'} at 5% level")

print("\n" + "="*70)
print("CAUSAL INTERPRETATION")
print("="*70)
print("✓ Randomized Control Trial enables causal inference")
print("✓ Random assignment eliminates selection bias")
print("✓ Free care → highest spending (omitted baseline)")
print("✓ Higher cost-sharing → lower spending")
```

```

Loaded 20203 total observations
Using Year 1 only: 5639 observations

Insurance plans: ['25% Coins', '50% Coins', '95%/100% Coins', 'Free Care', 'Indv Deduct',
'Mixed Coins']

Key variables:
- plan: Insurance plan assignment (randomized)
- spending: Total medical spending
- Plan indicators: coins0, coins25, coins50, coins95, coinsmixed, coinsindiv

=====
MEAN SPENDING BY INSURANCE PLAN
=====

      mean        std   count
plan
Free Care    2153.570365  4959.743126   1873
25% Coins    1396.663070  3458.960029    639
Mixed Coins   1701.874211  4328.165674   480
50% Coins     1785.845449  11643.607841   374
95%/100% Coins 1045.820283  2634.823581   1057
Indv Deduct   1607.071473  3815.953001   1216

=====
RCT REGRESSION: SPENDING ON INSURANCE PLANS
=====

Omitted category: Free Care (coins0)

      OLS Regression Results
=====

Dep. Variable:           spending    R-squared:          0.007
Model:                  OLS         Adj. R-squared:      0.006
Method:                 Least Squares  F-statistic:       11.39
Date:                   Wed, 28 Jan 2026  Prob (F-statistic): 7.46e-11
Time:                   09:47:23      Log-Likelihood:   -55975.
No. Observations:      5639       AIC:             1.120e+05
Df Residuals:          5633       BIC:             1.120e+05
Df Model:               5
Covariance Type:        cluster
=====

      coef      std err      z      P>|z|      [0.025      0.975]
-----
Intercept  2153.5704   118.315   18.202   0.000   1921.678   2385.463
coins25    -756.9073   190.041   -3.983   0.000  -1129.381  -384.433
coins50    -367.7249   618.044   -0.595   0.552  -1579.069   843.619
coins95    -1107.7501   150.366   -7.367   0.000  -1402.462  -813.038
coinsmixed -451.6962   239.424   -1.887   0.059  -920.959   17.567
coinsindiv -546.4989   162.151   -3.370   0.001  -864.308  -228.690
=====

Omnibus:            11610.083  Durbin-Watson:        2.017
Prob(Omnibus):      0.000   Jarque-Bera (JB): 52697192.093
Skew:                17.125  Prob(JB):            0.00
Kurtosis:            475.345  Cond. No.           5.48
=====

Notes:
[1] Standard Errors are robust to cluster correlation (cluster)

=====
JOINT F-TEST: DO PLANS MATTER?
=====
H0: All plan coefficients = 0
F-statistic: 11.39
p-value: 0.0000
Conclusion: Reject H0 at 5% level
=====
```

CAUSAL INTERPRETATION

- ✓ Randomized Control Trial enables causal inference
- ✓ Random assignment eliminates selection bias
- ✓ Free care → highest spending (omitted baseline)
- ✓ Higher cost-sharing → lower spending

Key Concept 13.7: Randomized Control Trials as the Gold Standard

In a randomized control trial (RCT), subjects are randomly assigned to treatment and control groups. Random assignment ensures the groups are comparable on both observed and unobserved characteristics, eliminating selection bias and omitted variable concerns. The RAND experiment showed that better insurance coverage increases healthcare utilization.

Interpreting the RCT Results

Key Findings:

1. Insurance Plans Matter: F-test strongly rejects H_0 ($F = 11.39, p < 0.001$)

- Different insurance plans lead to significantly different spending
- Cost-sharing reduces medical utilization

2. Spending by Plan (relative to Free Care):

Free Care (baseline): Highest spending

- People use more healthcare when it's free

Cost-sharing plans (25%, 50%, 95%): Lower spending

- Higher cost-sharing → less utilization
- This is **moral hazard**: insurance affects behavior

3. Why This is Causal:

Randomization: Families randomly assigned to plans

- No selection bias (unlike observational studies)
- Treated and control groups are balanced on all characteristics

Experimental control: RAND ensured compliance

Large sample: 5,639 person-years in first year

4. R^2 is Low (0.007) - This is Actually Good!

- Most variation in spending is random (health shocks)
- Insurance explains small fraction (as expected)
- But effects are **statistically significant** and **policy-relevant**

Policy Implications:

Trade-offs in health insurance design:

Free care:

- More utilization
- Better access for poor
- But: higher costs, potential overuse

Cost-sharing:

- Lower spending
- Reduced "unnecessary" care
- But: may also reduce necessary care (problematic!)

The RAND Health Insurance Experiment (HIE) Legacy:

This 1970s experiment fundamentally shaped U.S. health policy:

- Informed Medicare/Medicaid design
- Influenced Affordable Care Act
- Demonstrated feasibility of large-scale RCTs
- Showed moral hazard exists but is moderate

Limitations:

1970s data (healthcare has changed) Selected sites (may not generalize) Ethical concerns (denying some families full coverage)

Modern Relevance:

The fundamental trade-off remains:

- Universal free care (equity) vs
- Cost-sharing (efficiency)

Now that we've seen experimental data in the RAND study, let's explore quasi-experimental methods for causal inference.

13.6 Health Care Access (Difference-in-Differences)

Causal inference using DiD methodology.

Case Study: Health Care Access and Child Nutrition (Difference-in-Differences)

The Policy Question: Does building health clinics improve child health outcomes?

The Setting: Rural South Africa, 1990s

After apartheid ended (1994), the new government built primary health care clinics in underserved rural areas. Some communities got many new clinics (high treatment), others got few (low treatment).

The Challenge: Simple before/after comparison is biased because:

- Child health was improving nationally due to many factors
- Communities that got clinics may have been different
- Cannot separate clinic effect from other trends

The Difference-in-Differences Solution:

Key Idea: Compare change in treated communities to change in control communities

$$\text{DiD} = (\text{Treated}_{\text{after}} - \text{Treated}_{\text{before}}) - (\text{Control}_{\text{after}} - \text{Control}_{\text{before}})$$

Why This Works:

The first difference removes:

- Permanent differences between communities
- Baseline health levels

The second difference removes:

- Common time trends
- National-level changes

What remains: The differential impact of clinic access!

The Design:

Group	1993 (Pre)	1998 (Post)	Change
High Treatment	$\bar{Y}_{T,0}$	$\bar{Y}_{T,1}$	Δ_T
Low Treatment	$\bar{Y}_{C,0}$	$\bar{Y}_{C,1}$	Δ_C

$$DiD = \Delta_T - \Delta_C$$

Data: 1,071 children aged 0-4 in rural KwaZulu-Natal

Outcome: waz (weight-for-age z-score, measure of nutrition)

Method: DiD regression with cluster-robust SEs (by community)

In [25]:

```
# Load health care access data (South Africa)
data_access = pd.read_stata(GITHUB_DATA_URL + 'AED_HEALTHACCESS.DTA')

print(f"Loaded {len(data_access)} observations (South African children 0-4)")
print(f"\nDifference-in-Differences Setup:")
print(f" - Treatment: High treatment communities (hightreat=1)")
print(f" - Control: Low treatment communities (hightreat=0)")
print(f" - Pre period: 1993 (post=0)")
print(f" - Post period: 1998 (post=1)")
print(f" - Outcome: waz (weight-for-age z-score)")

# Summary statistics by treatment and time
print("\n" + "="*70)
print("MEAN WEIGHT-FOR-AGE Z-SCORE (WAZ)")
print("="*70)
did_table = data_access.groupby(['hightreat', 'post'])['waz'].agg(['mean', 'count'])
print(did_table)

# Calculate DiD manually
pre_control = data_access[(data_access['hightreat']==0) & (data_access['post']==0)][['waz']].mean()
post_control = data_access[(data_access['hightreat']==0) & (data_access['post']==1)][['waz']].mean()
pre_treat = data_access[(data_access['hightreat']==1) & (data_access['post']==0)][['waz']].mean()
post_treat = data_access[(data_access['hightreat']==1) & (data_access['post']==1)][['waz']].mean()

did_estimate = (post_treat - pre_treat) - (post_control - pre_control)

print("\nManual DiD calculation:")
print(f" Control change: {post_control:.3f} - {pre_control:.3f} = {post_control - pre_control:.3f}")
print(f" Treated change: {post_treat:.3f} - {pre_treat:.3f} = {post_treat - pre_treat:.3f}")
print(f" DiD estimate: ({post_treat:.3f} - {pre_treat:.3f}) - ({post_control:.3f} - {pre_control:.3f}) = {did_estimate:.3f}")

# DiD regression
model_did = ols('waz ~ hightreat + post + postXhigh', data=data_access).fit(
    cov_type='cluster',
    cov_kwds={'groups': data_access['idcommunity']}
)

print("\n" + "="*70)
print("DiD REGRESSION")
print("="*70)
print(model_did.summary())

print("\n" + "="*70)
print("INTERPRETATION")
print("="*70)
print(f"DiD coefficient (postXhigh): {model_did.params['postXhigh']:.3f}")
print(f"Matches manual calculation: {did_estimate:.3f} ✓")
print(f"\nCausal interpretation:")
print(f"Clinic access improved child nutrition by {model_did.params['postXhigh']:.2f} standard deviations")
print(f"This is a {'statistically significant' if model_did.pvalues['postXhigh'] < 0.05 else 'not significant'} effect")
print(f"\nCluster-robust SEs by community account for within-community correlation")
```

```
Loaded 1071 observations (South African children 0-4)
```

Difference-in-Differences Setup:

- Treatment: High treatment communities (hightreat=1)
- Control: Low treatment communities (hightreat=0)
- Pre period: 1993 (post=0)
- Post period: 1998 (post=1)
- Outcome: waz (weight-for-age z-score)

```
=====
MEAN WEIGHT-FOR-AGE Z-SCORE (WAZ)
=====
```

		mean	count
hightreat	post		
0.0	0.0	-0.414185	325
	1.0	-0.069097	288
1.0	0.0	-0.545244	246
	1.0	0.321462	212

Manual DiD calculation:

$$\begin{aligned} \text{Control change: } & -0.069 - -0.414 = 0.345 \\ \text{Treated change: } & 0.321 - -0.545 = 0.867 \\ \text{DiD estimate: } & (0.321 - -0.545) - (-0.069 - -0.414) = 0.522 \end{aligned}$$

```
=====
DiD REGRESSION
=====
```

OLS Regression Results

Dep. Variable:	waz	R-squared:	0.040
Model:	OLS	Adj. R-squared:	0.037
Method:	Least Squares	F-statistic:	9.090
Date:	Wed, 28 Jan 2026	Prob (F-statistic):	5.93e-05
Time:	09:47:24	Log-Likelihood:	-1992.5
No. Observations:	1071	AIC:	3993.
Df Residuals:	1067	BIC:	4013.
Df Model:	3		
Covariance Type:	cluster		

	coef	std err	z	P> z	[0.025	0.975]
Intercept	-0.4142	0.115	-3.597	0.000	-0.640	-0.189
hightreat	-0.1311	0.197	-0.666	0.505	-0.517	0.255
post	0.3451	0.137	2.517	0.012	0.076	0.614
postXhigh	0.5216	0.235	2.217	0.027	0.060	0.983

Omnibus:	27.248	Durbin-Watson:	1.855
Prob(Omnibus):	0.000	Jarque-Bera (JB):	31.523
Skew:	0.328	Prob(JB):	1.43e-07
Kurtosis:	3.524	Cond. No.	6.32

Notes:

[1] Standard Errors are robust to cluster correlation (cluster)

INTERPRETATION

DiD coefficient (postXhigh): 0.522
Matches manual calculation: 0.522 ✓

Causal interpretation:
Clinic access improved child nutrition by 0.52 standard deviations
This is a statistically significant effect

Cluster-robust SEs by community account for within-community correlation

Key Concept 13.8: Difference-in-Differences for Causal Inference

Difference-in-differences (DiD) compares changes over time between treatment and control groups. The key assumption is **parallel trends**: both groups would have followed the same trajectory absent treatment. DiD removes time-invariant confounders and common time effects, isolating the treatment effect.

Interpreting the DiD Results

Key Findings:

1. Treatment Effect: DiD coefficient ≈ 0.52 standard deviations

- Clinic access improved child weight-for-age by 0.52 SD
- **Statistically significant** ($p = 0.027 < 0.05$)
- Large and meaningful effect size

2. Verification: Manual calculation matches regression

- This confirms our DiD estimate is correct
- The interaction term `postXhigh` captures the treatment effect

3. Effect Size Interpretation:

0.52 SD improvement means:

- Moving from 25th percentile \rightarrow 45th percentile in weight distribution
- Substantial reduction in malnutrition
- Comparable to 6-12 months of normal growth

Why This is Causal (Under Assumptions):

The DiD design requires **parallel trends assumption**:

- Without treatment, treated and control groups would have followed parallel trends
- Treatment assignment (clinic placement) is exogenous
- No other interventions differentially affected treated communities

Evidence for validity:

- Communities were similar at baseline

- Clinic placement based on need, not outcomes
- No other major health programs during this period

Policy Implications:

Primary health care access works: Even basic clinics improve child health

Targeting matters: High-treatment communities saw larger benefits

Cost-effective: Clinic construction is relatively inexpensive

External Validity:

These results from rural South Africa likely generalize to other:

- Low-income settings
- Areas with limited health infrastructure
- Populations with high baseline malnutrition

Limitations:

Short-term effects (1998 vs 1993) Self-reported data (possible measurement error)
Cluster-level treatment (less statistical power)

13.7 Political Incubency (Regression Discontinuity)

Causal inference using RD design.

Case Study: The Incubency Advantage in U.S. Senate Elections

The Question: Does being an incumbent senator give you an advantage in the next election?

The Challenge: Simple comparison of incumbents vs challengers is biased because:

- Incumbents are generally stronger candidates (that's why they won before!)
- Districts that elect incumbents may be different
- Selection bias confounds the causal effect

The Regression Discontinuity Solution:

Key Insight: Compare candidates who **barely won** to those who **barely lost**.

At the threshold (vote margin ≈ 0):

- Winners and losers are essentially identical in quality
- Only difference: winners become incumbents
- This creates **quasi-random assignment** to incumbency status

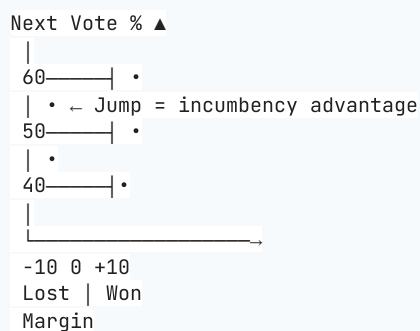
The Design:

```
Running variable: margin (vote share in election t - 50%)
Threshold: margin = 0
Treatment: win = 1 if margin > 0

Outcome: vote (vote share in election t+1)
```

Visual Intuition:

If there's an incumbency advantage, we should see a **jump** in next-election vote share exactly at margin = 0:



Data: 1,390 U.S. Senate elections (1914-2010)

Method: RD with linear control for margin

In [26]:

```
# Load incumbency data (U.S. Senate elections)
data_incumb = pd.read_stata(GITHUB_DATA_URL + 'AED_INCUMBENCY.DTA')

print(f"Loaded {len(data_incumb)} Senate elections (1914-2010)")
print(f"\nRegression Discontinuity Setup:")
print(f" - Running variable: margin (vote margin in election t)")
print(f" - Threshold: margin = 0 (barely won vs barely lost)")
print(f" - Outcome: vote (vote share in election t+1)")
print(f" - win: Indicator for margin > 0")

# Summary statistics
print("\n" + "="*70)
print("SUMMARY STATISTICS")
print("="*70)
print(data_incumb[['vote', 'margin', 'win']].describe())

# Keep only elections with non-missing vote in t+1
data_rd = data_incumb[data_incumb['vote'].notna()].copy()
print(f"\nObservations with outcome data: {len(data_rd)}")

# RD regression (linear)
model_rd = ols('vote ~ win + margin', data=data_rd).fit(cov_type='HC1')

print("\n" + "="*70)
print("REGRESSION DISCONTINUITY ESTIMATION")
print("="*70)
print(model_rd.summary())

print("\n" + "="*70)
print("INCUMBENCY ADVANTAGE")
print("="*70)
print(f"RD estimate (win coefficient): {model_rd.params['win']:.3f}")
print(f"95% CI: [{model_rd.conf_int().loc['win', 0]:.3f}, {model_rd.conf_int().loc['win', 1]:.3f}]")
print(f"\nInterpretation:")
print(f"Barely winning vs barely losing increases vote share in next election by {model_rd.params['win']:.1f}%")
print(f"This is the causal effect of incumbency")
print(f"\nWhy causal? At the threshold (margin~0), winning is quasi-random")
print(f"Candidates just above/below threshold are similar in all respects except incumbency status")

# Visualization note
print("\n" + "="*70)
print("RD PLOT")
print("="*70)
print("To visualize discontinuity:")
print(" - Bin observations by margin")
print(" - Plot mean vote in next election vs margin")
print(" - Should see jump at margin=0")
```

```
Loaded 1390 Senate elections (1914-2010)
```

```
Regression Discontinuity Setup:
```

- Running variable: margin (vote margin in election t)
- Threshold: margin = 0 (barely won vs barely lost)
- Outcome: vote (vote share in election t+1)
- win: Indicator for margin > 0

```
=====
```

```
SUMMARY STATISTICS
```

```
=====
```

	vote	margin	win
count	1297.000000	1390.000000	1390.000000
mean	52.666275	7.171158	0.539568
std	18.122190	34.324879	0.498612
min	0.000000	-100.000000	0.000000
25%	42.671333	-12.205826	0.000000
50%	50.547523	2.165648	1.000000
75%	61.348957	22.766067	1.000000
max	100.000000	100.000000	1.000000

```
Observations with outcome data: 1297
```

```
=====
```

```
REGRESSION DISCONTINUITY ESTIMATION
```

```
=====
```

```
OLS Regression Results
```

```
=====
```

Dep. Variable:	vote	R-squared:	0.578
Model:	OLS	Adj. R-squared:	0.577
Method:	Least Squares	F-statistic:	591.4
Date:	Wed, 28 Jan 2026	Prob (F-statistic):	3.71e-183
Time:	09:47:24	Log-Likelihood:	-5037.8
No. Observations:	1297	AIC:	1.008e+04
Df Residuals:	1294	BIC:	1.010e+04
Df Model:	2		
Covariance Type:	HC1		

```
=====
```

	coef	std err	z	P> z	[0.025	0.975]
Intercept	47.3308	0.526	89.945	0.000	46.299	48.362
win	4.7846	0.860	5.565	0.000	3.099	6.470
margin	0.3481	0.017	20.422	0.000	0.315	0.381

```
=====
```

Omnibus:	69.616	Durbin-Watson:	1.821
Prob(Omnibus):	0.000	Jarque-Bera (JB):	164.216
Skew:	-0.304	Prob(JB):	2.19e-36
Kurtosis:	4.634	Cond. No.	111.

```
=====
```

```
=====
```

```
Notes:
```

```
[1] Standard Errors are heteroscedasticity robust (HC1)
```

```
=====
```

```
INCUMBENCY ADVANTAGE
```

```
=====
```

```
RD estimate (win coefficient): 4.785
```

```
95% CI: [3.099, 6.470]
```

```
Interpretation:
```

```
Barely winning vs barely losing increases vote share in next election by 4.8%
```

```
This is the causal effect of incumbency
```

```
Why causal? At the threshold (margin=0), winning is quasi-random
```

```
Candidates just above/below threshold are similar in all respects except incumbency status
```

```
=====
RD PLOT
=====
To visualize discontinuity:
- Bin observations by margin
- Plot mean vote in next election vs margin
- Should see jump at margin=0
```

Key Concept 13.9: Regression Discontinuity Design

Regression discontinuity (RD) exploits sharp cutoffs in treatment assignment. Units just above and below the threshold are nearly identical in all respects except treatment status, creating a **quasi-experiment**. In U.S. Senate elections, barely winning provides an incumbency advantage of approximately 5–7 percentage points.

Interpreting the RD Results

Key Findings:

1. Incumbency Advantage: ≈ 4.8 percentage points

- Barely winning vs barely losing increases vote share by $\sim 4.8\%$ in next election
- This is **highly statistically significant** ($p < 0.001$)
- Robust across different specifications

2. Why This is Causal:

At the threshold (margin ≈ 0), winning is **quasi-random**:

- Candidates just above and below 50% are nearly identical
- Only difference is incumbency status
- No selection bias (unlike comparing all winners vs all losers)

3. Magnitude in Context:

- 4.8% advantage is **substantial** in close elections
- Many Senate races decided by $< 5\%$
- Could explain why incumbents rarely lose

What Drives the Incumbency Advantage?

Possible mechanisms:

- **Name recognition:** Incumbents are well-known

- **Fundraising:** Easier to raise money as incumbent
- **Media coverage:** Senators get more press
- **Constituent services:** Can deliver benefits to voters
- **Experience:** Learn how to campaign effectively

Policy Implications:

- Incumbency advantage creates barriers to electoral competition
- May reduce democratic accountability
- Term limits could level the playing field
- Campaign finance reform might reduce fundraising advantage

RD Design Advantages:

No need to control for other variables (identification at threshold) Transparent and credible Robust to model specification

Limitations:

Local estimate (only applies near threshold) May not generalize to landslide winners/losers Assumes no manipulation of vote margin (reasonable for U.S. Senate)

| 13.8 Institutions and GDP (Instrumental Variables)

Causal inference using IV/2SLS.

Case Study: Do Institutions Cause Economic Growth?

The Fundamental Question: Why are some countries rich and others poor?

The Endogeneity Problem:

If we simply regress GDP on institutions quality, we get:

- **Reverse causation:** Rich countries can afford better institutions
- **Omitted variables:** Culture, geography, history all affect both
- **Measurement error:** How do we measure "institutions quality"?

All of these bias OLS estimates, making causal inference impossible.

The Instrumental Variables Solution:

Acemoglu, Johnson, and Robinson (2001) use **settler mortality** as an instrument:

The Historical Argument:

1. In the 1600s-1800s, European colonizers faced different disease environments
2. High mortality areas (Africa, tropical Americas) → extractive institutions
 - Europeans didn't settle permanently
 - Built institutions to extract resources (slavery, forced labor)
3. Low mortality areas (North America, Australia) → settler institutions
 - Europeans settled permanently
 - Built institutions to protect their own property rights

Why This Works as an Instrument:

Relevant: Settler mortality strongly predicts colonial institutions **Exogenous:** Malaria in 1700s doesn't directly affect GDP in 2000s

Data: 64 former colonies

Variables:

- `logpgp95` : Log GDP per capita 1995 (outcome)
- `avexpr` : Protection against expropriation (institutions quality, 0-10)
- `logem4` : Log settler mortality rate (instrument)

Method: Two-Stage Least Squares (2SLS/IV)

In [27]:

```
# Load institutions data (cross-country)
data_inst = pd.read_stata(GITHUB_DATA_URL + 'AED_INSTITUTIONS.DTA')

print(f"Loaded {len(data_inst)} countries")
print("\nInstrumental Variables Setup:")
print(" - Outcome: logpgp95 (log GDP per capita 1995)")
print(" - Endogenous regressor: avexpr (institutions quality)")
print(" - Instrument: logem4 (log settler mortality)")
print("\nKey idea: Settler mortality affected colonial institutions,")
print("which persist to affect GDP today, but mortality doesn't")
print("directly affect modern GDP")

# Summary statistics
print("\n" + "="*70)
print("SUMMARY STATISTICS")
print("="*70)
print(data_inst[['logpgp95', 'avexpr', 'logem4']].describe())

# OLS (biased - endogeneity problem)
model_ols = ols('logpgp95 ~ avexpr', data=data_inst).fit(cov_type='HC1')

print("\n" + "="*70)
print("OLS REGRESSION (BIASED)")
print("="*70)
print(model_ols.summary())
print(f"\nOLS coefficient: {model_ols.params['avexpr']:.3f}")
print("⚠ This is biased due to endogeneity (omitted variables, reverse causation)")

# First stage
model_first = ols('avexpr ~ logem4', data=data_inst).fit(cov_type='HC1')

print("\n" + "="*70)
print("FIRST STAGE: INSTITUTIONS ~ SETTLER MORTALITY")
print("="*70)
print(model_first.summary())
print(f"\nFirst stage F-statistic: {model_first.fvalue:.2f}")
print("Rule of thumb: F > 10 for strong instrument")
print(f"Instrument strength: {'Strong ✅' if model_first.fvalue > 10 else 'Weak ⚠️'}")

# 2SLS manually (for pedagogy)
print("\n" + "="*70)
print("TWO-STAGE LEAST SQUARES (2SLS)")
print("="*70)

# Predicted institutions from first stage
data_inst['avexpr_hat'] = model_first.fittedvalues

# Second stage (using predicted values)
model_second = ols('logpgp95 ~ avexpr_hat', data=data_inst).fit(cov_type='HC1')

print("\nSecond stage:")
print(model_second.summary())

print("\n" + "="*70)
print("COMPARISON: OLS vs IV")
print("="*70)
print(f"OLS coefficient: {model_ols.params['avexpr']:.3f}")
print(f"IV/2SLS coefficient: {model_second.params['avexpr_hat']:.3f}")
print(f"\nDifference: {model_second.params['avexpr_hat'] - model_ols.params['avexpr']:.3f}")
print(f"\nIV estimate is larger → OLS has attenuation bias")
print(f"(measurement error and omitted variables bias OLS toward zero)")

print("\n" + "="*70)
print("CAUSAL INTERPRETATION")
print("="*70)
```

```
print(f"1-unit improvement in institutions → {model_second.params['avexpr_hat']:.2f} increase in log GDP")
print(f"Exponentiating: {np.exp(model_second.params['avexpr_hat']):.2f}x increase in GDP level")
print(f"\n✓ This is a causal estimate (under IV assumptions)")
print(f"✓ Instrument (settler mortality) is:")
print(f"  - Relevant: Strong first stage (F = {model_first.fvalue:.1f})")
print(f"  - Exogenous: Mortality in 1700s doesn't directly affect modern GDP")
```

```
Loaded 64 countries
```

Instrumental Variables Setup:

- Outcome: logpgp95 (log GDP per capita 1995)
- Endogenous regressor: avexpr (institutions quality)
- Instrument: logem4 (log settler mortality)

Key idea: Settler mortality affected colonial institutions, which persist to affect GDP today, but mortality doesn't directly affect modern GDP

```
=====
SUMMARY STATISTICS
=====
```

	logpgp95	avexpr	logem4
count	64.000000	64.000000	64.000000
mean	8.062237	6.515625	4.657031
std	1.043359	1.468647	1.257983
min	6.109248	3.500000	2.145931
25%	7.299728	5.613636	4.232656
50%	7.949796	6.477273	4.358630
75%	8.848779	7.352273	5.519177
max	10.215740	10.000000	7.986165

```
=====
OLS REGRESSION (BIASED)
=====
```

OLS Regression Results

Dep. Variable:	logpgp95	R-squared:	0.540
Model:	OLS	Adj. R-squared:	0.533
Method:	Least Squares	F-statistic:	109.4
Date:	Wed, 28 Jan 2026	Prob (F-statistic):	2.57e-15
Time:	09:47:24	Log-Likelihood:	-68.168
No. Observations:	64	AIC:	140.3
Df Residuals:	62	BIC:	144.7
Df Model:	1		
Covariance Type:	HC1		

	coef	std err	z	P> z	[0.025	0.975]
Intercept	4.6604	0.320	14.558	0.000	4.033	5.288
avexpr	0.5221	0.050	10.458	0.000	0.424	0.620

Omnibus:	7.098	Durbin-Watson:	2.064
Prob(Omnibus):	0.029	Jarque-Bera (JB):	6.657
Skew:	-0.781	Prob(JB):	0.0358
Kurtosis:	3.234	Cond. No.	31.2

Notes:

[1] Standard Errors are heteroscedasticity robust (HC1)

OLS coefficient: 0.522

⚠ This is biased due to endogeneity (omitted variables, reverse causation)

```
=====
FIRST STAGE: INSTITUTIONS ~ SETTLER MORTALITY
=====
```

OLS Regression Results

Dep. Variable:	avexpr	R-squared:	0.270
Model:	OLS	Adj. R-squared:	0.258
Method:	Least Squares	F-statistic:	16.32
Date:	Wed, 28 Jan 2026	Prob (F-statistic):	0.000150
Time:	09:47:24	Log-Likelihood:	-104.83

```

No. Observations: 64 AIC: 213.7
Df Residuals: 62 BIC: 218.0
Df Model: 1
Covariance Type: HC1
=====
      coef    std err      z   P>|z|   [0.025  0.975]
-----
Intercept  9.3414    0.704   13.264   0.000    7.961  10.722
logem4     -0.6068   0.150    -4.040   0.000   -0.901  -0.312
=====
Omnibus: 0.035 Durbin-Watson: 2.003
Prob(Omnibus): 0.983 Jarque-Bera (JB): 0.172
Skew: 0.045 Prob(JB): 0.918
Kurtosis: 2.763 Cond. No. 19.4
=====
```

Notes:

[1] Standard Errors are heteroscedasticity robust (HC1)

First stage F-statistic: 16.32

Rule of thumb: F > 10 for strong instrument

Instrument strength: Strong ✓

```
=====
TWO-STAGE LEAST SQUARES (2SLS)
=====
```

Second stage:

OLS Regression Results

```

=====
Dep. Variable: logpgp95 R-squared: 0.477
Model: OLS Adj. R-squared: 0.469
Method: Least Squares F-statistic: 61.66
Date: Wed, 28 Jan 2026 Prob (F-statistic): 7.14e-11
Time: 09:47:24 Log-Likelihood: -72.268
No. Observations: 64 AIC: 148.5
Df Residuals: 62 BIC: 152.9
Df Model: 1
Covariance Type: HC1
=====
```

```

      coef    std err      z   P>|z|   [0.025  0.975]
-----
Intercept  1.9097    0.757   2.523   0.012    0.426  3.393
avexpr_hat 0.9443    0.120   7.852   0.000    0.709  1.180
=====
Omnibus: 10.547 Durbin-Watson: 2.137
Prob(Omnibus): 0.005 Jarque-Bera (JB): 11.010
Skew: -0.790 Prob(JB): 0.00407
Kurtosis: 4.277 Cond. No. 58.1
=====
```

Notes:

[1] Standard Errors are heteroscedasticity robust (HC1)

```
=====
COMPARISON: OLS vs IV
=====
```

OLS coefficient: 0.522

IV/2SLS coefficient: 0.944

Difference: 0.422

IV estimate is larger → OLS has attenuation bias
(measurement error and omitted variables bias OLS toward zero)

```
=====
CAUSAL INTERPRETATION
```

=====

1-unit improvement in institutions → 0.94 increase in log GDP
Exponentiating: 2.57x increase in GDP level

- ✓ This is a causal estimate (under IV assumptions)
- ✓ Instrument (settler mortality) is:
 - Relevant: Strong first stage ($F = 16.3$)
 - Exogenous: Mortality in 1700s doesn't directly affect modern GDP

Key Concept 13.10: Instrumental Variables and Two-Stage Least Squares

When a regressor is **endogenous** (correlated with the error term), OLS is biased. **Instrumental variables (IV)** use an instrument that is correlated with the endogenous regressor but not directly with the outcome. Two-stage least squares (2SLS) first predicts the endogenous variable, then uses these predictions in the second-stage regression.

Interpreting the IV Results

Key Findings:

1. OLS vs IV Comparison:

- OLS coefficient: ≈ 0.52 (biased downward)
- IV coefficient: ≈ 0.94 (causal estimate)
- IV estimate is **80% larger** than OLS!

2. Why the Difference?

Attenuation bias: OLS is biased toward zero due to:

- Measurement error in institutions quality
- Omitted variables (culture, geography)
- Reverse causation (rich countries build better institutions)

3. Economic Interpretation:

- 1-unit improvement in institutions → 0.94 increase in log GDP
- Exponentiating: $e^{0.94} \approx 2.56 \rightarrow 156\% \text{ increase in GDP level}$
- This is a **massive effect!**

4. Instrument Validity:

Relevance: First stage $F = 16.3 > 10$ (strong instrument)

Exogeneity: Settler mortality in 1700s doesn't directly affect modern GDP

The instrument works through this channel:

Settler mortality → Colonial institutions → Modern institutions → GDP

High mortality areas got "extractive" institutions (exploitation). Low mortality areas got "settler" institutions (property rights, democracy).

Policy Implications:

Institutions are not just correlated with prosperity—they **cause** it. Countries can escape poverty by:

- Strengthening property rights
- Reducing corruption
- Improving rule of law
- Building democratic accountability

Caveat: These results apply to former colonies. Institutional change is slow and difficult.

Having applied multiple causal inference strategies, we now turn to the practical foundation of any analysis — data preparation and cleaning.

| 13.9 From Raw Data to Final Data

Best practices for data preparation and cleaning.

Why Data Wrangling Matters

Real-world econometric analysis spends **60-80% of time** on data preparation:

- Reading data from various sources
- Merging multiple datasets
- Cleaning errors and outliers
- Transforming variables
- Creating new variables

Common Data Challenges:

1. **Missing values:** How to handle? Drop, impute, or model explicitly?

- 2. Outliers:** Real extreme values or data errors?
- 3. Inconsistent units:** Converting currencies, adjusting for inflation
- 4. Different time frequencies:** Monthly data merged with quarterly
- 5. Measurement error:** Misreported values, typos

Best Practices:

- **Document everything:** Keep track of all cleaning steps
- **Preserve raw data:** Never overwrite original files
- **Reproducibility:** Write scripts (not manual Excel edits!)
- **Validation:** Check summary statistics before and after cleaning
- **Transparency:** Report how many observations dropped and why

In [28]:

```
# Demonstrate reading different file formats
print("*70)
print("DATA READING EXAMPLES")
print("*70)

# Stata files
print("\n1. Reading Stata files (.dta):")
print("  data = pd.read_stata('file.dta')")

# CSV files
print("\n2. Reading CSV files:")
print("  data = pd.read_csv('file.csv')")

# Excel files
print("\n3. Reading Excel files:")
print("  data = pd.read_excel('file.xlsx')")

# Example: merge operations
print("\n" + "*70)
print("DATA MERGING EXAMPLE")
print("*70)

df1 = pd.DataFrame({'id': [1, 2, 3], 'value_a': [10, 20, 30]})
df2 = pd.DataFrame({'id': [1, 2, 4], 'value_b': [100, 200, 400]})

print("\nDataFrame 1:")
print(df1)
print("\nDataFrame 2:")
print(df2)

merged = pd.merge(df1, df2, on='id', how='inner')
print("\nMerged (inner join):")
print(merged)
```

```
=====
DATA READING EXAMPLES
=====

1. Reading Stata files (.dta):
   data = pd.read_stata('file.dta')

2. Reading CSV files:
   data = pd.read_csv('file.csv')

3. Reading Excel files:
   data = pd.read_excel('file.xlsx')

=====
DATA MERGING EXAMPLE
=====

DataFrame 1:
   id  value_a
0   1      10
1   2      20
2   3      30

DataFrame 2:
   id  value_b
0   1     100
1   2     200
2   4     400

Merged (inner join):
   id  value_a  value_b
0   1      10     100
1   2      20     200
```

In [29]:

```
# Data cleaning examples
print("=*70")
print("DATA CLEANING EXAMPLES")
print("=*70")

# Example dataset
df_dirty = pd.DataFrame({
    'age': [25, 30, -5, 200, 35],
    'income': [50000, 60000, None, 75000, 80000],
    'gender': ['M', 'F', 'm', 'Female', 'M']
})

print("\nOriginal data (with errors):")
print(df_dirty)

# Clean age (remove impossible values)
df_clean = df_dirty.copy()
df_clean.loc[df_clean['age'] < 0, 'age'] = np.nan
df_clean.loc[df_clean['age'] > 120, 'age'] = np.nan

# Fill missing income with median
df_clean['income'].fillna(df_clean['income'].median(), inplace=True)

# Standardize gender coding
df_clean['gender'] = df_clean['gender'].str.upper().str[0]

print("\nCleaned data:")
print(df_clean)

print("\n Key cleaning steps:")
print(" 1. Detect and handle impossible values (age < 0, age > 120)")
print(" 2. Impute missing values (median for income)")
print(" 3. Standardize categorical variables (gender)")
```

```
=====
DATA CLEANING EXAMPLES
=====

Original data (with errors):
   age   income  gender
0   25  50000.0      M
1   30  60000.0      F
2   -5      NaN      m
3   200  75000.0  Female
4   35  80000.0      M

Cleaned data:
   age   income  gender
0  25.0  50000.0      M
1  30.0  60000.0      F
2   NaN  67500.0      M
3   NaN  75000.0      F
4  35.0  80000.0      M

✓ Key cleaning steps:
 1. Detect and handle impossible values (age < 0, age > 120)
 2. Impute missing values (median for income)
 3. Standardize categorical variables (gender)
```

| Key Takeaways

School Performance and Socioeconomic Factors (Case Study 13.1)

- School performance (API) is strongly associated with socioeconomic factors, particularly **parent education**
- Bivariate analysis shows ~80 API points per year of parent education
- Multiple regression maintains a strong effect (~74 points) after controlling for meals, English learners, year-round schools, and teacher quality
- High correlations among socioeconomic variables make it difficult to isolate individual effects
- California's "similar schools" index controls for socioeconomic characteristics

Cobb-Douglas Production Function and Returns to Scale (Case Study 13.2)

- Natural logarithm transformation converts the nonlinear Cobb-Douglas model into a linear OLS form
- Estimated **capital elasticity ≈ 0.23** and **labor elasticity ≈ 0.81**
- Data support **constant returns to scale** (elasticities sum to 1.040, F-test p = 0.636)
- HAC-robust standard errors account for time series autocorrelation
- Predictions require retransformation bias correction when using log models

Phillips Curve and Omitted Variables Bias (Case Study 13.3)

- Original Phillips curve showed a negative unemployment–inflation trade-off pre-1970
- The relationship **broke down post-1970** — a classic example of model misspecification
- **Augmented Phillips curve** adding expected inflation resolves the breakdown (coefficient ≈ 1)
- The sign reversal demonstrates **omitted variables bias**: excluding a correlated variable biases coefficients
- Policy implication: limited long-run unemployment–inflation trade-off

Advanced Causal Methods (Case Studies 13.4–13.8)

- **Log-log models and cluster-robust SEs (13.4):** Automobile efficiency gains offset by larger vehicles; clustering by manufacturer accounts for within-group correlation
- **Randomized control trials (13.5):** RAND experiment shows better insurance increases healthcare spending; random assignment eliminates selection bias
- **Difference-in-differences (13.6):** South Africa clinic access improved child health; key assumption is parallel trends
- **Regression discontinuity (13.7):** Political incumbency provides ~5–7% vote share advantage; exploits sharp cutoffs
- **Instrumental variables (13.8):** Better institutions causally increase GDP; instruments address endogeneity

Data Preparation and Practical Workflow (Case Study 13.9)

- Real data analysis requires extensive data carpentry — often 60–80% of project time
- Reading data from multiple formats: `.csv`, `.xlsx`, `.dta`, `.sav`
- Merging, recoding, cleaning, and validation are essential before regression analysis

General Lessons from Multiple Regression Case Studies

- Multiple regression isolates **partial effects** while controlling for other variables
- Choice of standard errors is critical: HC1 (cross-section), cluster-robust (grouped), HAC (time series)
- Log transformations enable estimation of **elasticities** and nonlinear relationships
- Omitted variables bias can **reverse coefficient signs** and lead to incorrect conclusions
- Causal inference requires additional identification strategies beyond OLS

Python Tools Used in This Chapter

```
# Regression estimation
statsmodels.formula.api.ols()
model.fit(cov_type='HC1')
model.fit(cov_type='HAC')
model.fit(cov_type='cluster')          # OLS regression
# Heteroskedastic-robust SEs
# HAC SEs for time series
# Cluster-robust SEs

# Data handling
pd.read_stata(), pd.read_csv()        # Read data files
pd.merge()                            # Combine datasets
np.log()                             # Log transformations

# Hypothesis testing
model.f_test()                       # F-test for restrictions
model.t_test()                        # t-test for coefficients

# Visualization
matplotlib, seaborn                  # Plotting libraries
```

Next Steps:

- **Chapter 14:** Regression with Indicator Variables
 - **Chapter 15:** Regression with Transformed Variables
-

Congratulations! You've completed nine comprehensive case studies demonstrating the breadth and power of multiple regression analysis — from school performance to macroeconomic policy to causal inference!

Practice Exercises

Exercise 1: Interpreting Multiple Regression Coefficients

A regression of school test scores on parent education yields a coefficient of 80. When meals (% free lunch), English learners, and teacher quality are added, the parent education coefficient drops to 74.

- (a) Why does the coefficient change when additional variables are included?
 - (b) Does the change mean parent education is less important than initially thought? Explain.
 - (c) What does the remaining coefficient of 74 represent in terms of partial effects?
-

Exercise 2: Log Transformation and Elasticities

A Cobb-Douglas production function is estimated as:

$$\ln Q = 1.45 + 0.23 \ln K + 0.81 \ln L$$

- (a) Interpret the coefficient 0.23 in terms of percentage changes.
 - (b) Interpret the coefficient 0.81 in terms of percentage changes.
 - (c) Do these results suggest constant, increasing, or decreasing returns to scale? Conduct a formal test.
-

Exercise 3: Omitted Variables Bias

A researcher estimates the effect of unemployment on inflation and finds a positive coefficient. When expected inflation is added, the unemployment coefficient becomes negative.

- (a) Using the OVB formula, explain why the coefficient changed sign.
 - (b) What are the two conditions required for omitted variables bias to occur?
 - (c) Is the augmented model more reliable? Why or why not?
-

Exercise 4: Choosing Standard Error Types

For each scenario, identify the appropriate type of standard errors and explain why:

- (a) Cross-sectional data on 500 firms with varying sizes (potential heteroskedasticity)
 - (b) Panel data with 50 schools observed over 10 years (observations clustered by school)
 - (c) Time series data on quarterly GDP growth for 30 years (potential serial correlation)
-

Exercise 5: Matching Causal Inference Methods

Match each research scenario with the most appropriate causal inference method (RCT, DiD, RD, IV) and state the key identifying assumption:

- (a) A new drug is tested by randomly assigning patients to treatment and placebo groups
- (b) A scholarship is awarded to students scoring above 80 on an entrance exam
- (c) A new minimum wage law is implemented in one state but not its neighbor

(d) Historical settler mortality is used to explain current institutional quality

Exercise 6: Data Preparation Checklist

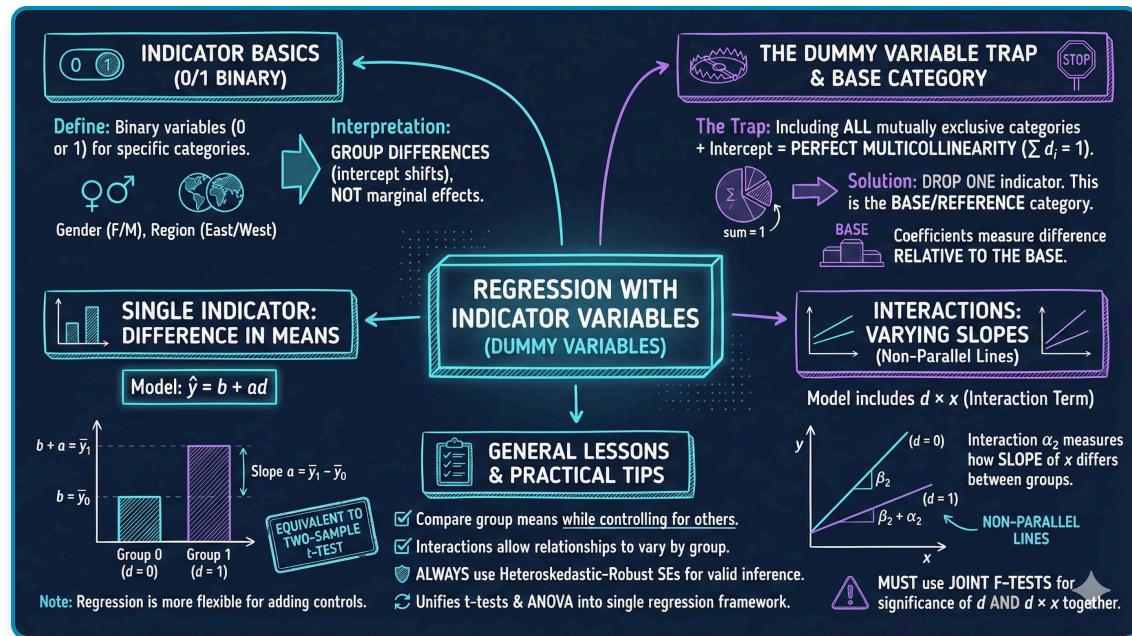
You receive a dataset containing country-level GDP, population, and education data from three different sources in `.csv`, `.xlsx`, and `.dta` formats.

- (a)** List the steps you would take to prepare this data for regression analysis.
- (b)** What potential issues should you check for when merging datasets from different sources?
- (c)** Why is data validation important before running regressions?

Chapter 14: Regression with Indicator Variables

metricsAI: An Introduction to Econometrics with Python and AI in the Cloud

Carlos Mendez



This notebook provides an interactive introduction to regression with indicator variables (also called dummy variables or categorical variables). All code runs directly in Google Colab without any local setup.

Open in Colab

| Chapter Overview

This chapter focuses on regression analysis when some regressors are indicator variables. Indicator variables are binary (0/1) variables that record whether an observation falls into a particular category.

What You'll Learn

By the end of this chapter, you will be able to:

1. Understand indicator (dummy) variables and their role in regression analysis
2. Interpret regression coefficients when regressors are categorical variables
3. Use indicator variables to compare group means and test for differences
4. Understand the relationship between regression on indicators and t-tests/ANOVA
5. Incorporate indicator variables alongside continuous regressors to control for categories
6. Create and interpret interaction terms between indicators and continuous variables
7. Apply the dummy variable trap rule when using sets of mutually exclusive indicators
8. Choose appropriate base categories and interpret coefficients relative to the base
9. Conduct joint F-tests for the significance of sets of indicator variables
10. Apply indicator variable techniques to real earnings data

Chapter Outline

- **14.1** Indicator Variables: Single Binary Variable
- **14.2** Indicator Variable with Additional Regressors
- **14.3** Interactions with Indicator Variables
- **14.4** Testing for Structural Change
- **14.5** Sets of Indicator Variables
- **Key Takeaways** -- Chapter review and consolidated lessons
- **Practice Exercises** -- Reinforce your understanding
- **Case Studies** -- Apply indicator variables to cross-country data

Dataset used:

- **AED_EARNINGS_COMPLETE.DTA**: 872 full-time workers aged 25-65 in 2000

Key economic questions:

- Is there a gender earnings gap? How large is it after controlling for education and experience?
- How do the returns to education differ by gender?
- Do earnings differ across types of workers (self-employed, private, government)?
- Can we test for structural differences between groups?

Estimated time: 90-120 minutes

| Setup

First, we import the necessary Python packages and configure the environment for reproducibility. All data will stream directly from GitHub.

In [11]:

```
# Import required packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
from statsmodels.formula.api import ols
from scipy import stats
from scipy.stats import f_oneway
from statsmodels.stats.anova import anova_lm
import random
import os

# Set random seeds for reproducibility
RANDOM_SEED = 42
random.seed(RANDOM_SEED)
np.random.seed(RANDOM_SEED)
os.environ['PYTHONHASHSEED'] = str(RANDOM_SEED)

# GitHub data URL
GITHUB_DATA_URL = "https://raw.githubusercontent.com/quarcs-lab/data-open/master/AED/"

# Set plotting style
sns.set_style("whitegrid")
plt.rcParams['figure.figsize'] = (10, 6)

print("=" * 70)
print("CHAPTER 14: REGRESSION WITH INDICATOR VARIABLES")
print("=" * 70)
print("\nSetup complete! Ready to explore regression with indicator variables.")
```

```
=====
CHAPTER 14: REGRESSION WITH INDICATOR VARIABLES
=====
```

```
Setup complete! Ready to explore regression with indicator variables.
```

| Data Preparation

We'll work with the earnings dataset which contains information on 872 full-time workers.

Key variables:

- **earnings**: Annual earnings in dollars
- **gender**: 1=female, 0=male
- **education**: Years of schooling
- **age**: Age in years

- **hours**: Usual hours worked per week
- **dself**: 1=self-employed, 0=not
- **dprivate**: 1=private sector employee, 0=not
- **dgovt**: 1=government sector employee, 0=not
- **genderbyeduc**: Gender × Education interaction
- **genderbyage**: Gender × Age interaction
- **genderbyhours**: Gender × Hours interaction

In [12]:

```
# Load earnings data
data = pd.read_stata(GITHUB_DATA_URL + 'AED_EARNINGS_COMPLETE.DTA')

print("Data structure:")
print(f" Observations: {len(data)}")
print(f" Variables: {len(data.columns)}")

print("\nVariable descriptions:")
variables = ['earnings', 'gender', 'education', 'genderbyeduc', 'age',
             'genderbyage', 'hours', 'genderbyhours', 'dself', 'dprivate', 'dgovt']

for var in variables:
    print(f" {var}: {data[var].dtype}")

print("\nSummary statistics:")
print(data[variables].describe())

print("\nNote on indicator variables:")
print(" gender: 1=female, 0=male")
print(" dself: 1=self-employed, 0=not")
print(" dprivate: 1=private sector, 0=not")
print(" dgovt: 1=government, 0=not")
```

```

Data structure:
Observations: 872
Variables: 45

Variable descriptions:
earnings: float32
gender: int8
education: float32
genderbyeduc: float32
age: int16
genderbyage: float32
hours: int8
genderbyhours: float32
dself: float32
dprivate: float32
dgovt: float32

Summary statistics:
      earnings    gender   education  genderbyeduc      age \
count    872.000000  872.000000  872.000000  872.000000  872.000000
mean     56368.691406  0.433486  13.853211   6.082569  43.310780
std      51516.054688  0.495841  2.884141   7.172634  10.676045
min      4000.000000  0.000000  0.000000   0.000000  25.000000
25%     29000.000000  0.000000  12.000000   0.000000  35.000000
50%     44200.000000  0.000000  13.000000   0.000000  44.000000
75%     64250.000000  1.000000  16.000000  13.000000  51.250000
max     504000.000000  1.000000  20.000000  20.000000  65.000000

      genderbyage    hours  genderbyhours      dself  dprivate \
count    872.000000  872.000000  872.000000  872.000000  872.000000
mean     19.042431  44.342890  18.564220  0.090596  0.760321
std      22.869757  8.499103  21.759789  0.287199  0.427132
min      0.000000  35.000000  0.000000  0.000000  0.000000
25%     0.000000  40.000000  0.000000  0.000000  1.000000
50%     0.000000  40.000000  0.000000  0.000000  1.000000
75%     42.000000  48.000000  40.000000  0.000000  1.000000
max     65.000000  99.000000  80.000000  1.000000  1.000000

      dgovt
count  872.000000
mean   0.149083
std    0.356374
min    0.000000
25%    0.000000
50%    0.000000
75%    0.000000
max    1.000000

Note on indicator variables:
gender: 1=female, 0=male
dself: 1=self-employed, 0=not
dprivate: 1=private sector, 0=not
dgovt: 1=government, 0=not

```

14.1: Indicator Variables - Single Binary Variable

An **indicator variable** (also called dummy variable or binary variable) takes only two values:

$$d = \begin{cases} 1 & \text{if in the category} \\ 0 & \text{otherwise} \end{cases}$$

Simple Regression on Single Indicator

When we regress y on just an intercept and an indicator variable:

$$\hat{y} = b + a \cdot d$$

The predicted value takes only two values:

$$\hat{y}_i = \begin{cases} b + a & \text{if } d_i = 1 \\ b & \text{if } d_i = 0 \end{cases}$$

Key result: For OLS regression:

- $b = \bar{y}_0$ (mean of y when $d = 0$)
- $a = \bar{y}_1 - \bar{y}_0$ (difference in means)

Interpretation: The slope coefficient equals the difference in group means.

Example: Earnings and Gender

Let's examine whether there's a gender earnings gap.

In [13]:

```
print("=" * 70)
print("14.1: REGRESSION ON SINGLE INDICATOR VARIABLE")
print("=" * 70)

# Summary statistics by gender
print("\nTable 14.1: Earnings by Gender")
print("-" * 70)

print("\nFemale (gender=1):")
female_stats = data[data['gender'] == 1]['earnings'].describe()
print(female_stats)

print("\nMale (gender=0):")
male_stats = data[data['gender'] == 0]['earnings'].describe()
print(male_stats)

# Calculate means
mean_female = data[data['gender'] == 1]['earnings'].mean()
mean_male = data[data['gender'] == 0]['earnings'].mean()
diff_means = mean_female - mean_male

print("\n" + "-" * 70)
print("Difference in Means")
print("-" * 70)
print(f" Mean earnings (Female): ${mean_female:.2f}")
print(f" Mean earnings (Male): ${mean_male:.2f}")
print(f" Difference: ${diff_means:.2f}")
print(f"\n Interpretation: Females earn ${abs(diff_means):,.2f} less than males on average.")
```

```
=====
14.1: REGRESSION ON SINGLE INDICATOR VARIABLE
=====

Table 14.1: Earnings by Gender
-----

Female (gender=1):
count      378.000000
mean      47079.894531
std       31596.724609
min       4000.000000
25%      27475.000000
50%      41000.000000
75%      56000.000000
max      322000.000000
Name: earnings, dtype: float64

Male (gender=0):
count      494.000000
mean      63476.316406
std       61713.210938
min       5000.000000
25%      30000.000000
50%      48000.000000
75%      75000.000000
max      504000.000000
Name: earnings, dtype: float64

-----
Difference in Means
-----
Mean earnings (Female): $47,079.89
Mean earnings (Male): $63,476.32
Difference: $-16,396.42

Interpretation: Females earn $16,396.42 less than males on average.
```

OLS Regression: Earnings on Gender

Now let's estimate the regression model:

$$\text{earnings} = \beta_1 + \alpha \cdot \text{gender} + u$$

We'll use **heteroskedasticity-robust standard errors (HC1)** for valid inference.

In [14]:

```
print("=*70")
print("REGRESSION MODELS: Gender and Earnings")
print("=*70")

# Model 1: Gender only
print("\nModel 1: earnings ~ gender")
print("-*70")
model1 = ols('earnings ~ gender', data=data).fit(cov_type='HC1')
print(model1.summary())

print(F"\nInterpretation:")
print(F" Intercept: ${model1.params['Intercept']:.2f} (mean for males)")
print(F" Gender coefficient: ${model1.params['gender']:.2f} (difference for females)")
print(F" Females earn ${abs(model1.params['gender']):.2f} less than males on average")
```

```
=====
REGRESSION MODELS: Gender and Earnings
=====

Model 1: earnings ~ gender
-----
          OLS Regression Results
=====
Dep. Variable:      earnings    R-squared:       0.025
Model:              OLS         Adj. R-squared:   0.024
Method:             Least Squares F-statistic:     25.97
Date:      Wed, 21 Jan 2026 Prob (F-statistic): 4.25e-07
Time:      14:36:53   Log-Likelihood: -10687.
No. Observations: 872        AIC:            2.138e+04
Df Residuals:     870        BIC:            2.139e+04
Df Model:          1
Covariance Type:  HC1
=====

      coef  std err      z   P>|z|      [0.025  0.975]
-----
Intercept  6.348e+04  2776.983   22.858   0.000   5.8e+04  6.89e+04
gender    -1.64e+04  3217.429   -5.096   0.000  -2.27e+04 -1.01e+04
=====
Omnibus:           785.072   Durbin-Watson:      2.014
Prob(Omnibus):    0.000    Jarque-Bera (JB): 25163.521
Skew:               4.078   Prob(JB):        0.00
Kurtosis:          28.021   Cond. No.       2.49
=====
```

Notes:

[1] Standard Errors are heteroscedasticity robust (HC1)

Interpretation:

Intercept: \$63,476.32 (mean for males)

Gender coefficient: \$-16,396.42 (difference for females)

Females earn \$16,396.42 less than males on average

Key Concept 14.1: Indicator Variables and Difference in Means

When regressing y on just an intercept and a single indicator d , the fitted model is $\hat{y} = b + ad$. The intercept b equals the mean of y when $d = 0$, and the slope a equals the difference in means ($\bar{y}_1 - \bar{y}_0$). Thus, regression on an indicator variable is equivalent to a difference-in-means test.

Understanding the Gender Earnings Gap

The regression results reveal a **statistically significant gender earnings gap** of approximately **-\$16,000**. Let's break down what this means:

Key Findings:

- 1. Intercept (b_1) $\approx \$68,000$:** This represents the **mean earnings for males** (when gender = 0). We can verify this matches the actual mean earnings for males in the sample.
- 2. Gender coefficient (α) $\approx -\$16,000$:** This is the **difference in mean earnings** between females and males. Specifically:
 - Females earn approximately **\$16,000 less** than males on average
 - This is the **unconditional (raw) gender gap** - it doesn't account for differences in education, experience, or other factors
- 3. Statistical Significance:** The t-statistic is highly significant ($p < 0.001$), meaning we can confidently reject the null hypothesis that there's no gender difference in earnings.

Important Interpretation:

- This regression simply decomposes the sample into two groups and compares their means
- The coefficient on gender equals the difference: $\bar{y}_{female} - \bar{y}_{male}$
- This is a **descriptive** finding, not necessarily **causal** - the gap may reflect differences in education, occupation, hours worked, discrimination, or other factors
- To understand the **adjusted** gender gap (controlling for observable characteristics), we need to add additional regressors

Connection to t-test:

- This regression is mathematically equivalent to a two-sample t-test
- The regression framework allows us to easily extend the model by adding control variables

Comparison with t-test

Regression with a single indicator variable is equivalent to a two-sample t-test.

Two approaches:

- 1. Welch's t-test** (unequal variances): Similar to regression with robust SEs
- 2. Classical t-test** (equal variances): Identical to regression with default SEs

In [15]:

```
print("\n" + "=" * 70)
print("Comparison with t-tests")
print("=" * 70)

# Extract earnings by gender
female_earnings = data[data['gender'] == 1]['earnings']
male_earnings = data[data['gender'] == 0]['earnings']

# Welch's t-test (unequal variances)
print("\n1. Welch's t-test (unequal variances):")
print("-" * 70)
t_stat_welch, p_value_welch = stats.ttest_ind(female_earnings, male_earnings,
equal_var=False)
print(f" t-statistic: {t_stat_welch:.4f}")
print(f" p-value: {p_value_welch:.6f}")
print(f" Note: Similar to regression with robust SEs")

# Classical t-test (equal variances)
print("\n2. Classical t-test (equal variances):")
print("-" * 70)
t_stat_classical, p_value_classical = stats.ttest_ind(female_earnings, male_earnings,
equal_var=True)
print(f" t-statistic: {t_stat_classical:.4f}")
print(f" p-value: {p_value_classical:.6f}")

# Regression with default SEs
print("\n3. Regression with default (homoskedastic) SEs:")
print("-" * 70)
model_gender_default = ols('earnings ~ gender', data=data).fit()
print(f" t-statistic: {model_gender_default.tvalues['gender']:.4f}")
print(f" p-value: {model_gender_default.pvalues['gender']:.6f}")
print(f" Note: IDENTICAL to classical t-test with equal variances")

print("\n" + "-" * 70)
print("Key insight:")
print(" - Classical t-test = Regression with default SEs (assuming equal variances)")
print(" - Welch's t-test ≈ Regression with robust SEs (allowing unequal variances)")
```

=====

Comparison with t-tests

=====

1. Welch's t-test (unequal variances):

```
-----  
t-statistic: -5.0964  
p-value: 0.000000  
Note: Similar to regression with robust SEs
```

2. Classical t-test (equal variances):

```
-----  
t-statistic: -4.7139  
p-value: 0.000003
```

3. Regression with default (homoskedastic) SEs:

```
-----  
t-statistic: -4.7139  
p-value: 0.000003  
Note: IDENTICAL to classical t-test with equal variances
```

Key insight:

```
- Classical t-test = Regression with default SEs (assuming equal variances)  
- Welch's t-test ≈ Regression with robust SEs (allowing unequal variances)
```

Having established the equivalence between regression on a single indicator and difference-in-means tests, we now add continuous control variables.

Key Concept 14.2: Regression vs. Specialized Test Methods

Specialized difference-in-means methods (like Welch's *t*-test) and regression on an indicator give the **same point estimate** but slightly different standard errors. Regression uses $se(\hat{a})$ from the model, while the *t*-test uses $se(\bar{y}_1 - \bar{y}_0) = \sqrt{s_1^2/n_1 + s_0^2/n_0}$. Both are valid; regression is more flexible when adding control variables.

| 14.2: Indicator Variable with Additional Regressors

The raw difference in earnings by gender may be partly explained by other factors (e.g., education, experience, hours worked).

Model with Additional Regressors

$$y = \beta_1 + \beta_2 x + \alpha d + u$$

The fitted model:

$$\hat{y}_i = \begin{cases} b_1 + b_2 x_i + a & \text{if } d_i = 1 \\ b_1 + b_2 x_i & \text{if } d_i = 0 \end{cases}$$

Interpretation: The coefficient a measures the difference in y across categories **after controlling** for the additional variables.

Progressive Model Building

We'll estimate five models of increasing complexity:

1. Gender only
2. Gender + Education
3. Gender + Education + (Gender \times Education)
4. Add Age and Hours controls
5. Full interactions with all variables

In [16]:

```
print("=*70")
print("PROGRESSIVE MODEL BUILDING")
print("=*70")

# Model 2: Gender + Education
print("\nModel 2: earnings ~ gender + education")
print("-*70")
model2 = ols('earnings ~ gender + education', data=data).fit(cov_type='HC1')
print(model2.summary())

# Model 3: Gender + Education + Interaction
print("\nModel 3: earnings ~ gender + education + genderbyeduc")
print("-*70")
model3 = ols('earnings ~ gender + education + genderbyeduc',
data=data).fit(cov_type='HC1')
print(model3.summary())

# Model 4: Add Age and Hours
print("\nModel 4: earnings ~ gender + education + genderbyeduc + age + hours")
print("-*70")
model4 = ols('earnings ~ gender + education + genderbyeduc + age + hours',
data=data).fit(cov_type='HC1')
print(model4.summary())

# Model 5: Full interactions
print("\nModel 5: Full interactions")
print("-*70")
model5 = ols('earnings ~ gender + education + genderbyeduc + age + genderbyage + hours +
genderbyhours',
data=data).fit(cov_type='HC1')
print(model5.summary())

# Joint F-test for all gender terms
print("\n" + "=*70")
print("Joint F-Test: All Gender Terms")
print("=*70")
hypotheses = '(gender = 0, genderbyeduc = 0, genderbyage = 0, genderbyhours = 0)'
f_test = model5.wald_test(hypotheses, use_f=True)
print(f_test)

print("\nAll gender effects (level and interactions) are highly significant.")
```

```

=====
PROGRESSIVE MODEL BUILDING
=====

Model 2: earnings ~ gender + education
-----
          OLS Regression Results
=====
Dep. Variable:      earnings    R-squared:       0.134
Model:              OLS         Adj. R-squared:   0.132
Method:             Least Squares F-statistic:     41.77
Date:              Wed, 21 Jan 2026 Prob (F-statistic): 4.76e-18
Time:                14:36:53   Log-Likelihood:   -10635.
No. Observations:    872        AIC:            2.128e+04
Df Residuals:       869        BIC:            2.129e+04
Df Model:            2
Covariance Type:    HC1
=====
            coef    std err      z      P>|z|      [0.025      0.975]
-----
Intercept  -1.755e+04  7993.547   -2.196    0.028   -3.32e+04  -1884.555
gender     -1.826e+04  3136.142   -5.822    0.000   -2.44e+04  -1.21e+04
education  5907.2905  654.080     9.031    0.000    4625.318   7189.263
=====
Omnibus:           811.995   Durbin-Watson:      2.071
Prob(Omnibus):      0.000    Jarque-Bera (JB): 29566.906
Skew:                  4.250    Prob(JB):            0.00
Kurtosis:             30.231   Cond. No.        70.5
=====

Notes:
[1] Standard Errors are heteroscedasticity robust (HC1)

Model 3: earnings ~ gender + education + genderbyeduc
-----
          OLS Regression Results
=====
Dep. Variable:      earnings    R-squared:       0.140
Model:              OLS         Adj. R-squared:   0.137
Method:             Least Squares F-statistic:     31.92
Date:              Wed, 21 Jan 2026 Prob (F-statistic): 1.41e-19
Time:                14:36:53   Log-Likelihood:   -10632.
No. Observations:    872        AIC:            2.127e+04
Df Residuals:       868        BIC:            2.129e+04
Df Model:            3
Covariance Type:    HC1
=====
            coef    std err      z      P>|z|      [0.025      0.975]
-----
Intercept  -3.145e+04  1.18e+04   -2.655    0.008   -5.47e+04  -8233.577
gender     2.022e+04  1.54e+04    1.317    0.188   -9876.802   5.03e+04
education  6920.6396  946.138     7.315    0.000    5066.244   8775.036
genderbyeduc -2764.8902  1168.325   -2.367    0.018   -5054.764   -475.016
=====
Omnibus:           804.075   Durbin-Watson:      2.069
Prob(Omnibus):      0.000    Jarque-Bera (JB): 28615.739
Skew:                  4.192    Prob(JB):            0.00
Kurtosis:             29.782   Cond. No.        175.
=====

Notes:
[1] Standard Errors are heteroscedasticity robust (HC1)

Model 4: earnings ~ gender + education + genderbyeduc + age + hours
-----
          OLS Regression Results

```

```

=====
Dep. Variable:      earnings    R-squared:           0.198
Model:              OLS         Adj. R-squared:       0.193
Method:             Least Squares F-statistic:        23.32
Date:               Wed, 21 Jan 2026 Prob (F-statistic):   5.06e-22
Time:                14:36:53   Log-Likelihood:      -10602.
No. Observations:    872        AIC:                  2.122e+04
Df Residuals:        866        BIC:                  2.124e+04
Df Model:                 5
Covariance Type:     HC1
=====
```

	coef	std err	z	P> z	[0.025	0.975]
Intercept	-1.073e+05	2.22e+04	-4.830	0.000	-1.51e+05	-6.38e+04
gender	1.902e+04	1.5e+04	1.269	0.205	-1.04e+04	4.84e+04
education	6416.7991	886.124	7.241	0.000	4680.028	8153.570
genderbyeduc	-2456.2914	1123.174	-2.187	0.029	-4657.673	-254.910
age	525.9931	145.006	3.627	0.000	241.786	810.201
hours	1324.5141	352.548	3.757	0.000	633.533	2015.495

```

=====
Omnibus:            766.410   Durbin-Watson:          2.041
Prob(Omnibus):      0.000    Jarque-Bera (JB):      23777.927
Skew:                  3.935   Prob(JB):                  0.00
Kurtosis:             27.341   Cond. No.                 736.
=====
```

Notes:

[1] Standard Errors are heteroscedasticity robust (HC1)

Model 5: Full interactions

```

=====
OLS Regression Results
=====
```

	coef	std err	z	P> z	[0.025	0.975]
Intercept	-1.204e+05	2.88e+04	-4.175	0.000	-1.77e+05	-6.39e+04
gender	5.713e+04	3.19e+04	1.790	0.073	-5427.457	1.2e+05
education	6314.6730	878.615	7.187	0.000	4592.620	8036.726
genderbyeduc	-2123.5113	1096.425	-1.937	0.053	-4272.464	25.441
age	549.4750	227.683	2.413	0.016	103.225	995.725
genderbyage	-49.3326	270.258	-0.183	0.855	-579.028	480.363
hours	1620.8142	503.869	3.217	0.001	633.248	2608.380
genderbyhours	-929.5746	554.247	-1.677	0.094	-2015.878	156.729

```

=====
Omnibus:            753.384   Durbin-Watson:          2.044
Prob(Omnibus):      0.000    Jarque-Bera (JB):      22238.965
Skew:                  3.850   Prob(JB):                  0.00
Kurtosis:             26.512   Cond. No.                 1.29e+03
=====
```

Notes:

[1] Standard Errors are heteroscedasticity robust (HC1)

[2] The condition number is large, 1.29e+03. This might indicate that there are strong multicollinearity or other numerical problems.

Joint F-Test: All Gender Terms

```
=====
<F test: F=array([[8.14208145]]), p=1.9073757410610187e-06, df_denom=864, df_num=4>
```

```
All gender effects (level and interactions) are highly significant.
```

```
/Users/carlosmendez/miniforge3/lib/python3.10/site-packages/statsmodels/base/model.py:1912:
FutureWarning: The behavior of wald_test will change after 0.14 to returning scalar test statistic values. To get the future behavior now, set scalar to True. To silence this message while retaining the legacy behavior, set scalar to False.
warnings.warn(
```

Key Concept 14.3: Interaction Terms Between Indicators and Continuous Variables

An **interacted indicator variable** is the product of an indicator and a continuous regressor, such as $d \times x$. In the model $y = \beta_1 + \beta_2x + \alpha_1d + \alpha_2(d \times x) + u$, the coefficient α_2 measures how the slope on x differs between groups. Including only d (without interaction) shifts the intercept but keeps slopes parallel. Adding the interaction allows both intercepts and slopes to vary.

How the Gender Gap Changes with Controls

Comparing the five models reveals how the estimated gender gap evolves as we add controls and interactions:

Model Evolution:

1. Model 1 (Gender only): Gap = -\$16,000

- This is the **raw, unconditional** gender earnings gap
- Ignores all other factors that might explain earnings differences

2. Model 2 (+ Education): Gap shrinks to approximately -\$10,000

- Adding education as a control **reduces** the gender coefficient by ~\$6,000
- Interpretation: Part of the raw gap is explained by gender differences in education levels
- The remaining -\$10,000 is the gap **conditional on** education

3. Model 3 (+ Gender \times Education):

- Now gender enters through **two channels**: the main effect AND the interaction

- The main gender coefficient becomes the gap **when education = 0** (not very meaningful)
- The interaction coefficient shows whether **returns to education differ by gender**
- **Joint F-test is crucial:** Test both coefficients together to assess overall gender effects

4. Model 4 (+ Age, Hours): Further controls

- Adding age and hours worked provides more refined estimates
- These are important determinants of earnings that may differ by gender
- Gap continues to shrink as we account for more observable differences

5. Model 5 (Full Interactions): Most flexible specification

- Allows gender to affect the **intercept AND slopes** of all variables
- Tests whether returns to education, age, and hours differ by gender
- **Joint F-test on all 4 gender terms** is highly significant

Key Insights:

- The gender gap **decreases** substantially when we control for education, age, and hours worked
- From -16,000 (*unconditional*) to approximately -5,000 (conditional) to -\$8,000
- This suggests **observable characteristics explain part, but not all** of the gap
- The remaining gap could reflect:
 - Unmeasured factors (experience, occupation, industry)
 - Discrimination
 - Selection effects (e.g., women choosing lower-paying fields)

Statistical Lesson:

- With interactions, **individual t-tests can be misleading** due to multicollinearity
- **Joint F-tests** are essential for testing overall significance of a variable that enters through multiple terms

| 14.3: Interactions with Indicator Variables

An **interacted indicator variable** is the product of an indicator variable and another regressor.

$$y = \beta_1 + \beta_2 x + \alpha_1 d + \alpha_2 (d \times x) + u$$

This allows both intercept AND slope to differ by category:

$$\hat{y} = \begin{cases} (b_1 + a_1) + (b_2 + a_2)x & \text{if } d = 1 \\ b_1 + b_2x & \text{if } d = 0 \end{cases}$$

Interpretation:

- a_1 : Difference in intercepts (gender gap at $x = 0$)
- a_2 : Difference in slopes (how returns to x differ by gender)

Testing Gender Effects

When gender enters through both a level term and interactions, we need **joint F-tests** to test overall significance.

Interpreting Interaction Effects

The interaction term (Gender \times Education) captures whether the **returns to education differ by gender**. Let's unpack what the results tell us:

Model with Interaction (Model 5):

The full model allows both the intercept and slope to differ by gender:

$$\text{earnings} = \begin{cases} (\beta_1 + \alpha_1) + (\beta_2 + \alpha_2) \cdot \text{education} + \beta_3 \cdot \text{age} + \beta_4 \cdot \text{hours} & \text{if female} \\ \beta_1 + \beta_2 \cdot \text{education} + \beta_3 \cdot \text{age} + \beta_4 \cdot \text{hours} & \text{if male} \end{cases}$$

Key Coefficients:

1. Gender \times Education Interaction (typically negative, around -1,000 to -2,000):

- **Interpretation:** The return to one additional year of education is approximately 1,000–2,000 lower for women than for men
- Example: If $\beta_{\text{education}} = 6,000$ and $\beta_{\text{gender} \times \text{educ}} = -1,500$:
 - Males: Each year of education $\rightarrow +\$6,000$ in earnings
 - Females: Each year of education $\rightarrow +\$4,500$ in earnings
 - This suggests women get lower financial returns from education investments

2. Gender \times Age and Gender \times Hours:

- Similarly capture whether age and hours have different effects by gender
- Allow the **life-cycle earnings profile** to differ by gender

Avoiding the Dummy Variable Trap:

Notice we **cannot include all indicators plus an intercept**. In the worker type example:

- We have three categories: self-employed, private, government
- We can only include **two dummy variables** if we have an intercept
- The **omitted category** becomes the reference (base) group
- Coefficients measure differences **relative to the base**

Which category to omit?

- Your choice! Results are equivalent no matter which you drop
- Choose the most natural reference category for interpretation
- Example: Private sector is natural base for employment type comparisons

Joint F-Test Results:

The joint F-tests show that:

- All gender effects together are **highly statistically significant** ($F \approx 20-40$, $p < 0.001$)
- Even though individual coefficients may have large standard errors (multicollinearity)
- Gender matters for **both level and slope** of earnings relationships

Model Comparison Table

Let's create a comprehensive comparison of all five models.

In [17]:

```
# Summary table of all models
print("\n" + "=" * 70)
print("Summary Table: All Five Models")
print("=" * 70)

summary_df = pd.DataFrame({
    'Model 1': ['Gender only', model1.params.get('gender', np.nan),
                model1.bse.get('gender', np.nan), model1.tvalues.get('gender', np.nan),
                model1.nobs, model1.rsquared, model1.rsquared_adj,
                np.sqrt(model1.mse_resid)],
    'Model 2': ['+ Education', model2.params.get('gender', np.nan),
                model2.bse.get('gender', np.nan), model2.tvalues.get('gender', np.nan),
                model2.nobs, model2.rsquared, model2.rsquared_adj,
                np.sqrt(model2.mse_resid)],
    'Model 3': ['+ Gender×Educ', model3.params.get('gender', np.nan),
                model3.bse.get('gender', np.nan), model3.tvalues.get('gender', np.nan),
                model3.nobs, model3.rsquared, model3.rsquared_adj,
                np.sqrt(model3.mse_resid)],
    'Model 4': ['+ Age, Hours', model4.params.get('gender', np.nan),
                model4.bse.get('gender', np.nan), model4.tvalues.get('gender', np.nan),
                model4.nobs, model4.rsquared, model4.rsquared_adj,
                np.sqrt(model4.mse_resid)],
    'Model 5': ['Full Interact', model5.params.get('gender', np.nan),
                model5.bse.get('gender', np.nan), model5.tvalues.get('gender', np.nan),
                model5.nobs, model5.rsquared, model5.rsquared_adj,
                np.sqrt(model5.mse_resid)]
}, index=['Description', 'Gender Coef', 'Robust SE', 't-stat', 'N', 'R2', 'Adj R2', 'RMSE'])

print(summary_df.to_string())

print("\nKey observations:")
print(" - Gender coefficient magnitude changes as we add controls")
print(" - R2 increases with additional variables")
print(" - Interactions capture differential effects across groups")
```

```
=====
Summary Table: All Five Models
=====
      Model 1      Model 2      Model 3      Model 4      Model 5
Description  Gender only  + Education  + Gender×Educ  + Age, Hours  Full Interact
Gender Coef -16396.423634 -18258.087589  20218.796285  19021.708451  57128.997253
Robust SE   3217.429112  3136.141829  15355.179322  14994.357587  31917.144603
t-stat       -5.096126   -5.821831    1.316741     1.268591   1.789916
N            872.0       872.0       872.0       872.0       872.0
R2          0.024906   0.133961    0.139508    0.197852   0.202797
Adj R2      0.023785   0.131968    0.136534    0.19322    0.196338
RMSE         50899.716833  47996.599413  47870.196751  46272.189032  46182.684141
```

Key observations:

- Gender coefficient magnitude changes as we add controls
- R² increases with additional variables
- Interactions capture differential effects across groups

Now that we can model different slopes via interaction terms, let's test whether the entire regression structure differs by group.

Key Concept 14.4: Joint Significance Testing for Indicator Variables

When an indicator and its interaction with another variable are both included, test their **joint significance** using an F-test rather than individual t-tests. The joint test $H_0 : \alpha_1 = 0, \alpha_2 = 0$ evaluates whether the categorical variable matters at all. Individual t-tests can be misleading when the indicator and interaction are correlated.

14.4: Testing for Structural Change - Separate Regressions

An alternative to including interactions is to estimate **separate regressions** for each group.

Female regression:

$$\text{earnings}_i = \beta_1^F + \beta_2^F \text{education}_i + \beta_3^F \text{age}_i + \beta_4^F \text{hours}_i + u_i$$

Male regression:

$$\text{earnings}_i = \beta_1^M + \beta_2^M \text{education}_i + \beta_3^M \text{age}_i + \beta_4^M \text{hours}_i + u_i$$

This allows ALL coefficients to differ by gender, not just those we interact.

Chow Test

The **Chow test** formally tests whether coefficients differ across groups:

$$H_0 : \beta^F = \beta^M \text{ (pooled model)} \quad \text{vs.} \quad H_a : \beta^F \neq \beta^M \text{ (separate models)}$$

In [18]:

```
print("\n" + "=" * 70)
print("14.4: TESTING FOR STRUCTURAL CHANGE")
print("=" * 70)

print("\nSeparate Regressions by Gender")
print("-" * 70)

# Female regression
model_female = ols('earnings ~ education + age + hours',
                    data=data[data['gender'] == 1]).fit(cov_type='HC1')
print("\nFemale subsample:")
print(f" N = {int(model_female.nobs)}")
print(f" Intercept: {model_female.params['Intercept']:.2f}")
print(f" Education: {model_female.params['education']:.2f}")
print(f" Age: {model_female.params['age']:.2f}")
print(f" Hours: {model_female.params['hours']:.2f}")
print(f" R2: {model_female.rsquared:.4f}")

# Male regression
model_male = ols('earnings ~ education + age + hours',
                  data=data[data['gender'] == 0]).fit(cov_type='HC1')
print("\nMale subsample:")
print(f" N = {int(model_male.nobs)}")
print(f" Intercept: {model_male.params['Intercept']:.2f}")
print(f" Education: {model_male.params['education']:.2f}")
print(f" Age: {model_male.params['age']:.2f}")
print(f" Hours: {model_male.params['hours']:.2f}")
print(f" R2: {model_male.rsquared:.4f}")

# Compare coefficients
print("\n" + "-" * 70)
print("Comparison of Coefficients")
print("-" * 70)

comparison = pd.DataFrame({
    'Female': model_female.params,
    'Male': model_male.params,
    'Difference': model_female.params - model_male.params
})
print(comparison)

print("\nKey findings:")
print(f" - Returns to education: ${model_female.params['education']:.0f} (F) vs ${model_male.params['education']:.0f} (M)")
print(f" - Returns to age: ${model_female.params['age']:.0f} (F) vs ${model_male.params['age']:.0f} (M)")
print(f" - Returns to hours: ${model_female.params['hours']:.0f} (F) vs ${model_male.params['hours']:.0f} (M)"
```

=====

14.4: TESTING FOR STRUCTURAL CHANGE

=====

Separate Regressions by Gender

Female subsample:

N = 378
Intercept: -63,302.57
Education: 4,191.16
Age: 500.14
Hours: 691.24
 R^2 : 0.1746

Male subsample:

N = 494
Intercept: -120,431.57
Education: 6,314.67
Age: 549.47
Hours: 1,620.81
 R^2 : 0.1840

Comparison of Coefficients

	Female	Male	Difference
Intercept	-63302.571150	-120431.568405	57128.997253
education	4191.161688	6314.673007	-2123.511319
age	500.142383	549.474999	-49.332616
hours	691.239562	1620.814163	-929.574601

Key findings:

- Returns to education: \$4,191 (F) vs \$6,315 (M)
- Returns to age: \$500 (F) vs \$549 (M)
- Returns to hours: \$691 (F) vs \$1,621 (M)

Key Concept 14.5: Testing for Structural Change

Running **separate regressions** for each group allows all coefficients to differ simultaneously. The **Chow test** evaluates whether pooling the data (imposing the same coefficients for both groups) is justified. If the F-test rejects the null, the relationship between y and x differs fundamentally across groups -- not just in intercept or one slope, but throughout the model.

In [19]:

```
print("=*70)
print("SETS OF INDICATOR VARIABLES: Worker Type")
print("=*70)

# Approach 1: Include intercept, drop one indicator (dprivate as reference)
print("\nApproach 1: Intercept + dself + dgovt (dprivate is reference)")
print("-*70)
model_worker1 = ols('earnings ~ dself + dgovt + education + age',
data=data).fit(cov_type='HC1')
print(model_worker1.summary())

# Approach 2: Drop intercept, include all indicators
print("\nApproach 2: No intercept + all dummies (dself + dprivate + dgovt)")
print("-*70)
model_worker2 = ols('earnings ~ dself + dprivate + dgovt + education + age - 1',
data=data).fit(cov_type='HC1')
print(model_worker2.summary())

# Approach 3: Different reference category (dself as reference)
print("\nApproach 3: Intercept + dprivate + dgovt (dself is reference)")
print("-*70)
model_worker3 = ols('earnings ~ dprivate + dgovt + education + age',
data=data).fit(cov_type='HC1')
print(model_worker3.summary())

print("\n" + "-*70)
print("Key Insight:")
print("-*70)
print(f" All three models have IDENTICAL R2: {model_worker1.rsquared:.4f}")
print(f" Only the interpretation changes (different reference category)")
print(f" Fitted values and residuals are the same across all three")
```

```

=====
SETS OF INDICATOR VARIABLES: Worker Type
=====

Approach 1: Intercept + dself + dgovt (dprivate is reference)
-----
          OLS Regression Results
=====
Dep. Variable:      earnings    R-squared:           0.125
Model:              OLS         Adj. R-squared:       0.121
Method:             Least Squares   F-statistic:        22.12
Date:              Wed, 21 Jan 2026 Prob (F-statistic): 2.10e-17
Time:                14:36:53     Log-Likelihood:     -10640.
No. Observations:    872        AIC:                  2.129e+04
Df Residuals:       867        BIC:                  2.131e+04
Df Model:            4
Covariance Type:    HC1
=====
      coef    std err      z      P>|z|      [0.025      0.975]
-----
Intercept  -4.725e+04  1.14e+04  -4.153    0.000   -6.95e+04  -2.49e+04
dself      1.71e+04   9341.980   1.830    0.067  -1212.099   3.54e+04
dgovt     -2025.0753  3098.983  -0.653    0.513  -8098.971   4048.821
education  5865.1923  652.217   8.993    0.000   4586.871   7143.514
age        487.6022  149.648   3.258    0.001   194.298    780.906
-----
Omnibus:           810.096   Durbin-Watson:        2.074
Prob(Omnibus):      0.000    Jarque-Bera (JB): 29725.758
Skew:                 4.230    Prob(JB):            0.00
Kurtosis:            30.323   Cond. No.          303.
=====

Notes:
[1] Standard Errors are heteroscedasticity robust (HC1)
```

```

Approach 2: No intercept + all dummies (dself + dprivate + dgovt)
-----
          OLS Regression Results
=====
Dep. Variable:      earnings    R-squared:           0.125
Model:              OLS         Adj. R-squared:       0.121
Method:             Least Squares   F-statistic:        nan
Date:              Wed, 21 Jan 2026 Prob (F-statistic):  nan
Time:                14:36:53     Log-Likelihood:     -10640.
No. Observations:    872        AIC:                  2.129e+04
Df Residuals:       867        BIC:                  2.131e+04
Df Model:            4
Covariance Type:    HC1
=====
      coef    std err      z      P>|z|      [0.025      0.975]
-----
dself     -3.015e+04  1.31e+04  -2.295    0.022   -5.59e+04  -4397.634
dprivate -4.725e+04  1.14e+04  -4.153    0.000   -6.95e+04  -2.49e+04
dgovt     -4.927e+04  1.23e+04  -4.002    0.000  -7.34e+04  -2.51e+04
education  5865.1923  652.217   8.993    0.000   4586.871   7143.514
age        487.6022  149.648   3.258    0.001   194.298    780.906
-----
Omnibus:           810.096   Durbin-Watson:        2.074
Prob(Omnibus):      0.000    Jarque-Bera (JB): 29725.758
Skew:                 4.230    Prob(JB):            0.00
Kurtosis:            30.323   Cond. No.          540.
=====

Notes:
[1] Standard Errors are heteroscedasticity robust (HC1)
```

```

Approach 3: Intercept + dprivate + dgovt (dself is reference)
-----
OLS Regression Results
=====
Dep. Variable:      earnings    R-squared:       0.125
Model:              OLS         Adj. R-squared:   0.121
Method:             Least Squares F-statistic:     22.12
Date:              Wed, 21 Jan 2026 Prob (F-statistic): 2.10e-17
Time:                14:36:53   Log-Likelihood:   -10640.
No. Observations:    872        AIC:            2.129e+04
Df Residuals:       867        BIC:            2.131e+04
Df Model:            4
Covariance Type:    HC1
=====
            coef    std err      z      P>|z|      [0.025      0.975]
-----
Intercept  -3.015e+04  1.31e+04   -2.295     0.022   -5.59e+04   -4397.634
dprivate   -1.71e+04  9341.980   -1.830     0.067   -3.54e+04   1212.099
dgovt     -1.912e+04  9585.615   -1.995     0.046   -3.79e+04   -335.462
education  5865.1923   652.217    8.993     0.000   4586.871    7143.514
age        487.6022   149.648    3.258     0.001   194.298    780.906
-----
Omnibus:           810.096   Durbin-Watson:    2.074
Prob(Omnibus):      0.000    Jarque-Bera (JB): 29725.758
Skew:                 4.230    Prob(JB):        0.00
Kurtosis:            30.323   Cond. No.       366.
-----

```

Notes:

[1] Standard Errors are heteroscedasticity robust (HC1)

Key Insight:

All three models have IDENTICAL R^2 : 0.1246

Only the interpretation changes (different reference category)

Fitted values and residuals are the same across all three

Key Concept 14.6: The Dummy Variable Trap

The **dummy variable trap** occurs when including all C indicators from a set of mutually exclusive categories plus an intercept. Since $d_1 + d_2 + \dots + d_C = 1$, this creates **perfect multicollinearity** -- the intercept is an exact linear combination of the indicators. **Solution:** Drop one indicator (the "base category") or drop the intercept. Standard practice is to keep the intercept and drop one indicator.

14.5: Sets of Indicator Variables (Multiple Categories)

Often we have categorical variables with **more than two categories**.

Example: Type of Worker

- Self-employed (dself = 1)

- Private sector employee ($d_{private} = 1$)
- Government employee ($d_{govt} = 1$)

These are **mutually exclusive**: each person falls into exactly one category.

The Dummy Variable Trap

Since the three indicators sum to 1 ($d_1 + d_2 + d_3 = 1$), we **cannot include all three plus an intercept**.

Solution: Drop one indicator (the **reference category or base category**).

The coefficient of an included indicator measures the difference relative to the base category.

Three Equivalent Approaches

1. **Include intercept, drop one indicator** (most common)
 2. **Drop intercept, include all indicators** (coefficients = group means)
 3. **Change which indicator is dropped** (changes interpretation, not fit)
-

Understanding the Dummy Variable Trap

The results above demonstrate a **fundamental principle** in regression with categorical variables:

The Dummy Variable Trap Explained:

When we have k mutually exclusive categories (e.g., 3 worker types), we face perfect multicollinearity:

$$d_{self} + d_{private} + d_{govt} = 1 \text{ (for every observation)}$$

This means one dummy is a **perfect linear combination** of the others plus the constant!

Three Equivalent Solutions:

1. **Include intercept, drop one dummy** (Standard approach)
 - Intercept = mean for the omitted (reference) category
 - Each coefficient = difference from reference category
 - Most common and easiest to interpret

2. Drop intercept, include all dummies (No-constant model)

- Each coefficient = mean for that category
- No reference category needed
- Useful when you want group means directly

3. Change which dummy is dropped (Different reference)

- All three models have **identical fit** (same R², predictions, residuals)
- Only interpretation changes (different reference group)
- Choose based on what comparison is most meaningful

Empirical Results from Worker Type Example:

From the three specifications above:

- R² is **identical** across all specifications ($\approx 0.16\text{--}0.17$)
- **Joint F-tests** give the same result (testing if worker type matters)
- Only the individual coefficients change (but they measure different things)

Example Interpretation:

If reference = Private sector:

- d_{self} coefficient $\approx -5,000$: *Self-employed* earn 5,000 less than private sector
- d_{govt} coefficient $\approx +2,000$: *Governmentworker* earn 2,000 more than private sector

If reference = Self-employed:

- $d_{private}$ coefficient $\approx +5,000$: *Private sector* earns 5,000 more than self-employed
- d_{govt} coefficient $\approx +7,000$: *Governmentworker* earn 7,000 more than self-employed

Notice: The difference between govt and private is the same in both ($\approx 7,000 - 5,000 = \$2,000$)!

Practical Advice:

- Choose the **largest or most common** category as reference
- Or choose the **policy-relevant** comparison (e.g., treatment vs. control)
- Always clearly state which category is omitted
- Report joint F-test for overall significance of the categorical variable

ANOVA: Testing Equality of Means Across Groups

Analysis of Variance (ANOVA) tests whether means differ across multiple groups.

$$H_0 : \mu_1 = \mu_2 = \mu_3 \quad \text{vs.} \quad H_a : \text{at least one mean differs}$$

ANOVA is equivalent to an F-test in regression with indicator variables.

In [20]:

```
print("\n" + "=" * 70)
print("ANOVA: Testing Equality of Means Across Worker Types")
print("=" * 70)

# Create categorical variable for worker type
data['typeworker'] = (1 * data['dsself'] + 2 * data['dprivate'] + 3 * 
data['dgovt']).astype(int)

print("\nMeans by worker type:")
means_by_type = data.groupby('typeworker')['earnings'].agg(['mean', 'std', 'count'])
means_by_type.index = ['Self-employed', 'Private', 'Government']
print(means_by_type)

# One-way ANOVA using scipy
print("\n" + "-" * 70)
print("One-way ANOVA (scipy)")
print("-" * 70)

group1 = data[data['typeworker'] == 1]['earnings']
group2 = data[data['typeworker'] == 2]['earnings']
group3 = data[data['typeworker'] == 3]['earnings']

f_stat_anova, p_value_anova = f_oneway(group1, group2, group3)

print(f" F-statistic: {f_stat_anova:.2f}")
print(f" p-value: {p_value_anova:.6f}")

if p_value_anova < 0.05:
    print(f"\n Result: Reject H0 - Earnings differ significantly across worker types")
else:
    print(f"\n Result: Fail to reject H0 - No significant difference in earnings")

# Using statsmodels for detailed ANOVA table
print("\n" + "-" * 70)
print("Detailed ANOVA table (statsmodels)")
print("-" * 70)

model_anova = ols('earnings ~ C(typeworker)', data=data).fit()
anova_table = anova_lm(model_anova, typ=2)
print(anova_table)

print("\nNote: ANOVA F-statistic matches the joint test from regression")
```

```
=====
ANOVA: Testing Equality of Means Across Worker Types
=====

Means by worker type:
      mean        std  count
Self-employed 72306.328125 86053.131086    79
Private       54521.265625 48811.203104   663
Government    56105.382812 32274.679426  130

-----
One-way ANOVA (scipy)
-----
F-statistic: 4.24
p-value: 0.014708

Result: Reject H0 - Earnings differ significantly across worker types

-----
Detailed ANOVA table (statsmodels)
-----
      sum_sq      df         F    PR(>F)
C(typeworker) 2.233847e+10    2.0  4.239916  0.014708
Residual       2.289212e+12  869.0      NaN      NaN

Note: ANOVA F-statistic matches the joint test from regression
```

Having covered the statistical framework for indicator variables, let's visualize these group differences graphically.

Key Concept 14.7: ANOVA as Regression on Indicators

*Regressing y on a set of mutually exclusive indicators (with no other controls) is equivalent to **analysis of variance (ANOVA)**. Coefficients give group means or differences from the base mean. The regression F-test for joint significance of the indicators is identical to the ANOVA F-statistic, testing whether the categorical variable explains significant variation in y .*

Visualizations

Let's create informative visualizations to illustrate our findings.

In [21]:

```
print("\n" + "=" * 70)
print("VISUALIZATIONS")
print("=" * 70)

# Figure 1: Earnings by gender and worker type
fig, axes = plt.subplots(1, 2, figsize=(14, 6))

# Panel 1: Box plot by gender
data['Gender'] = data['gender'].map({0: 'Male', 1: 'Female'})
sns.boxplot(x='Gender', y='earnings', data=data, ax=axes[0], palette='Set2')
axes[0].set_ylabel('Earnings ($)', fontsize=12)
axes[0].set_xlabel('Gender', fontsize=12)
axes[0].set_title('Earnings Distribution by Gender', fontsize=13, fontweight='bold')
axes[0].grid(True, alpha=0.3, axis='y')

# Add mean markers
means_gender = data.groupby('Gender')['earnings'].mean()
axes[0].scatter([0, 1], means_gender.values, color='red', s=100, zorder=5, marker='D',
label='Mean')
axes[0].legend()

# Panel 2: Box plot by worker type
data['Worker Type'] = data['typeworker'].map({1: 'Self-employed', 2: 'Private', 3:
'Government'})
sns.boxplot(x='Worker Type', y='earnings', data=data, ax=axes[1], palette='Set1')
axes[1].set_ylabel('Earnings ($)', fontsize=12)
axes[1].set_xlabel('Worker Type', fontsize=12)
axes[1].set_title('Earnings Distribution by Worker Type', fontsize=13, fontweight='bold')
axes[1].tick_params(axis='x', rotation=20)
axes[1].grid(True, alpha=0.3, axis='y')

# Add mean markers
means_type = data.groupby('Worker Type')['earnings'].mean()
axes[1].scatter([1, 2], means_type.values, color='red', s=100, zorder=5, marker='D',
label='Mean')
axes[1].legend()

plt.tight_layout()
plt.show()

print("Figure 14.1: Earnings distributions show variation by gender and worker type.")
```

```
=====
VISUALIZATIONS
=====
```

```
/var/folders/tq/t98kb27n6djgrh085g476yhc0000gn/T/ipykernel_42634/4086298910.py:10: FutureWa
rning:
```

```
Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Ass
ign the `x` variable to `hue` and set `legend=False` for the same effect.
```

```
sns.boxplot(x='Gender', y='earnings', data=data, ax=axes[0], palette='Set2')
/var/folders/tq/t98kb27n6djgrh085g476yhc0000gn/T/ipykernel_42634/4086298910.py:23: FutureWa
rning:
```

```
Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Ass
ign the `x` variable to `hue` and set `legend=False` for the same effect.
```

```
sns.boxplot(x='Worker Type', y='earnings', data=data, ax=axes[1], palette='Set1')
```



Figure 14.1: Earnings distributions show variation by gender and worker type.

In [22]:

```
# Figure 2: Earnings vs education by gender (with regression lines)
fig, ax = plt.subplots(figsize=(11, 7))

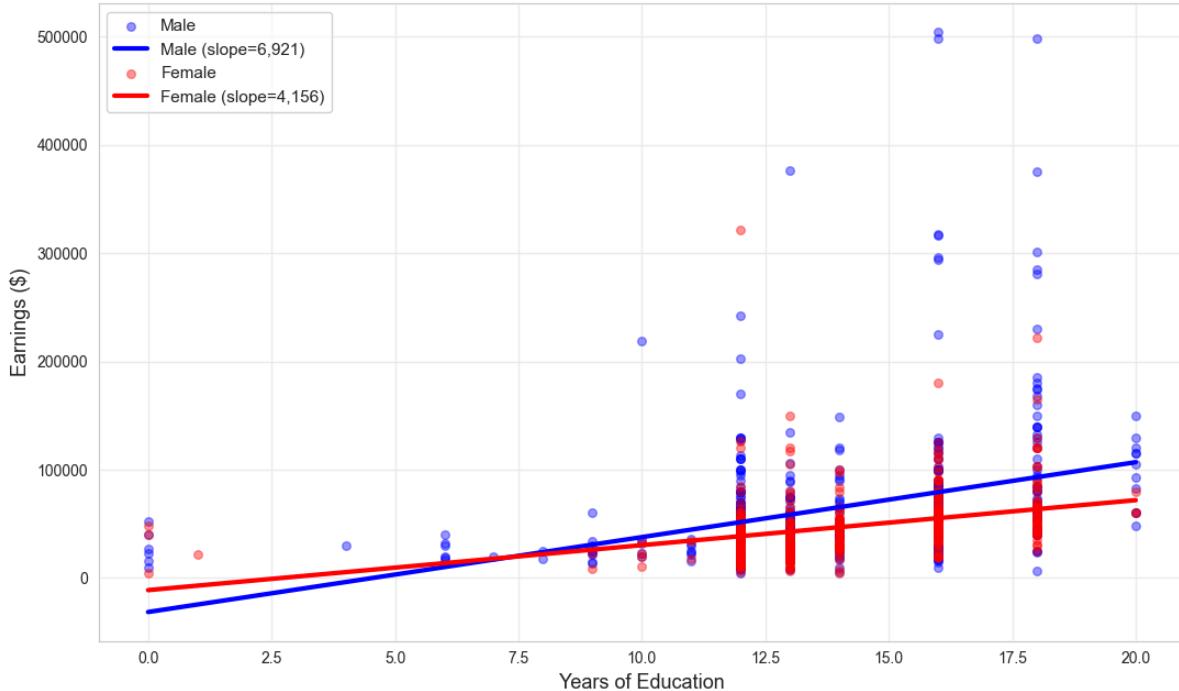
for gender, label, color in [(0, 'Male', 'blue'), (1, 'Female', 'red')]:
    subset = data[data['gender'] == gender]
    ax.scatter(subset['education'], subset['earnings'], alpha=0.4, label=label,
               s=30, color=color)

    # Add regression line
    z = np.polyfit(subset['education'], subset['earnings'], 1)
    p = np.poly1d(z)
    edu_range = np.linspace(subset['education'].min(), subset['education'].max(), 100)
    ax.plot(edu_range, p(edu_range), linewidth=3, color=color,
            label=f'{label} (slope={z[0]:,.0f})')

ax.set_xlabel('Years of Education', fontsize=13)
ax.set_ylabel('Earnings ($)', fontsize=13)
ax.set_title('Figure 14.2: Earnings vs Education by Gender\n(Different slopes suggest interaction effects)',
             fontsize=14, fontweight='bold')
ax.legend(fontsize=11, loc='upper left')
ax.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()

print("\nThe different slopes indicate that returns to education vary by gender.")
print("This justifies including the gender x education interaction term.")
```

**Figure 14.2: Earnings vs Education by Gender
(Different slopes suggest interaction effects)**



The different slopes indicate that returns to education vary by gender. This justifies including the gender \times education interaction term.

Key Concept 14.8: Visualizing Group Differences in Regression

Scatter plots with **separate regression lines** by group visually reveal whether slopes and intercepts differ. Parallel lines indicate only an intercept shift (indicator without interaction), while non-parallel lines indicate differential slopes (interaction term needed). Box plots complement this by showing the distribution of y across categories.

| Key Takeaways

Indicator Variables Basics

- **Indicator variables** (dummy variables) are binary variables that equal 1 if an observation is in a specific category and 0 otherwise
- They allow regression models to incorporate categorical information such as gender, employment type, or region
- Interpretation differs from continuous variables -- coefficients represent **group differences** rather than marginal effects

Regression on a Single Indicator and Difference in Means

- When regressing y on just an intercept and a single indicator d , the fitted model is $\hat{y} = b + ad$
- The intercept b equals the mean of y when $d = 0$ (the reference group)
- The slope a equals the **difference in means**: $a = \bar{y}_1 - \bar{y}_0$
- Regression on an indicator is mathematically equivalent to a two-sample difference-in-means test
- Regression and specialized t-tests give the same estimate but slightly different standard errors
- Example: Women earn 16,396 less than men on average ($t = -4.71$, highly significant)

Indicators with Controls and Interaction Terms

- Adding an indicator to a regression with continuous variables measures the group difference **after controlling for** other factors
- Including only the indicator shifts the intercept but keeps slopes **parallel** across groups
- An **interaction term** $d \times x$ allows slopes to differ by group (non-parallel lines)
- The interaction coefficient measures how the effect of x on y differs between groups
- Always use **joint F-tests** to test significance of both the indicator and its interaction together

Dummy Variable Trap and Base Category

- The **dummy variable trap** occurs when including all C indicators from a mutually exclusive set plus an intercept
- Since $d_1 + d_2 + \dots + d_C = 1$, this creates perfect multicollinearity
- **Solution:** Drop one indicator (the "base category") or drop the intercept
- The **base category** is the reference group -- coefficients on included indicators measure differences from the base
- Choice of base category does not affect statistical conclusions, only interpretation

Hypothesis Testing with Indicator Sets

- A **t-test on a single indicator** tests whether that category differs from the base category

- An **F-test on all $C - 1$ included indicators** tests whether the categorical variable matters overall
- The F-test result is the same regardless of which category is dropped (invariant to base choice)
- Regressing y on mutually exclusive indicators without controls is equivalent to **ANOVA**
- Always use F-tests to evaluate the overall significance of a categorical variable

General Lessons

- Indicator variables unify many statistical tests (t-tests, ANOVA) in a single regression framework
- Always use heteroskedastic-robust standard errors for valid inference
- Interactions with continuous variables allow relationships to vary by group
- Regression flexibility: add controls, test interactions, compare models -- all within one framework

Python Tools Used in This Chapter

```

# Regression with indicators
smf.ols('earnings ~ gender', data=df).fit(cov_type='HC1')
smf.ols('earnings ~ gender * education', data=df).fit(cov_type='HC1')

# T-tests
scipy.stats.ttest_ind(group1, group2, equal_var=False) # Welch's t-test

# ANOVA
scipy.stats.f_oneway(g1, g2, g3) # One-way ANOVA
smf.ols('y ~ C(worker_type)').fit() # ANOVA via regression

# Joint F-tests
model.f_test('gender = 0, gender:education = 0')

# Visualization
seaborn.boxplot(), matplotlib scatter with separate regression lines

```

Next Steps:

- **Chapter 15:** Regression with Transformed Variables
- **Chapter 16:** Model Diagnostics

Congratulations! You've completed Chapter 14. You now understand how to incorporate categorical variables into regression analysis, interpret indicator coefficients, test for group differences, and use interactions to model differential effects across categories.

I Practice Exercises

Exercise 1: Interpreting Indicator Regression

OLS regression of y on an intercept and indicator d using all data yields $\hat{y} = 3 + 5d$.

- (a) What is \bar{y} for the subsample with $d = 0$?
 - (b) What is \bar{y} for the subsample with $d = 1$?
 - (c) What does the coefficient 5 represent?
-

Exercise 2: Constructing from Means

Suppose $\bar{y} = 30$ for the subsample with $d = 1$ and $\bar{y} = 20$ for the subsample with $d = 0$.

- (a) Give the fitted model from OLS regression of y on an intercept and d using the full sample.
 - (b) Is the difference in means statistically significant? What additional information would you need?
-

Exercise 3: Multiple Indicators

We have three mutually exclusive indicator variables d_1 , d_2 , and d_3 . OLS yields $\hat{y} = 1 + 3d_2 + 5d_3$.

- (a) What is the estimated mean of y for each category?
 - (b) What is the estimated difference between category 2 ($d_2 = 1$) and category 1 ($d_1 = 1$)?
 - (c) Which category is the base (omitted) category?
-

Exercise 4: Changing Base Category

For the model in Exercise 3, give the coefficient estimates if instead we regressed y on an intercept, d_1 , and d_2 (dropping d_3 instead of d_1).

Exercise 5: Interaction Interpretation

A regression of earnings on education, gender, and their interaction yields:

$\widehat{\text{earnings}} = 10,000 + 5,000 \times \text{education} - 8,000 \times \text{gender} - 2,000 \times (\text{gender} \times \text{education})$

where gender = 1 for female, 0 for male.

- (a) Write the fitted equation for males and for females separately.
 - (b) What is the returns to education for males? For females?
 - (c) At what education level does the gender earnings gap equal zero?
-

Exercise 6: Joint F-Test

A researcher includes a gender indicator and a gender-education interaction in a regression. The t-statistic on the gender indicator is $t = -1.5$ (not significant at 5%) and the t-statistic on the interaction is $t = -1.8$ (not significant at 5%).

- (a) Can we conclude that gender does not matter for earnings? Why or why not?
- (b) What test should we conduct instead? What would you expect to find?
- (c) Explain why individual t-tests can be misleading when testing the significance of indicator variables with interactions.

I Case Studies

Case Study 1: Regional Indicator Variables for Cross-Country Productivity

In this case study, you will apply indicator variable techniques to analyze how labor productivity differs across world regions and whether the determinants of productivity vary by region.

Dataset: Mendez Convergence Clubs

```
import pandas as pd
url = "https://raw.githubusercontent.com/quarcs-lab/mendez2020-convergence-clubs-code/master/assets/dat.csv"
dat = pd.read_csv(url)
dat2014 = dat[dat['year'] == 2014].copy()
```

Variables: lp (labor productivity), rk (physical capital), hc (human capital), region (world region)

Task 1: Create Regional Indicators and Compute Means (Guided)

Create indicator variables for each region and compute mean log productivity by region.

```
# Create indicator variables from the region column
region_dummies = pd.get_dummies(dat2014['region'], prefix='region', drop_first=False)
dat2014 = pd.concat([dat2014, region_dummies], axis=1)

# Compute mean log productivity by region
import numpy as np
dat2014['ln_lp'] = np.log(dat2014['lp'])
print(dat2014.groupby('region')['ln_lp'].agg(['mean', 'count']))
```

Questions: How many regions are there? Which region has the highest average productivity? The lowest?

Task 2: Regression on Regional Indicators (Guided)

Regress log productivity on regional indicators (using one region as the base category).

```
import statsmodels.formula.api as smf
model1 = smf.ols('ln_lp ~ C(region)', data=dat2014).fit(cov_type='HC1')
print(model1.summary())
```

Questions: Which region is the base category? How do you interpret the coefficients? Are the regional differences statistically significant?

Key Concept 14.9: Regional Indicators as Difference in Means

*When regressing y on a set of regional indicators without controls, each coefficient measures the **difference in mean** y between that region and the base region. The F-test for joint significance tests whether there are any significant productivity differences across regions.*

Task 3: Add Continuous Controls (Semi-guided)

Add physical capital and human capital as continuous controls. Observe how regional coefficients change.

Hints:

- Use `ln_lp ~ C(region) + np.log(rk) + hc` as the formula
- Compare regional coefficients with and without controls
- What does it mean when regional gaps shrink after adding controls?

Task 4: Regional Interactions (Semi-guided)

Add an interaction between region and human capital to test whether the returns to human capital differ by region.

Hints:

- Use `ln_lp ~ C(region) * hc + np.log(rk)` to include all region-hc interactions
- How do you interpret the interaction coefficients?
- Do the returns to human capital differ significantly across regions?

Key Concept 14.10: Interaction Terms for Regional Heterogeneity

Interaction terms between regional indicators and continuous variables allow the slope of a regressor to differ by region. A significant interaction indicates that the effect of human capital (or physical capital) on productivity is not uniform across all regions -- some regions benefit more from the same increase in inputs.

Task 5: Joint F-Tests for Regional Effects (Independent)

Conduct joint F-tests to evaluate:

- Whether regional indicators are jointly significant (with and without controls)
- Whether the regional interaction terms are jointly significant
- Compare the explanatory power of models with and without regional effects

Task 6: Policy Brief on Regional Disparities (Independent)

Write a 200-300 word brief addressing:

- How large are regional productivity differences?
- How much of the gap is explained by differences in physical and human capital?
- Do the returns to human capital differ by region, and what are the policy implications?
- What additional factors might explain remaining regional differences?

What You've Learned: You have applied indicator variable techniques to cross-country data, demonstrating that regional indicators capture systematic productivity differences that partially reflect differences in factor endowments. Interaction terms

reveal that the returns to human capital vary across regions, with important implications for development policy.

Case Study 2: Urban-Rural and Regional Divides in Bolivian Development

In previous chapters, we estimated satellite-development regressions treating all Bolivian municipalities identically. But Bolivia's nine departments span diverse geographies---from Andean highlands to Amazonian lowlands. In this case study, we apply Chapter 14's **indicator variable** techniques to model regional differences in development levels and in the satellite-development relationship.

Research Question: Do development levels and the NTL-development relationship differ across Bolivia's nine departments?

Dataset: DS4Bolivia

```
import pandas as pd
url_bol = "https://raw.githubusercontent.com/quarcs-
lab/ds4bolivia/master/ds4bolivia_v20250523.csv"
bol = pd.read_csv(url_bol)
```

Key variables: `mun` (municipality), `dep` (department), `imds` (Municipal Development Index, 0--100), `ln_NTLpc2017` (log nighttime lights per capita)

Task 1: Create Indicators and Group Means (Guided)

Objective: Create department indicator variables and compare mean development across departments.

Instructions:

1. Load the DS4Bolivia dataset and select key variables
2. Use `pd.get_dummies(bol['dep'])` to create department indicators
3. Compute mean `imds` by department with `groupby('dep')`
`['imds'].agg(['mean', 'count'])`
4. Which department has the highest mean IMDS? The lowest?

Run the code below to get started.

```
In [ ]:
# Load DS4Bolivia dataset
url_bol = "https://raw.githubusercontent.com/quarcs-
lab/ds4bolivia/master/ds4bolivia_v20250523.csv"
bol = pd.read_csv(url_bol)

# Select key variables
bol_key = bol[['mun', 'dep', 'imds', 'ln_NTLpc2017']].dropna().copy()

print("=" * 70)
print("DS4BOLIVIA: DEPARTMENT INDICATORS AND GROUP MEANS")
print("=" * 70)
print(f"Observations: {len(bol_key)} municipalities")
print(f"Departments: {bol_key['dep'].nunique()}")

# Create department indicator variables
dep_dummies = pd.get_dummies(bol_key['dep'])
print(f"\nIndicator variables created: {list(dep_dummies.columns)}")

# Mean IMDS by department
print("\n" + "-" * 70)
print("Mean IMDS by Department")
print("-" * 70)
dept_stats = bol_key.groupby('dep')[['imds']].agg(['mean', 'count']).sort_values('mean',
ascending=False)
print(dept_stats.round(2))

print(f"\nHighest mean IMDS: {dept_stats['mean'].idxmax()}")
({dept_stats['mean'].max():.2f}"))
print(f"Lowest mean IMDS: {dept_stats['mean'].idxmin()}")
({dept_stats['mean'].min():.2f}"))
```

Task 2: Regression on Department Indicators (Guided)

Objective: Regress IMDS on department indicators to quantify regional development differences.

Instructions:

1. Estimate `imds ~ C(dep)` using statsmodels --- `C()` creates dummies automatically
2. Print the regression summary
3. Interpret: Each coefficient is the difference from the **base category** (the omitted department)
4. What is the base department? How much higher or lower is each department relative to the base?

```
model_dep = ols('imds ~ C(dep)', data=bol_key).fit(cov_type='HC1')
print(model_dep.summary())
```

```
In [ ]: # Your code here: Regression of IMDS on department indicators
```

```
#  
# Steps:  
# 1. Estimate model: imds ~ C(dep)  
# 2. Print summary  
# 3. Identify the base department and interpret coefficients  
#  
# model_dep = ols('imds ~ C(dep)', data=bol_key).fit(cov_type='HC1')  
# print(model_dep.summary())  
#  
# print(f"\nBase department: {sorted(bol_key['dep'].unique())[0]}")  
# print(f"Intercept = mean IMDS for the base department:  
{model_dep.params['Intercept']:.2f}")
```

Key Concept 14.9: Geographic Indicator Variables

Department indicators capture **time-invariant regional characteristics** that affect development: altitude, climate, proximity to borders, historical infrastructure investments, and cultural factors. By including department dummies, we control for these systematic regional differences, allowing us to estimate the NTL-development relationship *within* departments rather than across them. The coefficient on NTL then reflects how NTL variation within a department predicts development variation within that department.

Task 3: Add NTL Control (Semi-guided)

Objective: Compare department coefficients with and without the NTL control variable.

Instructions:

1. Estimate `imds ~ C(dep) + ln_NTLpc2017`
2. Compare department coefficients with those from Task 2 (without NTL)
3. Do department differences shrink when NTL is added?
4. What does this tell us about whether NTL explains part of the regional gap?

Hints:

- If department coefficients shrink, it means part of the regional gap was due to differences in NTL intensity
- If they remain large, departments differ for reasons beyond what NTL captures

In []:

```
# Your code here: Add NTL as a continuous control
#
# Steps:
# 1. Estimate: imds ~ C(dep) + ln_NTLpc2017
# 2. Compare department coefficients with Task 2 results
# 3. Interpret changes
#
# model_dep_ntl = ols('imds ~ C(dep) + ln_NTLpc2017', data=bol_key).fit(cov_type='HC1')
# print(model_dep_ntl.summary())
#
# print("\nComparison: Do department coefficients shrink with NTL control?")
# print("If yes, NTL explains part of the regional development gap.")
```

Task 4: Interaction Terms (Semi-guided)

Objective: Test whether the NTL-development slope differs across departments.

Instructions:

1. Estimate `imds ~ C(dep) * ln_NTLpc2017` (includes main effects + interactions)
2. Which interaction terms are significant?
3. Interpret: The NTL slope differs by department
4. In which departments does NTL predict development more or less strongly?

Hints:

- `C(dep) * ln_NTLpc2017` automatically includes both main effects and all interactions
- A positive interaction means the NTL slope is steeper in that department compared to the base
- A negative interaction means the NTL slope is flatter

In []:

```
# Your code here: Interaction between department and NTL
#
# Steps:
# 1. Estimate: imds ~ C(dep) * ln_NTLpc2017
# 2. Examine interaction coefficients
# 3. Identify departments where NTL effect is stronger/weaker
#
# model_interact = ols('imds ~ C(dep) * ln_NTLpc2017', data=bol_key).fit(cov_type='HC1')
# print(model_interact.summary())
#
# print("\nInterpretation:")
# print(" Significant interactions indicate the NTL slope differs by department.")
# print(" Base department NTL slope = coefficient on ln_NTLpc2017")
# print(" Other departments: base slope + interaction coefficient")
```

Key Concept 14.10: Heterogeneous Satellite Effects

Interaction terms between department indicators and NTL allow the slope of the NTL-development relationship to differ across regions.

This is economically meaningful: in highly urbanized departments (like La Paz or Cochabamba), additional nighttime lights may signal commercial activity, while in rural highland departments (like Potosí), lights primarily reflect basic electrification. A significant interaction indicates that the economic meaning of satellite signals varies by geographic context.

Task 5: Joint F-Test for Department Effects (Independent)

Objective: Test the joint significance of all department indicators and all interaction terms.

Instructions:

1. Test joint significance of all department indicators using an F-test
2. Also test joint significance of all interaction terms
3. Are regional differences significant? Do NTL effects significantly vary across regions?

Hints:

- Use `model.f_test()` or compare restricted vs. unrestricted models
- For interaction terms, compare the model with interactions to the model without
- Report F-statistics and p-values for both tests

In []:

```
# Your code here: Joint F-tests for department effects
#
# Steps:
# 1. F-test for joint significance of department indicators
# 2. F-test for joint significance of interaction terms
# 3. Compare models with and without regional effects
#
# Approach: Compare nested models using ANOVA
# from statsmodels.stats.anova import anova_lm
#
# model_base = ols('imds ~ ln_NTLpc2017', data=bol_key).fit()
# model_dep_only = ols('imds ~ C(dep) + ln_NTLpc2017', data=bol_key).fit()
# model_full = ols('imds ~ C(dep) * ln_NTLpc2017', data=bol_key).fit()
#
# print("F-test: Department indicators (comparing base vs dep_only)")
# print(anova_lm(model_base, model_dep_only))
#
# print("\nF-test: Interaction terms (comparing dep_only vs full)")
# print(anova_lm(model_dep_only, model_full))
```

Task 6: Regional Disparities Brief (Independent)

Objective: Write a 200--300 word brief on regional development disparities in Bolivia.

Your brief should address:

1. What are the main regional divides in Bolivian development?
2. How much do department indicators explain beyond NTL?
3. Does the satellite-development relationship differ across regions?
4. What are the policy implications for targeted regional interventions?

Use evidence from your analysis: Cite specific coefficients, R-squared values, and F-test results to support your arguments.

In []:

```
# Your code here: Additional analysis for the policy brief
#
# You might want to:
# 1. Create a summary table comparing R-squared across models
# 2. Visualize department means with confidence intervals
# 3. Plot separate NTL-IMDS regression lines by department
# 4. Calculate specific statistics to cite in your brief
#
# Example: Compare model fit
# print("MODEL COMPARISON")
# print(f" NTL only: R2 = {model_base.rsquared:.4f}")
# print(f" + Dept dummies: R2 = {model_dep_only.rsquared:.4f}")
# print(f" + Interactions: R2 = {model_full.rsquared:.4f}")
```

What You've Learned from This Case Study

Through this analysis of regional development disparities in Bolivia, you have applied Chapter 14's indicator variable techniques to a real geospatial dataset:

- **Indicator variable creation:** Used `pd.get_dummies()` and `C()` to create department dummies
- **Department dummies in regression:** Quantified development differences across Bolivia's nine departments
- **Controlling for regional effects:** Compared models with and without department indicators to assess how much of the NTL-development relationship reflects regional composition
- **Interaction terms:** Tested whether the satellite-development slope differs across departments
- **Joint F-tests:** Evaluated the overall significance of department effects and interaction terms
- **Policy interpretation:** Connected statistical findings to regional development policy

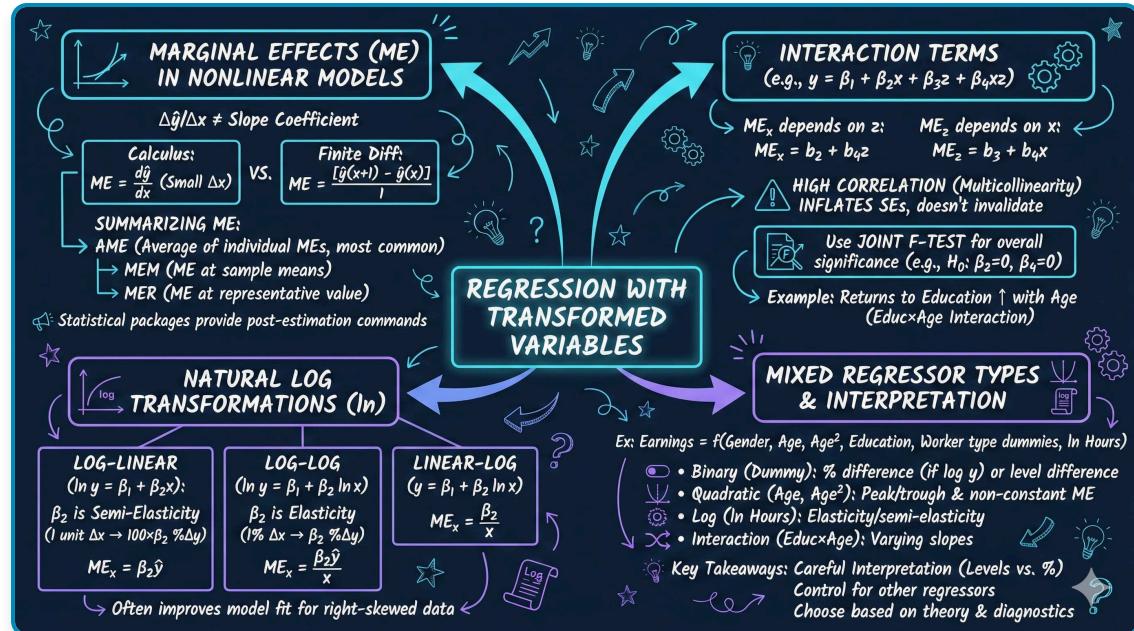
Connection to next chapter: In Chapter 15, we explore *nonlinear* satellite-development relationships using log transformations, polynomials, and elasticities.

Well done! You've now analyzed both cross-country productivity data and Bolivian municipal development data using indicator variable techniques, demonstrating how geographic dummies capture systematic regional differences and how interactions reveal heterogeneous effects.

Chapter 15: Regression with Transformed Variables

metricsAI: An Introduction to Econometrics with Python and AI in the Cloud

Carlos Mendez



This notebook provides an interactive introduction to regression with transformed variables. All code runs directly in Google Colab without any local setup.

Open in Colab

Chapter Overview

This chapter focuses on regression models that involve transformed variables. Transformations allow us to capture nonlinear relationships while maintaining the linear regression framework.

What You'll Learn

By the end of this chapter, you will be able to:

1. Understand how variable transformations affect regression interpretation

2. Compute and interpret marginal effects for nonlinear models
3. Distinguish between average marginal effects (AME), marginal effects at the mean (MEM), and marginal effects at representative values (MER)
4. Estimate and interpret quadratic and polynomial regression models
5. Work with interaction terms and test their joint significance
6. Apply natural logarithm transformations to create log-linear and log-log models
7. Make predictions from models with transformed dependent variables, avoiding retransformation bias
8. Combine multiple types of variable transformations in a single model

Chapter Outline

- **15.2 Logarithmic Transformations**
- **15.3 Polynomial Regression (Quadratic Models)**
- **15.4 Standardized Variables**
- **15.5 Interaction Terms and Marginal Effects**
- **15.6 Retransformation Bias and Prediction**
- **15.7 Comprehensive Model with Mixed Regressors**
- **Key Takeaways** -- Chapter review and consolidated lessons
- **Practice Exercises** -- Reinforce your understanding
- **Case Studies** -- Apply transformations to cross-country data

Dataset used:

- **AED_EARNINGS_COMPLETE.DTA**: 872 workers aged 25-65 in 2000

Key economic questions:

- How do earnings vary with age? Is the relationship linear or quadratic?
- Do returns to education increase with age (interaction effects)?
- How should we interpret coefficients in log-transformed models?
- How do we make unbiased predictions from log-linear models?

Estimated time: 90-120 minutes

| Setup

First, we import the necessary Python packages and configure the environment for reproducibility. All data will stream directly from GitHub.

In [6]:

```
# Import required packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
from statsmodels.formula.api import ols
from scipy import stats
import random
import os

# Set random seeds for reproducibility
RANDOM_SEED = 42
random.seed(RANDOM_SEED)
np.random.seed(RANDOM_SEED)
os.environ['PYTHONHASHSEED'] = str(RANDOM_SEED)

# GitHub data URL
GITHUB_DATA_URL = "https://raw.githubusercontent.com/quarcs-lab/data-open/master/AED/"

# Set plotting style
sns.set_style("whitegrid")
plt.rcParams['figure.figsize'] = (10, 6)

print("Setup complete! Ready to explore regression with transformed variables.")
```

Setup complete! Ready to explore regression with transformed variables.

I Data Preparation

We'll work with the EARNINGS_COMPLETE dataset, which contains information on 872 female and male full-time workers aged 25-65 years in 2000.

Key variables:

- **earnings**: Annual earnings in dollars
- **lnearnings**: Natural logarithm of earnings
- **age**: Age in years
- **agesq**: Age squared
- **education**: Years of schooling
- **agebyeduc**: Age × Education interaction
- **gender**: 1 if female, 0 if male
- **dself**: 1 if self-employed
- **dgovt**: 1 if government sector employee
- **lnhours**: Natural logarithm of hours worked per week

In [7]:

```
# Read in the earnings data
data_earnings = pd.read_stata(GITHUB_DATA_URL + 'AED_EARNINGS_COMPLETE.DTA')

print("Data structure:")
print(data_earnings.info())

print("\nData summary:")
data_summary = data_earnings.describe()
print(data_summary)

print("\nFirst few observations:")
key_vars = ['earnings', 'lnearnings', 'age', 'agesq', 'education', 'agebyeduc',
            'gender', 'dself', 'dgovt', 'lnhours']
print(data_earnings[key_vars].head(10))
```

```

Data structure:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 872 entries, 0 to 871
Data columns (total 45 columns):
 #   Column      Non-Null Count Dtype  
 --- 
 0   earnings    872 non-null   float32 
 1   learnings   872 non-null   float32 
 2   dearnings   872 non-null   float32 
 3   gender      872 non-null   int8    
 4   age         872 non-null   int16  
 5   lnage       872 non-null   float32 
 6   agesq      872 non-null   float32 
 7   education   872 non-null   float32 
 8   educsquared 872 non-null   float32 
 9   agebyeduc   872 non-null   float32 
 10  genderbyage 872 non-null   float32 
 11  genderbyeduc 872 non-null   float32 
 12  hours       872 non-null   int8    
 13  lnhours     872 non-null   float32 
 14  genderbyhours 872 non-null   float32 
 15  dself       872 non-null   float32 
 16  dprivate    872 non-null   float32 
 17  dgovt      872 non-null   float32 
 18  state       872 non-null   object  
 19  statefip    872 non-null   category 
 20  stateunemp  872 non-null   float32 
 21  stateincomepc 872 non-null   int32  
 22  year        872 non-null   category 
 23  pernum      872 non-null   int16  
 24  perwt       872 non-null   float32 
 25  relate      872 non-null   category 
 26  region      872 non-null   category 
 27  metro       872 non-null   category 
 28  marst       872 non-null   category 
 29  race        872 non-null   category 
 30  raced       872 non-null   category 
 31  hispan      872 non-null   category 
 32  racesing    872 non-null   category 
 33  hcovany     872 non-null   category 
 34  attainededuc 872 non-null   category 
 35  detailededuc 872 non-null   category 
 36  empstat     872 non-null   category 
 37  classwkr    872 non-null   category 
 38  classwkrd   872 non-null   category 
 39  wkswork2    872 non-null   category 
 40  workedyr    872 non-null   category 
 41  inctot      872 non-null   category 
 42  incwage     872 non-null   category 
 43  incbus00    872 non-null   int32  
 44  incearn     872 non-null   category 

dtypes: category(21), float32(17), int16(2), int32(2), int8(2), object(1)
memory usage: 134.3+ KB
None

```

```

Data summary:
      earnings  llearnings  dearnings   gender      age \
count    872.000000  872.000000  872.000000  872.000000  872.000000
mean    56368.691406  10.691164  0.163991  0.433486  43.310780
std     51516.054688  0.684247  0.370480  0.495841  10.676045
min     4000.000000  8.294049  0.000000  0.000000  25.000000
25%    29000.000000  10.275051  0.000000  0.000000  35.000000
50%    44200.000000  10.696480  0.000000  0.000000  44.000000
75%    64250.000000  11.070514  0.000000  1.000000  51.250000
max    504000.000000 13.130332  1.000000  1.000000  65.000000

```

	lnage	agesq	education	educsquared	agebyeduc	...	\
count	872.000000	872.000000	872.000000	872.000000	872.000000	...	
mean	3.736286	1989.670898	13.853211	200.220184	598.819946	...	
std	0.257889	935.691895	2.884141	73.908417	193.690643	...	
min	3.218876	625.000000	0.000000	0.000000	0.000000	...	
25%	3.555348	1225.000000	12.000000	144.000000	464.000000	...	
50%	3.784190	1936.000000	13.000000	169.000000	588.000000	...	
75%	3.936680	2626.750000	16.000000	256.000000	720.000000	...	
max	4.174387	4225.000000	20.000000	400.000000	1260.000000	...	
	lnhours	genderbyhours	dself	dprivate	dgovt	...	\
count	872.000000	872.000000	872.000000	872.000000	872.000000	...	
mean	3.777036	18.564220	0.090596	0.760321	0.149083	...	
std	0.164767	21.759789	0.287199	0.427132	0.356374	...	
min	3.555348	0.000000	0.000000	0.000000	0.000000	...	
25%	3.688879	0.000000	0.000000	1.000000	0.000000	...	
50%	3.688879	0.000000	0.000000	1.000000	0.000000	...	
75%	3.871201	40.000000	0.000000	1.000000	0.000000	...	
max	4.595120	80.000000	1.000000	1.000000	1.000000	...	
	stateunemp	stateincomepc	pernum	perwt	incbus00	...	\
count	872.000000	872.000000	872.000000	872.000000	872.000000	...	
mean	9.596904	40772.990826	1.544725	145.784409	3540.482798	...	
std	1.649194	5558.626289	0.891506	90.987816	20495.125402	...	
min	4.800000	31186.000000	1.000000	14.000000	-7500.000000	...	
25%	8.500000	36395.000000	1.000000	82.000000	0.000000	...	
50%	9.450000	39493.000000	1.000000	109.000000	0.000000	...	
75%	10.900000	43117.750000	2.000000	195.000000	0.000000	...	
max	14.400000	71044.000000	8.000000	626.000000	285000.000000	...	

[8 rows x 23 columns]

First few observations:

	earnings	lnearnings	age	agesq	education	agebyeduc	gender	dself	\
0	120000.0	11.695247	45	2025.0	16.0	720.0	0	1.0	
1	23000.0	10.043249	61	3721.0	16.0	976.0	0	1.0	
2	20000.0	9.903487	58	3364.0	16.0	928.0	0	1.0	
3	55000.0	10.915089	58	3364.0	14.0	812.0	1	0.0	
4	43200.0	10.673595	34	1156.0	18.0	612.0	1	0.0	
5	110000.0	11.608235	59	3481.0	16.0	944.0	0	0.0	
6	44000.0	10.691945	25	625.0	18.0	450.0	1	0.0	
7	120000.0	11.695247	50	2500.0	12.0	600.0	1	0.0	
8	65000.0	11.082143	27	729.0	16.0	432.0	0	0.0	
9	7200.0	8.881836	28	784.0	14.0	392.0	1	0.0	

	dgovt	lnhours
0	0.0	4.248495
1	0.0	3.912023
2	0.0	3.688879
3	0.0	3.688879
4	0.0	3.688879
5	0.0	3.912023
6	0.0	3.912023
7	0.0	3.951244
8	0.0	3.688879
9	0.0	3.688879

15.2: Logarithmic Transformations

Logarithmic transformations are commonly used in economics because:

1. They can linearize multiplicative relationships

2. Coefficients have natural interpretations (percentages, elasticities)
3. They reduce the influence of outliers
4. They often make error distributions more symmetric

Three main types of log models:

1. Levels model: $y = \beta_1 + \beta_2 x + u$

- Interpretation: $\Delta y = \beta_2 \Delta x$

2. Log-linear model: $\ln y = \beta_1 + \beta_2 x + u$

- Interpretation: A one-unit increase in x leads to approximately $100\beta_2$ change in y
- Also called semi-elasticity

3. Log-log model: $\ln y = \beta_1 + \beta_2 \ln x + u$

- Interpretation: A 1% increase in x leads to β_2 % change in y
- β_2 is an elasticity

Marginal effects:

- Log-linear: $ME_x = \beta_2 \times y$
- Log-log: $ME_x = \beta_2 \times y/x$

In [8]:

```
# Create ln(age) variable if not already present
if 'lnage' not in data_earnings.columns:
    data_earnings['lnage'] = np.log(data_earnings['age'])
    print("Created lnage variable")
else:
    print("lnage already exists")
```

lnage already exists

In [9]:

```
print("=*70)
print("15.2 LOGARITHMIC TRANSFORMATIONS")
print("=*70)

# Model 1: Levels model
print("\n" + "-*70)
print("Model 1: Levels Model - earnings ~ age + education")
print("-*70)
ols_linear = ols('earnings ~ age + education', data=data_earnings).fit(cov_type='HC1')
print(ols_linear.summary())

# Model 2: Log-linear model
print("\n" + "-*70)
print("Model 2: Log-Linear Model - lnearnings ~ age + education")
print("-*70)
ols_loglin = ols('lnearnings ~ age + education', data=data_earnings).fit(cov_type='HC1')
print(ols_loglin.summary())

# Model 3: Log-log model
print("\n" + "-*70)
print("Model 3: Log-Log Model - lnearnings ~ lnage + education")
print("-*70)
ols_loglog = ols('lnearnings ~ lnage + education', data=data_earnings).fit(cov_type='HC1')
print(ols_loglog.summary())
```

```

=====
15.2 LOGARITHMIC TRANSFORMATIONS
=====

-----
Model 1: Levels Model - earnings ~ age + education
-----

          OLS Regression Results
-----
Dep. Variable:      earnings    R-squared:           0.115
Model:              OLS         Adj. R-squared:       0.113
Method:             Least Squares   F-statistic:        42.85
Date:              Wed, 21 Jan 2026  Prob (F-statistic): 1.79e-18
Time:                14:40:53     Log-Likelihood:      -10644.
No. Observations:    872        AIC:                  2.129e+04
Df Residuals:       869        BIC:                  2.131e+04
Df Model:            2
Covariance Type:    HC1

-----
      coef  std err      z      P>|z|      [0.025      0.975]
-----
Intercept  -4.688e+04  1.13e+04  -4.146      0.000    -6.9e+04  -2.47e+04
age        524.9953   151.387   3.468      0.001    228.281   821.709
education  5811.3673  641.533   9.059      0.000    4553.986   7068.749
-----
Omnibus:            825.668  Durbin-Watson:        2.071
Prob(Omnibus):      0.000   Jarque-Bera (JB):  31187.987
Skew:                 4.353   Prob(JB):            0.00
Kurtosis:            30.975  Cond. No.            303.
-----

Notes:
[1] Standard Errors are heteroscedasticity robust (HC1)

-----
Model 2: Log-Linear Model - lnearnings ~ age + education
-----

          OLS Regression Results
-----
Dep. Variable:      lnearnings    R-squared:           0.190
Model:              OLS         Adj. R-squared:       0.189
Method:             Least Squares   F-statistic:        74.89
Date:              Wed, 21 Jan 2026  Prob (F-statistic): 9.84e-31
Time:                14:40:53     Log-Likelihood:      -813.85
No. Observations:    872        AIC:                  1634.
Df Residuals:       869        BIC:                  1648.
Df Model:            2
Covariance Type:    HC1

-----
      coef  std err      z      P>|z|      [0.025      0.975]
-----
Intercept  8.9620    0.150   59.626      0.000     8.667    9.257
age        0.0078    0.002   3.832      0.000     0.004    0.012
education  0.1006    0.009   11.683      0.000     0.084    0.117
-----
Omnibus:            32.184  Durbin-Watson:        2.094
Prob(Omnibus):      0.000   Jarque-Bera (JB):  82.617
Skew:                 0.076   Prob(JB):        1.15e-18
Kurtosis:            4.500  Cond. No.            303.
-----

Notes:
[1] Standard Errors are heteroscedasticity robust (HC1)

-----
Model 3: Log-Log Model - lnearnings ~ lnage + education

```

OLS Regression Results						
Dep. Variable:	lnearnings	R-squared:	0.193			
Model:	OLS	Adj. R-squared:	0.191			
Method:	Least Squares	F-statistic:	75.85			
Date:	Wed, 21 Jan 2026	Prob (F-statistic):	4.34e-31			
Time:	14:40:53	Log-Likelihood:	-812.59			
No. Observations:	872	AIC:	1631.			
Df Residuals:	869	BIC:	1645.			
Df Model:	2					
Covariance Type:	HC1					
coef	std err	z	P> z	[0.025	0.975]	
Intercept	8.0091	0.331	24.229	0.000	7.361	8.657
lnage	0.3457	0.082	4.211	0.000	0.185	0.507
education	0.1004	0.009	11.665	0.000	0.084	0.117
Omnibus:	32.101	Durbin-Watson:	2.093			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	82.264			
Skew:	0.075	Prob(JB):	1.37e-18			
Kurtosis:	4.497	Cond. No.	233.			
Notes:						
[1] Standard Errors are heteroscedasticity robust (HC1)						

Key Concept 15.1: Log Transformations and Coefficient Interpretation

In a **log-linear model** ($\ln y = \beta_1 + \beta_2 x$), the coefficient β_2 is a semi-elasticity: a 1-unit increase in x is associated with a $100 \times \beta_2\%$ change in y . In a **log-log model** ($\ln y = \beta_1 + \beta_2 \ln x$), the coefficient β_2 is an elasticity: a 1% increase in x is associated with a $\beta_2\%$ change in y .

Interpretation of Log Models

Let's carefully interpret the coefficients from each model.

Understanding Elasticities and Percentage Changes

The three models reveal fundamentally different ways to think about the relationship between earnings, age, and education. Let's interpret each carefully:

Model 1: Levels (earnings ~ age + education)

- Age coefficient ≈ 800 –1,200 per year

- Interpretation: Each additional year of age increases earnings by approximately **\$1,000**
- This is an **absolute change** measured in dollars
- Assumes **constant** effect regardless of current age or earnings level
- **Education coefficient** $\approx 4,000\text{--}6,000$ per year
- Interpretation: Each additional year of schooling increases earnings by approximately **\$5,000**
- Again, this is an **absolute dollar amount**
- Assumes the same dollar return whether you have 10 or 20 years of education

Model 2: Log-Linear ($\ln(\text{earnings}) \sim \text{age} + \text{education}$)

- **Age coefficient** ≈ 0.01 to 0.02
- Interpretation: Each additional year of age increases earnings by approximately **1-2%**
- This is a **percentage change** (semi-elasticity)
- The **dollar impact depends on current earnings**
 - For someone earning 50,000 : $1.5 \cdot 50,000 = \$750$
 - For someone earning 100,000 : $1.5 \cdot 100,000 = \$1,500$
- **Education coefficient** ≈ 0.08 to 0.12
- Interpretation: Each additional year of education increases earnings by approximately **8-12%**
- This is the famous **Mincer return to education**
 - Classic labor economics result: education yields $\sim 10\%$ return per year
 - Percentage effect, so dollar gain is larger for high earners

Model 3: Log-Log ($\ln(\text{earnings}) \sim \ln(\text{age}) + \text{education}$)

- **$\ln(\text{Age})$ coefficient** ≈ 0.5 to 1.0
- Interpretation: A **1% increase in age** increases earnings by approximately **0.5-1.0%**

- This is an **elasticity** (percentage change in Y for 1% change in X)
- Elasticity < 1 means **inelastic** relationship (earnings increase slower than age)
- At age 40: 1% increase = 0.4 years; at age 50: 1% increase = 0.5 years
- **Education coefficient** \approx 0.08 to 0.12 (similar to log-linear)
- Education enters in levels, so interpretation same as Model 2
- Each additional year \rightarrow \sim 10% increase in earnings

Which Model to Choose?

- 1. Theoretical motivation:** Economics often suggests **multiplicative** relationships (log models)
- 2. Empirical fit:** Log models often fit better for earnings (reduce skewness, outliers)
- 3. Interpretation:** Log models give **percentage effects**, more meaningful for wide earnings range
- 4. Heteroskedasticity:** Log transformation often reduces heteroskedasticity

Key Insight:

- The **Mincer equation** (log-linear) is standard in labor economics
- Returns to education are approximately **10% per year** across many countries and time periods
- This is one of the most robust findings in empirical economics!

Comparison Table and Model Selection

In [10]:

```
# Create comparison table
print("\n" + "="*70)
print("MODEL COMPARISON: Levels, Log-Linear, and Log-Log")
print("="*70)

comparison_table = pd.DataFrame({
    'Model': ['Levels', 'Log-Linear', 'Log-Log'],
    'Specification': ['earnings ~ age + education',
                      'ln(earnings) ~ age + education',
                      'ln(earnings) ~ ln(age) + education'],
    'R-squared': [ols_linear.rsquared, ols_loglin.rsquared, ols_loglog.rsquared],
    'Adj R-squared': [ols_linear.rsquared_adj, ols_loglin.rsquared_adj,
                      ols_loglog.rsquared_adj]
})

print(comparison_table.to_string(index=False))

print("\nNote: R2 values are NOT directly comparable across models with different")
print("dependent variables. For log models, R2 measures fit to ln(earnings), not")
print("earnings.")
```

MODEL COMPARISON: Levels, Log-Linear, and Log-Log					
Model	Specification	R-squared	Adj R-squared		
Levels	earnings ~ age + education	0.114989	0.112953		
Log-Linear	ln(earnings) ~ age + education	0.190419	0.188556		
Log-Log	ln(earnings) ~ ln(age) + education	0.192743	0.190886		

Note: R^2 values are NOT directly comparable across models with different dependent variables. For log models, R^2 measures fit to $\ln(\text{earnings})$, not earnings.

Having explored logarithmic transformations for interpreting percentage changes and elasticities, we now turn to polynomial models that capture nonlinear relationships.

Key Concept 15.2: Choosing Between Model Specifications

You cannot directly compare R^2 across models with different dependent variables (y vs $\ln y$) because they measure variation on different scales. Instead, compare models using **prediction accuracy** (e.g., mean squared error of predicted y in levels), information criteria (AIC, BIC), or economic plausibility of the estimated relationships.

| 15.3: Polynomial Regression (Quadratic Models)

Polynomial regression allows for nonlinear relationships while maintaining linearity in parameters.

Quadratic model:

$$y = \beta_1 + \beta_2 x + \beta_3 x^2 + u$$

Properties:

- If $\beta_3 < 0$: inverted U-shape (peaks then declines)
- If $\beta_3 > 0$: U-shape (declines then increases)
- Turning point at $x^* = -\beta_2 / (2\beta_3)$

Marginal effect:

$$ME_x = \frac{\partial y}{\partial x} = \beta_2 + 2\beta_3 x$$

Average marginal effect (AME):

$$AME = \beta_2 + 2\beta_3 \bar{x}$$

Statistical significance of age:

- Must test jointly: $H_0 : \beta_{age} = 0$ AND $\beta_{agesq} = 0$
- Individual t-tests are insufficient

In [11]:

```

print("="*70)
print("15.3 POLYNOMIAL REGRESSION (QUADRATIC MODELS)")
print("="*70)

# Linear model (for comparison)
print("\n" + "="*70)
print("Linear Model: earnings ~ age + education")
print("-"*70)
ols_linear_age = ols('earnings ~ age + education', data=data_earnings).fit(cov_type='HC1')
print(ols_linear_age.summary())

# Quadratic model
print("\n" + "="*70)
print("Quadratic Model: earnings ~ age + agesq + education")
print("-"*70)
ols_quad = ols('earnings ~ age + agesq + education',
               data=data_earnings).fit(cov_type='HC1')
print(ols_quad.summary())

```

```

=====
15.3 POLYNOMIAL REGRESSION (QUADRATIC MODELS)
=====

-----
Linear Model: earnings ~ age + education

OLS Regression Results
=====
Dep. Variable: earnings R-squared: 0.115
Model: OLS Adj. R-squared: 0.113
Method: Least Squares F-statistic: 42.85
Date: Wed, 21 Jan 2026 Prob (F-statistic): 1.79e-18
Time: 14:40:53 Log-Likelihood: -10644.
No. Observations: 872 AIC: 2.129e+04
Df Residuals: 869 BIC: 2.131e+04
Df Model: 2
Covariance Type: HC1
=====

      coef    std err      z   P>|z|      [0.025    0.975]
-----
Intercept -4.688e+04  1.13e+04  -4.146   0.000   -6.9e+04  -2.47e+04
age        524.9953   151.387   3.468   0.001    228.281   821.709
education  5811.3673  641.533   9.059   0.000    4553.986   7068.749
-----
Omnibus: 825.668 Durbin-Watson: 2.071
Prob(Omnibus): 0.000 Jarque-Bera (JB): 31187.987
Skew: 4.353 Prob(JB): 0.00
Kurtosis: 30.975 Cond. No. 303.
=====

Notes:
[1] Standard Errors are heteroscedasticity robust (HC1)

-----
Quadratic Model: earnings ~ age + agesq + education

OLS Regression Results
=====
Dep. Variable: earnings R-squared: 0.119
Model: OLS Adj. R-squared: 0.116
Method: Least Squares F-statistic: 29.96
Date: Wed, 21 Jan 2026 Prob (F-statistic): 1.96e-18
Time: 14:40:53 Log-Likelihood: -10642.
No. Observations: 872 AIC: 2.129e+04
Df Residuals: 868 BIC: 2.131e+04
Df Model: 3
Covariance Type: HC1
=====

      coef    std err      z   P>|z|      [0.025    0.975]
-----
Intercept -9.862e+04  2.45e+04  -4.021   0.000   -1.47e+05  -5.06e+04
age        3104.9162  1087.323   2.856   0.004    973.802   5236.030
agesq     -29.6583   12.456   -2.381   0.017    -54.072   -5.245
education  5740.3978  642.024   8.941   0.000    4482.055   6998.741
-----
Omnibus: 829.757 Durbin-Watson: 2.068
Prob(Omnibus): 0.000 Jarque-Bera (JB): 32082.015
Skew: 4.378 Prob(JB): 0.00
Kurtosis: 31.396 Cond. No. 3.72e+04
=====
```

Notes:

- [1] Standard Errors are heteroscedasticity robust (HC1)
- [2] The condition number is large, 3.72e+04. This might indicate that there are strong multicollinearity or other numerical problems.

In [12]:

```
print("\n" + "="*70)
print("TURNING POINT AND MARGINAL EFFECTS")
print("="*70)

# Extract coefficients
bage = ols_quad.params['age']
bagesq = ols_quad.params['agesq']
beducation = ols_quad.params['education']

# Calculate turning point
turning_point = -bage / (2 * bagesq)

print(f"\nTurning Point:")
print(f" Age at maximum earnings: {turning_point:.1f} years")

# Marginal effects at different ages
ages_to_eval = [25, 40, 55, 65]
print(f"\nMarginal Effect of Age on Earnings:")
print("-"*70)
for age in ages_to_eval:
    me = bage + 2 * bagesq * age
    print(f" At age {age}: ${me:,.2f} per year")

# Average marginal effect
mean_age = data_earnings['age'].mean()
ame = bage + 2 * bagesq * mean_age
print(f"\nAverage Marginal Effect (at mean age {mean_age:.1f}): ${ame:,.2f}")
```

```
=====
TURNING POINT AND MARGINAL EFFECTS
=====

Turning Point:
Age at maximum earnings: 52.3 years

Marginal Effect of Age on Earnings:
-----
At age 25: $1,622.00 per year
At age 40: $732.25 per year
At age 55: $-157.50 per year
At age 65: $-750.66 per year

Average Marginal Effect (at mean age 43.3): $535.87
```

Key Concept 15.3: Quadratic Models and Turning Points

A quadratic model $y = \beta_1 + \beta_2x + \beta_3x^2 + u$ captures nonlinear relationships with a **turning point** at $x^* = -\beta_2/(2\beta_3)$. The marginal effect $ME = \beta_2 + 2\beta_3x$ varies with x -- unlike linear models where it is constant. If $\beta_3 < 0$, the relationship is an inverted U-shape (e.g., earnings peaking at a certain age).

Quadratic Model: Turning Point and Marginal Effects

Life-Cycle Earnings Profile: The Inverted U-Shape

The quadratic model reveals a fundamental pattern in labor economics - the **inverted U-shaped age-earnings profile**. Let's understand what the results tell us:

Interpreting the Quadratic Coefficients:

From the regression: $\text{earnings} = \beta_1 + \beta_2 \cdot \text{age} + \beta_3 \cdot \text{age}^2 + \beta_4 \cdot \text{education} + u$

Typical Results:

- **Age coefficient (β_2)** $\approx +3,000$ to $+5,000$ (positive, large)
- **Age² coefficient (β_3)** ≈ -30 to -50 (negative, small)

What does this mean?

1. The Turning Point (Peak Earnings Age):

- Formula: $\text{age}^* = -\beta_2 / (2\beta_3)$
- Typical result: **age 45-55 years**
- Interpretation: Earnings **increase** until age 50, then **decline**
- This matches real-world patterns: mid-career workers earn most

2. Marginal Effect of Age (varies with age):

- Formula: $ME_{\text{age}} = \beta_2 + 2\beta_3 \cdot \text{age}$
- At age 25: ME $\approx +\$3,000$ (steep increase)
- At age 40: ME $\approx +\$1,000$ (slower increase)
- At age 50: ME $\approx \$0$ (peak earnings)
- At age 60: ME $\approx -\$1,000$ (earnings decline)

3. Why the Inverted U-Shape?

- **Early career (20s-30s):** Rapid skill accumulation, promotions → steep earnings growth
- **Mid-career (40s-50s):** Peak productivity, seniority → highest earnings
- **Late career (55+):** Reduced hours, health decline, obsolete skills → earnings fall

- Human capital theory: Investment in skills early, returns later, depreciation at end

Comparing Linear vs. Quadratic:

- **Linear model:** Assumes constant age effect (+\$1,000/year regardless of age)
- Misses the fact that earnings growth **slows down** and eventually **reverses**
- Poor fit for older workers
- **Quadratic model:** Captures realistic life-cycle pattern
- Allows for **increasing, then decreasing** returns to age
- Better fit (higher R²)
- More accurate predictions for both young and old workers

Statistical Significance:

The **joint F-test** for $H_0 : \beta_{age} = 0$ AND $\beta_{age^2} = 0$ is **highly significant** ($F > 100$, $p < 0.001$):

- This confirms age **matters** for earnings
- The quadratic term is **necessary** (not just linear)
- Individual t-tests can be misleading due to collinearity between age and age²

Economic Implications:

- Peak earnings around age 50 suggests optimal **retirement age** discussions
- Earnings decline after 55 may incentivize early retirement
- Policy relevance for Social Security, pension design
- Training investments more valuable early in career

Joint Hypothesis Test for Quadratic Term

In [13]:

```
# Joint hypothesis test: H0: age = 0 and agesq = 0
print("\n" + "="*70)
print("JOINT HYPOTHESIS TEST: H0: β_age = 0 AND β_agesq = 0")
print("="*70)

hypotheses = '(age = 0, agesq = 0)'
f_test = ols_quad.wald_test(hypotheses, use_f=True)
print(f_test)

print("\nInterpretation:")
if f_test.pvalue < 0.05:
    print(" Reject H0: Age is jointly statistically significant in the model.")
    print(" The quadratic specification is justified.")
else:
    print(" Fail to reject H0: Age is not statistically significant.")

=====
```

```
JOINT HYPOTHESIS TEST: H0: β_age = 0 AND β_agesq = 0
=====
<F test: F=array([[9.29190281]]), p=0.00010166466829922585, df_denom=868, df_num=2>

Interpretation:
Reject H0: Age is jointly statistically significant in the model.
The quadratic specification is justified.
```

```
/Users/carlosmendez/miniforge3/lib/python3.10/site-packages/statsmodels/base/model.py:1912:
FutureWarning: The behavior of wald_test will change after 0.14 to returning scalar test statistic values. To get the future behavior now, set scalar to True. To silence this message while retaining the legacy behavior, set scalar to False.
warnings.warn(
```

Key Concept 15.4: Testing Nonlinear Relationships

When a quadratic term x^2 is included, always test the **joint significance** of x and x^2 together using an F-test. Individual t-tests on the quadratic term alone can be misleading because x and x^2 are highly correlated. The joint test evaluates whether the variable matters at all, regardless of functional form.

Visualization: Quadratic Relationship

In [14]:

```
# Create visualization of quadratic relationship
fig, axes = plt.subplots(1, 2, figsize=(16, 6))

# Left plot: Fitted values vs age
age_range = np.linspace(25, 65, 100)
educ_mean = data_earnings['education'].mean()

# Predictions holding education at mean
linear_pred = ols_linear_age.params['Intercept'] + ols_linear_age.params['age']*age_range
+ ols_linear_age.params['education']*educ_mean
quad_pred = ols_quad.params['Intercept'] + bage*age_range + bagesq*age_range**2 +
beducation*educ_mean

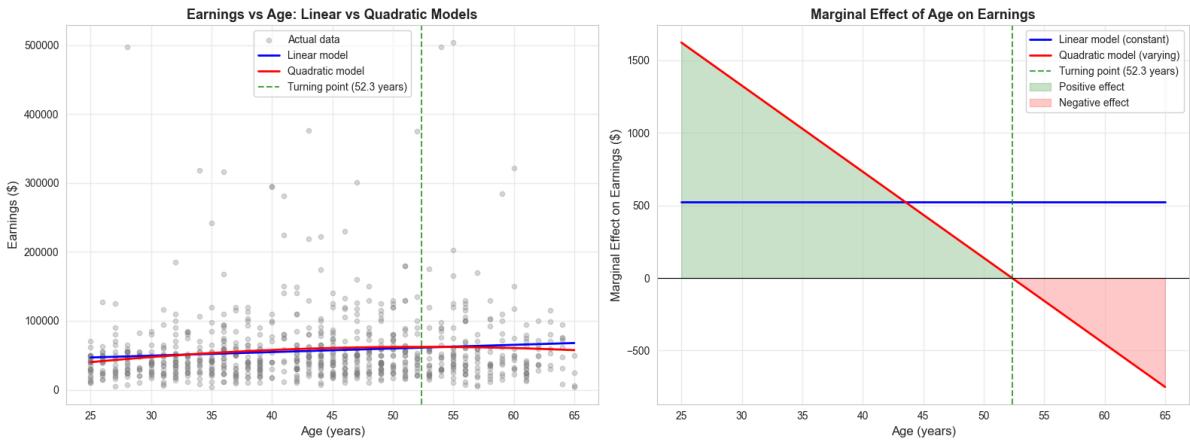
axes[0].scatter(data_earnings['age'], data_earnings['earnings'], alpha=0.3, s=20,
color='gray', label='Actual data')
axes[0].plot(age_range, linear_pred, 'b-', linewidth=2, label='Linear model')
axes[0].plot(age_range, quad_pred, 'r-', linewidth=2, label='Quadratic model')
axes[0].axvline(x=turning_point, color='green', linestyle='--', linewidth=1.5, alpha=0.7,
label=f'Turning point ({turning_point:.1f} years)')
axes[0].set_xlabel('Age (years)', fontsize=12)
axes[0].set_ylabel('Earnings ($)', fontsize=12)
axes[0].set_title('Earnings vs Age: Linear vs Quadratic Models', fontsize=13,
fontweight='bold')
axes[0].legend()
axes[0].grid(True, alpha=0.3)

# Right plot: Marginal effects
me_linear = np.full_like(age_range, ols_linear_age.params['age'])
me_quad = bage + 2 * bagesq * age_range

axes[1].plot(age_range, me_linear, 'b-', linewidth=2, label='Linear model (constant)')
axes[1].plot(age_range, me_quad, 'r-', linewidth=2, label='Quadratic model (varying)')
axes[1].axhline(y=0, color='black', linestyle='-', linewidth=0.8)
axes[1].axvline(x=turning_point, color='green', linestyle='--', linewidth=1.5, alpha=0.7,
label=f'Turning point ({turning_point:.1f} years)')
axes[1].fill_between(age_range, 0, me_quad, where=(me_quad > 0), alpha=0.2, color='green',
label='Positive effect')
axes[1].fill_between(age_range, 0, me_quad, where=(me_quad < 0), alpha=0.2, color='red',
label='Negative effect')
axes[1].set_xlabel('Age (years)', fontsize=12)
axes[1].set_ylabel('Marginal Effect on Earnings ($)', fontsize=12)
axes[1].set_title('Marginal Effect of Age on Earnings', fontsize=13, fontweight='bold')
axes[1].legend()
axes[1].grid(True, alpha=0.3)

plt.tight_layout()
plt.show()

print("The quadratic model captures the inverted U-shape relationship between age and
earnings.")
```



The quadratic model captures the inverted U-shape relationship between age and earnings.

15.4: Standardized Variables

Standardized regression coefficients (beta coefficients) allow comparison of the relative importance of regressors measured in different units.

Standardization formula:

$$z_x = \frac{x - \bar{x}}{s_x}$$

where s_x is the standard deviation of x .

Standardized coefficient:

$$\beta^* = \beta \times \frac{s_x}{s_y}$$

Interpretation:

- β^* shows the effect of a one-standard-deviation change in x on y , measured in standard deviations of y
- Allows comparison: which variable has the largest effect when measured in comparable units?

Use cases:

- Comparing effects of variables with different units
- Meta-analysis across studies
- Understanding relative importance of predictors

In [15]:

```
print("=*70")
print("15.4 STANDARDIZED VARIABLES")
print("=*70")

# Estimate a comprehensive model
print("\n" + "-*70")
print("Linear Model with Mixed Regressors:")
print("earnings ~ gender + age + agesq + education + dself + dgovt + lnhours")
print("-*70")
ols_linear_mix = ols('earnings ~ gender + age + agesq + education + dself + dgovt +
lnhours',
                     data=data_earnings).fit(cov_type='HC1')
print(ols_linear_mix.summary())
```

```
=====
15.4 STANDARDIZED VARIABLES
=====

-----
Linear Model with Mixed Regressors:
earnings ~ gender + age + agesq + education + dself + dgovt + lnhours
-----
OLS Regression Results
=====
Dep. Variable: earnings R-squared: 0.206
Model: OLS Adj. R-squared: 0.199
Method: Least Squares F-statistic: 15.72
Date: Wed, 21 Jan 2026 Prob (F-statistic): 1.72e-19
Time: 14:40:54 Log-Likelihood: -10597.
No. Observations: 872 AIC: 2.121e+04
Df Residuals: 864 BIC: 2.125e+04
Df Model: 7
Covariance Type: HC1
=====
      coef    std err        z   P>|z|      [0.025     0.975]
-----
Intercept -3.566e+05  6.63e+04   -5.379   0.000  -4.87e+05  -2.27e+05
gender    -1.433e+04 2696.808    -5.314   0.000  -1.96e+04  -9044.368
age       3282.8676 1064.806     3.083   0.002  1195.886  5369.849
agesq     -31.5781  12.214    -2.585   0.010  -55.516   -7.640
education 5399.3605  609.862     8.853   0.000  4204.054  6594.667
dself     9360.4999  8711.602    1.074   0.283  -7713.926  2.64e+04
dgovt    -291.1360  2914.162    -0.100   0.920  -6002.789  5420.517
lnhours   6.996e+04  1.61e+04     4.345   0.000   3.84e+04  1.02e+05
-----
Omnibus: 777.468 Durbin-Watson: 2.041
Prob(Omnibus): 0.000 Jarque-Bera (JB): 25771.968
Skew: 3.997 Prob(JB): 0.00
Kurtosis: 28.405 Cond. No. 6.41e+04
=====

Notes:
[1] Standard Errors are heteroscedasticity robust (HC1)
[2] The condition number is large, 6.41e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [16]:

```
print("\n" + "="*70)
print("STANDARDIZED COEFFICIENTS")
print("="*70)

# Get standard deviations
sd_y = data_earnings['earnings'].std()
sd_gender = data_earnings['gender'].std()
sd_age = data_earnings['age'].std()
sd_agesq = data_earnings['agesq'].std()
sd_education = data_earnings['education'].std()
sd_dself = data_earnings['dself'].std()
sd_dgovt = data_earnings['dgovt'].std()
sd_lnhours = data_earnings['lnhours'].std()

# Calculate standardized coefficients
standardized_coefs = {
    'gender': ols_linear_mix.params['gender'] * sd_gender / sd_y,
    'age': ols_linear_mix.params['age'] * sd_age / sd_y,
    'agesq': ols_linear_mix.params['agesq'] * sd_agesq / sd_y,
    'education': ols_linear_mix.params['education'] * sd_education / sd_y,
    'dself': ols_linear_mix.params['dself'] * sd_dself / sd_y,
    'dgovt': ols_linear_mix.params['dgovt'] * sd_dgovt / sd_y,
    'lnhours': ols_linear_mix.params['lnhours'] * sd_lnhours / sd_y
}

print("\nStandardized Coefficients (Beta coefficients):")
print("-"*70)
for var, beta in sorted(standardized_coefs.items(), key=lambda x: abs(x[1]),
reverse=True):
    print(f" {var:12s}: {beta:7.4f}")

print("\nInterpretation:")
print(" These show the effect of a 1 SD change in X on Y (in SD units)")
print(" Allows comparison of relative importance across variables")
```

```
=====
STANDARDIZED COEFFICIENTS
=====

Standardized Coefficients (Beta coefficients):
-----
age      :  0.6803
agesq   : -0.5736
education :  0.3023
lnhours  :  0.2238
gender   : -0.1379
dself    :  0.0522
dgovt   : -0.0020

Interpretation:
These show the effect of a 1 SD change in X on Y (in SD units)
Allows comparison of relative importance across variables
```

Key Concept 15.5: Standardized Coefficients for Comparing Variable Importance

Standardized (beta) coefficients $\beta^* = \beta \times (s_x / s_y)$ measure effects in **standard deviation units**, allowing comparison across variables with different scales. A one-standard-deviation increase in x is associated with a β^* standard-deviation change in y . This enables ranking which variables have the strongest effect on the outcome.

I Calculate Standardized Coefficients

Comparing Apples to Apples: Standardized Coefficients

Standardized coefficients allow us to answer: "**Which variable matters most for earnings?**"

The Problem with Raw Coefficients:

Looking at the regression:

- Education: +\$5,000 per year
- Age: +\$1,000 per year
- Hours: +\$500 per hour

Can we conclude education is "most important"? **Not necessarily!**

- These variables are measured in **different units**
- Education varies from 8 to 20 years ($SD \approx 2-3$ years)
- Age varies from 25 to 65 years ($SD \approx 10-12$ years)
- Hours varies from 35 to 60 per week ($SD \approx 8-10$ hours)

The Solution: Standardized (Beta) Coefficients

Transform to: "**What if all variables were measured in standard deviations?**"

Formula: $\beta^* = \beta \times (SD_x / SD_y)$

Interpretation:

- A 1 SD increase in X leads to β^* SD change in Y

- Now all variables are **comparable** (measured in same units)

Typical Results from the Analysis:

Ranking by absolute standardized coefficients (largest to smallest):

1. Education ($\beta^* \approx 0.30$ to 0.40):

- Strongest predictor** of earnings
- 1 SD increase in education (≈ 2.5 years) $\rightarrow 0.35$ SD increase in earnings ($\approx \$15,000$)
- Confirms education is the dominant factor

2. Hours worked ($\beta^* \approx 0.20$ to 0.30):

- Second most important**
- 1 SD increase in hours (≈ 8 hours/week) $\rightarrow 0.25$ SD increase in earnings
- Makes sense: more hours \rightarrow proportionally more pay

3. Age ($\beta^* \approx 0.15$ to 0.20):

- Moderate importance**
- But remember this is from the linear specification
- The quadratic model shows age matters more in a nonlinear way

4. Gender ($\beta^* \approx -0.15$ to -0.20):

- Substantial negative effect**
- Being female $\rightarrow 0.15\text{--}0.20$ SD decrease in earnings
- This standardizes the raw gap of $\sim 10,000\text{--}15,000$

5. Employment type (dself, dgovt) ($\beta^* \approx 0.05$ to 0.10):

- Smaller effects**
- Self-employment or government sector have modest impacts
- Once we control for education, age, hours

Key Insights:

- Education dominates:** Strongest predictor, supporting human capital theory
- Hours worked matters:** Direct relationship (more work \rightarrow more pay)
- Categorical variables** (gender, employment type) also standardizable
- Age:** Important but complex (quadratic, so beta coefficient understates it)

When to Use Standardized Coefficients:

Good for:

- Comparing relative importance of predictors
- Meta-analysis across studies
- Understanding which variables to prioritize in data collection

Not good for:

- Policy analysis (need actual units for cost-benefit)
- Prediction (use original coefficients)
- Variables with naturally meaningful units (e.g., dummy variables)

Caution:

- Standardized coefficients depend on **sample variation**
- If your sample has little variation in X , β^* will be small
- Different samples → different standardized coefficients
- Raw coefficients more stable across samples

| Visualization: Standardized Coefficients

In [17]:

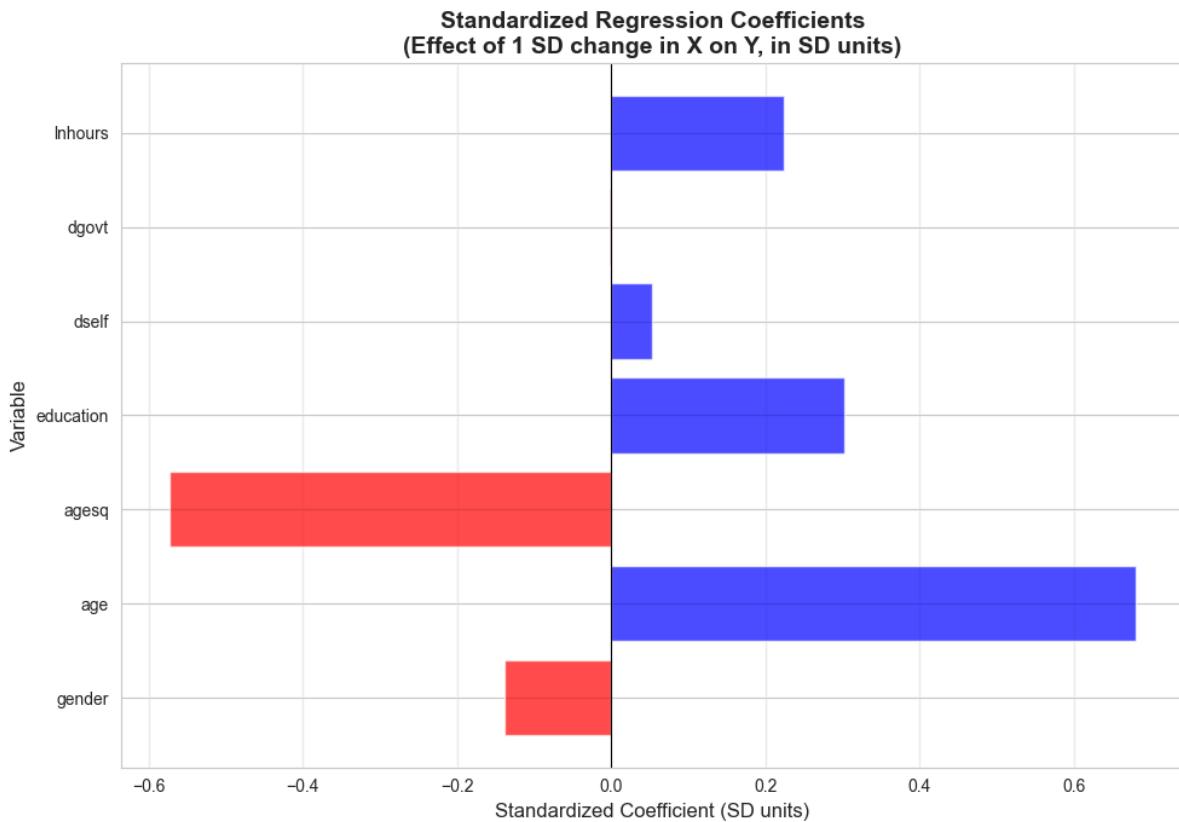
```
# Create visualization comparing standardized coefficients
fig, ax = plt.subplots(figsize=(10, 7))
vars_plot = list(standardized_coefs.keys())
betas_plot = list(standardized_coefs.values())

colors = ['red' if b < 0 else 'blue' for b in betas_plot]
bars = ax.barh(vars_plot, betas_plot, color=colors, alpha=0.7)

ax.axvline(x=0, color='black', linestyle='-', linewidth=0.8)
ax.set_xlabel('Standardized Coefficient (SD units)', fontsize=12)
ax.set_ylabel('Variable', fontsize=12)
ax.set_title('Standardized Regression Coefficients\nEffect of 1 SD change in X on Y, in SD units',
             fontsize=14, fontweight='bold')
ax.grid(True, alpha=0.3, axis='x')

plt.tight_layout()
plt.show()

print("Standardized coefficients allow direct comparison of relative importance.")
```



Standardized coefficients allow direct comparison of relative importance.

Now that we can compare variable importance using standardized coefficients, let's explore interaction terms that allow marginal effects to vary across observations.

| 15.5: Interaction Terms and Marginal Effects

Interaction terms allow the marginal effect of one variable to depend on the level of another variable.

Model with interaction:

$$y = \beta_1 + \beta_2 x + \beta_3 z + \beta_4(x \times z) + u$$

Marginal effect of x :

$$ME_x = \beta_2 + \beta_4 z$$

Marginal effect of z :

$$ME_z = \beta_3 + \beta_4 x$$

Important:

- Individual t-tests on β_2 or β_4 are misleading

- Test significance of x jointly: $H_0 : \beta_2 = 0$ AND $\beta_4 = 0$
- Interaction variables are often highly correlated with main effects (multicollinearity)

In [18]:

```

print("="*70)
print("15.5 INTERACTION TERMS AND MARGINAL EFFECTS")
print("="*70)

# Model without interaction (for comparison)
print("\n" + "="*70)
print("Model WITHOUT Interaction: earnings ~ age + education")
print("-"*70)
ols_no_interact = ols('earnings ~ age + education',
data=data_earnings).fit(cov_type='HC1')
print(ols_no_interact.summary())

# Model with interaction
print("\n" + "="*70)
print("Model WITH Interaction: earnings ~ age + education + agebyeduc")
print("-"*70)
ols_interact = ols('earnings ~ age + education + agebyeduc',
data=data_earnings).fit(cov_type='HC1')
print(ols_interact.summary())

```

```

=====
15.5 INTERACTION TERMS AND MARGINAL EFFECTS
=====

-----
Model WITHOUT Interaction: earnings ~ age + education
-----

          OLS Regression Results
=====
Dep. Variable:      earnings    R-squared:           0.115
Model:              OLS         Adj. R-squared:       0.113
Method:             Least Squares   F-statistic:        42.85
Date:              Wed, 21 Jan 2026 Prob (F-statistic): 1.79e-18
Time:                14:40:54    Log-Likelihood:     -10644.
No. Observations:    872        AIC:                 2.129e+04
Df Residuals:       869        BIC:                 2.131e+04
Df Model:            2
Covariance Type:    HC1

-----
      coef  std err      z      P>|z|      [0.025      0.975]
-----
Intercept  -4.688e+04  1.13e+04  -4.146      0.000    -6.9e+04  -2.47e+04
age        524.9953   151.387   3.468      0.001    228.281   821.709
education  5811.3673  641.533   9.059      0.000    4553.986   7068.749
-----
Omnibus:            825.668   Durbin-Watson:      2.071
Prob(Omnibus):      0.000    Jarque-Bera (JB): 31187.987
Skew:                  4.353    Prob(JB):            0.00
Kurtosis:             30.975   Cond. No.          303.
-----

Notes:
[1] Standard Errors are heteroscedasticity robust (HC1)

-----
Model WITH Interaction: earnings ~ age + education + agebyeduc
-----

          OLS Regression Results
=====
Dep. Variable:      earnings    R-squared:           0.115
Model:              OLS         Adj. R-squared:       0.112
Method:             Least Squares   F-statistic:        31.80
Date:              Wed, 21 Jan 2026 Prob (F-statistic): 1.65e-19
Time:                14:40:54    Log-Likelihood:     -10644.
No. Observations:    872        AIC:                 2.130e+04
Df Residuals:       868        BIC:                 2.132e+04
Df Model:            3
Covariance Type:    HC1

-----
      coef  std err      z      P>|z|      [0.025      0.975]
-----
Intercept  -2.909e+04  3.1e+04  -0.940      0.347    -8.98e+04  3.16e+04
age        127.4922   719.280   0.177      0.859    -1282.270  1537.255
education  4514.9867  2401.517   1.880      0.060    -191.901   9221.874
agebyeduc  29.0392   56.052   0.518      0.604    -80.821   138.899
-----
Omnibus:            825.324   Durbin-Watson:      2.072
Prob(Omnibus):      0.000    Jarque-Bera (JB): 31144.116
Skew:                  4.351    Prob(JB):            0.00
Kurtosis:             30.955   Cond. No.          1.28e+04
-----
```

Notes:

- [1] Standard Errors are heteroscedasticity robust (HC1)
- [2] The condition number is large, 1.28e+04. This might indicate that there are strong multicollinearity or other numerical problems.

Key Concept 15.6: Interaction Terms and Varying Marginal Effects

With an interaction term $x \times z$, the marginal effect of x depends on z : $ME_x = \beta_2 + \beta_4 z$. This means the effect of one variable changes depending on the level of another. Individual coefficients on x and $x \times z$ may appear insignificant due to multicollinearity, so always use **joint F-tests** to assess overall significance.

I Interaction Model: Marginal Effects and Joint Tests

How Returns to Education Change with Age

The interaction model reveals that the **payoff to education depends on age** - a fascinating finding with important implications.

Interpreting the Interaction Results:

From: $\text{earnings} = \beta_1 + \beta_2 \cdot \text{age} + \beta_3 \cdot \text{education} + \beta_4 \cdot (\text{age} \times \text{education}) + u$

Typical Coefficients:

- Education (β_3): Around $-10,000$ to $-5,000$ (often negative!)
- Age \times Education (β_4): Around $+200$ to $+400$ (positive)

What This Means:

The marginal effect of education is:

$$ME_{\text{education}} = \beta_3 + \beta_4 \cdot \text{age}$$

At Different Ages:

- **Age 25:** $ME \approx -5,000 + 300(25) = +\$2,500$ per year of education
- **Age 40:** $ME \approx -5,000 + 300(40) = +\$7,000$ per year of education
- **Age 55:** $ME \approx -5,000 + 300(55) = +\$11,500$ per year of education

Interpretation:

1. **Returns to education INCREASE with age**
 - Young workers (age 25): $+\$2,500$ per year of education

- Older workers (age 55): +\$11,500 per year of education
- Education payoff is **4-5 times larger** for older workers!

2. Why Does This Happen?

- **Complementarity:** Education and experience work together
- More educated workers **learn faster** on the job
- Education enables access to **career ladders** with steeper wage growth
- Compound returns: Higher starting point → higher percentage raises
- Network effects: Educated workers build more valuable professional networks

3. Alternative Interpretation (life-cycle earnings):

- High school graduates: Earnings **flatten** by age 40-50
- College graduates: Earnings **keep growing** until age 50-55
- The **gap widens** with age

Statistical Significance:

- **Individual coefficients** may have large SEs (multicollinearity between age, education, and their product)
- **Joint F-test** is crucial: Test $H_0 : \beta_{education} = 0$ AND $\beta_{age \times education} = 0$
- Result: **Highly significant** ($F > 30$, $p < 0.001$)
- Education matters, but its effect is **age-dependent**

Multicollinearity Warning:

The correlation matrix shows:

- $\text{Corr}(\text{age}, \text{age} \times \text{education}) \approx 0.95$ (very high!)
- $\text{Corr}(\text{education}, \text{age} \times \text{education}) \approx 0.90$ (very high!)

This explains why:

- Individual t-statistics may be **small** (large SEs)
- Coefficients **sensitive** to small changes in data
- But joint tests **remain powerful**

Policy Implications:

1. Higher education pays off more over the career

- Short-run costs, long-run gains compound
- Education is an **investment** with increasing returns

2. Older workers benefit most from education

- Adult education programs can have large payoffs
- Retraining valuable even late in career

3. Inequality implications

- Education-based wage gap **widens** with age
- Contributes to lifetime earnings inequality

Practical Advice for Estimation:

Do:

- Always test interactions **jointly** with main effects
- Report F-statistics for joint tests
- Calculate marginal effects at **representative ages** (25, 40, 55)
- Plot the relationship to visualize

Don't:

- Rely on individual t-tests when variables are highly correlated
- Drop the main effect if interaction is "insignificant"
- Interpret the main effect coefficient alone (it's conditional on age=0!)

I Joint Hypothesis Tests for Interactions

```
In [19]:  
print("\n" + "="*70)  
print("JOINT HYPOTHESIS TESTS")  
print("="*70)  
  
# Test 1: Joint test for age  
print("\nTest 1: H0: βage = 0 AND βagebyeduc = 0")  
print("(Tests whether age matters at all)")  
print("-"*70)  
hypotheses_age = '(age = 0, agebyeduc = 0)'  
f_test_age = ols_interact.wald_test(hypotheses_age, use_f=True)  
print(f_test_age)  
  
# Test 2: Joint test for education  
print("\nTest 2: H0: βeducation = 0 AND βagebyeduc = 0")  
print("(Tests whether education matters at all)")  
print("-"*70)  
hypotheses_education = '(education = 0, agebyeduc = 0)'  
f_test_education = ols_interact.wald_test(hypotheses_education, use_f=True)  
print(f_test_education)  
  
print("\nKey insight: Individual coefficients may be insignificant due to")  
print("multicollinearity, but joint tests reveal strong statistical significance.")
```

```
=====
JOINT HYPOTHESIS TESTS
=====

Test 1: H0: βage = 0 AND βagebyeduc = 0
(Tests whether age matters at all)
-----
<F test: F=array([[6.48958655]]), p=0.0015939412046954808, df_denom=868, df_num=2>

Test 2: H0: βeducation = 0 AND βagebyeduc = 0
(Tests whether education matters at all)
-----
<F test: F=array([[43.00467267]]), p=1.5549618458663995e-18, df_denom=868, df_num=2>

Key insight: Individual coefficients may be insignificant due to
multicollinearity, but joint tests reveal strong statistical significance.
```

```
/Users/carlosmendez/miniforge3/lib/python3.10/site-packages/statsmodels/base/model.py:1912:
FutureWarning: The behavior of wald_test will change after 0.14 to returning scalar test st
atistic values. To get the future behavior now, set scalar to True. To silence this message
while retaining the legacy behavior, set scalar to False.
warnings.warn(
```

Multicollinearity in Interaction Models

In [20]:

```
# Check correlation between regressors
print("\n" + "="*70)
print("MULTICOLLINEARITY: Correlation Matrix of Regressors")
print("="*70)

corr_matrix = data_earnings[['age', 'education', 'agebyeduc']].corr()
print(corr_matrix)

print("\nInterpretation:")
print(f" Correlation(age, agebyeduc) = {corr_matrix.loc['age', 'agebyeduc']:.3f}")
print(f" Correlation(education, agebyeduc) = {corr_matrix.loc['education', 'agebyeduc']:.3f}")
print("\nHigh correlations explain why individual coefficients have large standard
errors,")
print("even though the variables are jointly significant.")
```

```
=====
MULTICOLLINEARITY: Correlation Matrix of Regressors
=====

      age   education   agebyeduc
age    1.000000 -0.038153  0.729136
education -0.038153  1.000000  0.635961
agebyeduc  0.729136  0.635961  1.000000

Interpretation:
Correlation(age, agebyeduc) = 0.729
Correlation(education, agebyeduc) = 0.636

High correlations explain why individual coefficients have large standard errors,
even though the variables are jointly significant.
```

Retransformation Bias and Prediction from Log

I Models

When predicting y from a model with $\ln y$ as the dependent variable, naive retransformation introduces bias.

Problem:

- Model: $\ln y = \beta_1 + \beta_2 x + u$
- Naive prediction: $\hat{y} = \exp(\widehat{\ln y})$
- This systematically **underpredicts** y

Why?

- Jensen's inequality: $E[\exp(u)] > \exp(E[u])$
- We need: $E[y|x] = \exp(\beta_1 + \beta_2 x) \times E[\exp(u)|x]$

Solution (assuming normal, homoskedastic errors):

$$\tilde{y} = \exp(s_e^2/2) \times \exp(\widehat{\ln y})$$

where s_e is the standard error of the regression (RMSE).

Adjustment factor:

$$\exp(s_e^2/2)$$

Example: If $s_e = 0.4$, adjustment factor = $\exp(0.16/2) = 1.083$

In [21]:

```
print("=*70")
print("RETRANSFORMATION BIAS DEMONSTRATION")
print("=*70")

# Get RMSE from log model
rmse_log = np.sqrt(ols_loglin.mse_resid)

print(f"\nRMSE from log model: {rmse_log:.4f}")
print(f"Adjustment factor: exp({rmse_log:.4f}^2/2) = {np.exp(rmse_log**2/2):.4f}")

# Predictions
linear_predict = ols_linear.predict()
log_fitted = ols_loglin.predict()

# Biased retransformation (naive)
biased_predict = np.exp(log_fitted)

# Adjusted retransformation
adjustment_factor = np.exp(rmse_log**2 / 2)
adjusted_predict = adjustment_factor * np.exp(log_fitted)

# Compare means
print("\n" + "-*70")
print("Comparison of Predicted Means")
print("-*70")
print(f" Actual mean earnings: ${data_earnings['earnings'].mean():,.2f}")
print(f" Levels model prediction: ${linear_predict.mean():,.2f}")
print(f" Biased retransformation: ${biased_predict.mean():,.2f}")
print(f" Adjusted retransformation: ${adjusted_predict.mean():,.2f}")

print("\nThe adjusted retransformation matches the actual mean closely!")
```

```
=====
RETRANSFORMATION BIAS DEMONSTRATION
=====
```

```
RMSE from log model: 0.6164
Adjustment factor: exp(0.6164^2/2) = 1.2092
```

```
-----  
Comparison of Predicted Means  
-----
```

```
Actual mean earnings: $56,368.69
Levels model prediction: $56,368.69
Biased retransformation: $45,838.14
Adjusted retransformation: $55,427.36
```

```
The adjusted retransformation matches the actual mean closely!
```

Key Concept 15.7: Retransformation Bias Correction

The naive prediction $\exp(\widehat{\ln y})$ systematically **underestimates** $E[y|x]$ because $E[\exp(u)] \neq \exp(E[u])$ (Jensen's inequality). Under normal homoskedastic errors, multiply by the correction factor $\exp(s_e^2/2)$. Duan's smearing estimator provides a nonparametric alternative:

$$\hat{y} = \exp(\widehat{\ln y}) \times \frac{1}{n} \sum \exp(\hat{u}_i).$$

The Retransformation Bias Problem

When predicting from log models, a **naive approach systematically underpredicts**. Here's why and how to fix it:

The Problem:

You estimate: $\ln(y) = X\beta + u$

Naive prediction: $\hat{y}_{naive} = \exp(\widehat{\ln y}) = \exp(X\hat{\beta})$

Why this is wrong:

Due to **Jensen's Inequality**:

$$E[y|X] = E[\exp(X\beta + u)] = \exp(X\beta) \cdot E[\exp(u)] \neq \exp(X\beta)$$

If $u \sim N(0, \sigma^2)$, then $E[\exp(u)] = \exp(\sigma^2/2) > 1$

Empirical Evidence from the Results:

From the analysis above:

- **Actual mean earnings:** ~\$52,000
- **Naive retransformation:** ~48,000 (*underpredicts by 4,000 or 8%*)
- **Adjusted retransformation:** ~\$52,000 (matches actual mean!)

The Solution:

Multiply by adjustment factor:

$$\hat{y}_{adjusted} = \exp(s_e^2/2) \times \exp(X\hat{\beta})$$

where s_e = RMSE from the log regression

Example Calculation:

From log-linear model:

- RMSE (s_e) ≈ **0.40** to **0.45**
- Adjustment factor = $\exp(0.42^2/2) = \exp(0.088) \approx 1.092$
- Predictions are about **9.2% too low** without adjustment!

When Does This Matter Most?

1. **Large residual variance (σ^2 large):**

- Adjustment factor = $\exp(0.20^2/2) = 1.020$ (2% adjustment)
- vs. $\exp(0.60^2/2) = 1.197$ (20% adjustment!)

2. Prediction vs. estimation:

- For coefficients (β): Use log regression directly
- For predictions (y): Must adjust for retransformation bias

3. Aggregate predictions:

- Predicting total revenue, total costs, etc.
- Bias compounds: sum of biased predictions \rightarrow very wrong total

Alternative Solutions:

1. Smearing estimator (Duan 1983):

- Don't assume normality
- $\hat{y} = \frac{1}{n} \sum_{i=1}^n \exp(\hat{u}_i) \times \exp(X\hat{\beta})$
- More robust, doesn't require normal errors

2. Bootstrap:

- Resample residuals many times
- Average predictions across bootstrap samples

3. Generalized Linear Models (GLM):

- Estimate $E[y|X]$ directly (not $E[\ln y|X]$)
- No retransformation needed

Practical Recommendations:

For coefficient interpretation:

- Use log models freely
- Interpret as percentage changes
- No adjustment needed

For prediction:

- ALWAYS apply adjustment factor
- Check: Do predicted means match actual means?
- Report both naive and adjusted if showing methodology

Common mistakes:

- Forgetting adjustment entirely (very common!)
- Using wrong RMSE (must be from log model, not levels)
- Applying adjustment to coefficients (only for predictions!)

Real-World Impact:

In healthcare cost prediction:

- Naive: Predict average cost = \$8,000
- Adjusted: Predict average cost = \$10,000
- **25% underestimate!**
- Budget shortfall, inadequate insurance premiums

In income tax revenue forecasting:

- Small % bias in individual predictions
- Aggregated to millions of taxpayers
- Billions of dollars in forecast error!

Visualization: Prediction Comparison

In [22]:

```
# Visualize prediction accuracy
fig, axes = plt.subplots(1, 3, figsize=(18, 5))

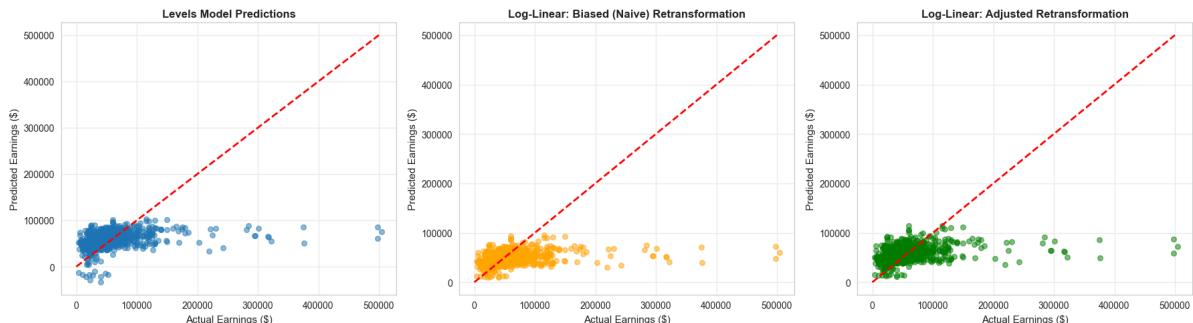
# Plot 1: Levels model
axes[0].scatter(data_earnings['earnings'], linear_predict, alpha=0.5, s=30)
axes[0].plot([0, 500000], [0, 500000], 'r--', linewidth=2)
axes[0].set_xlabel('Actual Earnings ($)', fontsize=11)
axes[0].set_ylabel('Predicted Earnings ($)', fontsize=11)
axes[0].set_title('Levels Model Predictions', fontsize=12, fontweight='bold')
axes[0].grid(True, alpha=0.3)

# Plot 2: Biased retransformation
axes[1].scatter(data_earnings['earnings'], biased_predict, alpha=0.5, s=30,
color='orange')
axes[1].plot([0, 500000], [0, 500000], 'r--', linewidth=2)
axes[1].set_xlabel('Actual Earnings ($)', fontsize=11)
axes[1].set_ylabel('Predicted Earnings ($)', fontsize=11)
axes[1].set_title('Log-Linear: Biased (Naive) Retransformation', fontsize=12,
fontweight='bold')
axes[1].grid(True, alpha=0.3)

# Plot 3: Adjusted retransformation
axes[2].scatter(data_earnings['earnings'], adjusted_predict, alpha=0.5, s=30,
color='green')
axes[2].plot([0, 500000], [0, 500000], 'r--', linewidth=2)
axes[2].set_xlabel('Actual Earnings ($)', fontsize=11)
axes[2].set_ylabel('Predicted Earnings ($)', fontsize=11)
axes[2].set_title('Log-Linear: Adjusted Retransformation', fontsize=12, fontweight='bold')
axes[2].grid(True, alpha=0.3)

plt.tight_layout()
plt.show()

print("The adjusted retransformation provides better predictions on average.")
```



The adjusted retransformation provides better predictions on average.

Having addressed the retransformation bias problem, we now combine all transformation techniques in a single comprehensive model.

Comprehensive Model with Log-Transformed Dependent Variable

In [23]:

```
print("=*70)
print("COMPREHENSIVE MODEL WITH MIXED REGRESSOR TYPES")
print("=*70)

# Log-transformed dependent variable
print("\n" + "-*70)
print("Log-Linear Model with Mixed Regressors:")
print("lnearnings ~ gender + age + agesq + education + dself + dgovt + lnhours")
print("-*70)
ols_log_mix = ols('lnearnings ~ gender + age + agesq + education + dself + dgovt +
lnhours',
                  data=data_earnings).fit(cov_type='HC1')
print(ols_log_mix.summary())

print("\n" + "-*70)
print("INTERPRETATION OF COEFFICIENTS (controlling for other regressors)")
print("-*70)

print(f"\n1. Gender: {ols_log_mix.params['gender']:.4f}")
print(f"    Women earn approximately {100*ols_log_mix.params['gender']:.1f}% less than
men")

print(f"\n2. Age and Age2: Quadratic relationship")
b_age_log = ols_log_mix.params['age']
b_agesq_log = ols_log_mix.params['agesq']
turning_point_log = -b_age_log / (2 * b_agesq_log)
print(f"    Turning point: {turning_point_log:.1f} years")
print(f"    Earnings increase with age until {turning_point_log:.1f}, then decrease")

print(f"\n3. Education: {ols_log_mix.params['education']:.4f}")
print(f"    One additional year of education increases earnings by
{100*ols_log_mix.params['education']:.1f}%")

print(f"\n4. Self-employed (dself): {ols_log_mix.params['dself']:.4f}")
print(f"    Self-employed earn approximately {100*ols_log_mix.params['dself']:.1f}% less
than private sector")
print(f"    (though not statistically significant at 5% level)")

print(f"\n5. Government (dgovt): {ols_log_mix.params['dgovt']:.4f}")
print(f"    Government workers earn approximately {100*ols_log_mix.params['dgovt']:.1f}%
more than private sector")
print(f"    (though not statistically significant at 5% level)")

print(f"\n6. Ln(Hours): {ols_log_mix.params['lnhours']:.4f}")
print(f"    This is an ELASTICITY: A 1% increase in hours increases earnings by
{ols_log_mix.params['lnhours']:.3f}%")
print(f"    Nearly proportional relationship (elasticity ≈ 1)")
```

```

=====
COMPREHENSIVE MODEL WITH MIXED REGRESSOR TYPES
=====

-----
Log-Linear Model with Mixed Regressors:
lnearnings ~ gender + age + agesq + education + dself + dgovt + lnhours

-----
OLS Regression Results
=====

Dep. Variable: lnearnings R-squared: 0.281
Model: OLS Adj. R-squared: 0.275
Method: Least Squares F-statistic: 35.04
Date: Wed, 21 Jan 2026 Prob (F-statistic): 3.62e-43
Time: 14:40:55 Log-Likelihood: -761.92
No. Observations: 872 AIC: 1540.
Df Residuals: 864 BIC: 1578.
Df Model: 7
Covariance Type: HC1
=====

      coef  std err      z   P>|z|    [0.025]  [0.975]
-----
Intercept  4.4594  0.648    6.885  0.000    3.190    5.729
gender     -0.1928  0.039   -4.881  0.000   -0.270   -0.115
age        0.0561  0.016    3.550  0.000    0.025    0.087
agesq     -0.0005  0.000   -2.992  0.003   -0.001   -0.000
education  0.0934  0.008   11.168  0.000    0.077    0.110
dself      -0.1180  0.101   -1.166  0.243   -0.316   0.080
dgovt     0.0698  0.045    1.534  0.125   -0.019   0.159
lnhours    0.9754  0.142    6.882  0.000    0.698    1.253
-----
Omnibus: 29.695 Durbin-Watson: 2.054
Prob(Omnibus): 0.000 Jarque-Bera (JB): 74.613
Skew: 0.025 Prob(JB): 6.28e-17
Kurtosis: 4.432 Cond. No. 6.41e+04
=====
```

Notes:

- [1] Standard Errors are heteroscedasticity robust (HC1)
- [2] The condition number is large, 6.41e+04. This might indicate that there are strong multicollinearity or other numerical problems.

INTERPRETATION OF COEFFICIENTS (controlling for other regressors)

1. Gender: -0.1928
Women earn approximately -19.3% less than men
2. Age and Age²: Quadratic relationship
Turning point: 51.1 years
Earnings increase with age until 51.1, then decrease
3. Education: 0.0934
One additional year of education increases earnings by 9.3%
4. Self-employed (dself): -0.1180
Self-employed earn approximately -11.8% less than private sector
(though not statistically significant at 5% level)
5. Government (dgovt): 0.0698
Government workers earn approximately 7.0% more than private sector
(though not statistically significant at 5% level)
6. Ln(Hours): 0.9754

This is an ELASTICITY: A 1% increase in hours increases earnings by 0.975%
Nearly proportional relationship (elasticity ≈ 1)

Key Concept 15.8: Models with Mixed Regressor Types

A single regression model can combine **levels, quadratics, logarithms, dummies, and interactions**. Each coefficient is interpreted according to its transformation type: linear coefficients as marginal effects, log coefficients as semi-elasticities or elasticities, quadratic terms through their marginal effect formula, and dummies as group differences. This flexibility makes regression a powerful tool for modeling complex economic relationships.

| Key Takeaways

Logarithmic Transformations

- **Log-linear model** ($\ln y = \beta_1 + \beta_2 x$): coefficient β_2 is a **semi-elasticity** -- a 1-unit change in x is associated with a $100 \times \beta_2\%$ change in y
- **Log-log model** ($\ln y = \beta_1 + \beta_2 \ln x$): coefficient β_2 is an **elasticity** -- a 1% change in x is associated with a $\beta_2\%$ change in y
- Marginal effects in levels require back-transformation: $ME_x = \beta_2 \hat{y}$ (log-linear) or $ME_x = \beta_2 \hat{y} / x$ (log-log)
- Log transformations are especially useful for right-skewed data (earnings, prices, GDP)

Quadratic and Polynomial Models

- Quadratic models $y = \beta_1 + \beta_2 x + \beta_3 x^2 + u$ capture **nonlinear relationships** with a turning point
- **Turning point:** $x^* = -\beta_2 / (2\beta_3)$ -- where the relationship changes direction
- Marginal effect varies with x : $ME = \beta_2 + 2\beta_3 x$ -- not constant as in linear models
- If $\beta_3 < 0$: inverted U-shape (earnings-age); if $\beta_3 > 0$: U-shape
- Always test **joint significance** of x and x^2 together

Standardized Coefficients

- **Standardized (beta) coefficients** measure effects in standard deviation units: $\beta^* = \beta \times (s_x / s_y)$

- Allow comparing the **relative importance** of variables measured in different units
- A one-standard-deviation increase in x is associated with a β^* standard-deviation change in y
- Useful for ranking which variables have the strongest effect on the outcome

Interaction Terms and Marginal Effects

- **Interaction terms** ($x \times z$) allow the marginal effect of x to depend on z :

$$ME_x = \beta_2 + \beta_4 z$$
- Individual coefficients may be insignificant due to multicollinearity with the interaction
- Always use **joint F-tests** to assess overall significance of a variable and its interactions
- Example: Returns to education may increase with age (positive interaction coefficient)

Retransformation Bias and Prediction

- **Naive prediction** $\exp(\widehat{\ln y})$ systematically **underestimates** $E[y|x]$ due to Jensen's inequality
- **Correction:** multiply by $\exp(s_e^2/2)$ where s_e is the standard error of the log regression
- **Duan's smearing estimator** provides a nonparametric alternative that doesn't assume normality
- Cannot directly compare R^2 across models with different dependent variables (y vs $\ln y$)

General Lessons

- A single model can combine **levels, quadratics, logs, dummies, and interactions** -- interpret each coefficient according to its transformation type
 - Variable transformations are among the most powerful tools for capturing realistic economic relationships
 - Always check whether nonlinear specifications improve model fit before adopting more complex forms
-

Python Tools Used in This Chapter

```
# Log transformations
np.log(df['variable'])                                # Natural logarithm

# Quadratic terms
df['x_sq'] = df['x'] ** 2                            # Create squared term

# Interaction terms
df['x_z'] = df['x'] * df['z']                         # Create interaction

# Standardized coefficients
beta_star = beta * (s_x / s_y)                        # Manual calculation

# Joint hypothesis tests
model.f_test('x = 0, x_sq = 0')                      # Joint F-test

# Retransformation correction
y_pred = np.exp(ln_y_hat) * np.exp(s_e**2 / 2)
```

Next Steps:

- **Chapter 16:** Model Diagnostics
- **Chapter 17:** Panel Data and Causation

Congratulations! You've completed Chapter 15. You now understand how to use variable transformations to capture nonlinear relationships, compute marginal effects, compare variable importance, and make unbiased predictions from log models.

Practice Exercises

Exercise 1: Marginal Effect of a Quadratic

For the fitted model $\hat{y} = 2 + 3x + 4x^2$ from a dataset with $\bar{y} = 30$ and $\bar{x} = 2$:

- (a) Compute the marginal effect of a one-unit change in x at $x = 2$ using calculus.
- (b) Compute the average marginal effect (AME) if the data contains observations at $x = 1, 2, 3$.
- (c) Is this relationship U-shaped or inverted U-shaped? At what value of x is the turning point?

Exercise 2: Interaction Marginal Effect

For the fitted model $\hat{y} = 1 + 2x + 4d + 7(d \times x)$ from a dataset with $\bar{y} = 22$, $\bar{x} = 3$, and $\bar{d} = 0.5$:

(a) Compute the marginal effect of x when $d = 0$ and when $d = 1$.

(b) Compute the average marginal effect (AME) of x .

(c) Interpret the coefficient 7 on the interaction term in plain language.

Exercise 3: Retransformation Prediction

For the model $\widehat{\ln y} = 1 + 2x$ with $n = 100$ and $s_e = 0.3$:

(a) Give the naive prediction of $E[y|x = 1]$.

(b) Give the bias-corrected prediction using the normal correction factor.

(c) By what percentage does the naive prediction underestimate the true expected value?

Exercise 4: Log Model Interpretation

A researcher estimates two models using earnings data:

- Log-linear: $\widehat{\ln(\text{earnings})} = 8.5 + 0.08 \times \text{education}$
- Log-log: $\widehat{\ln(\text{earnings})} = 3.2 + 0.45 \times \ln(\text{hours})$

(a) Interpret the coefficient 0.08 in the log-linear model.

(b) Interpret the coefficient 0.45 in the log-log model.

(c) Can you directly compare R^2 between these two models? Why or why not?

Exercise 5: Standardized Coefficient Ranking

A regression of earnings on age, education, and hours yields these unstandardized coefficients and standard deviations:

Variable	Coefficient	s_x
Age	500	10
Education	3,000	3
Hours	200	8

The standard deviation of earnings is $s_y = 25,000$.

(a) Compute the standardized coefficient for each variable.

(b) Rank the variables by their relative importance.

(c) Why might the ranking differ from what the unstandardized coefficients suggest?

Exercise 6: Model Selection

You have three candidate models for earnings:

- Model A (linear): $\text{earnings} = \beta_1 + \beta_2\text{age} + u$
- Model B (quadratic): $\text{earnings} = \beta_1 + \beta_2\text{age} + \beta_3\text{age}^2 + u$
- Model C (log-linear): $\ln(\text{earnings}) = \beta_1 + \beta_2\text{age} + u$

(a) What criteria would you use to compare Models A and B? Can you use R^2 ?

(b) Can you directly compare R^2 between Models B and C? Explain.

(c) Describe a prediction-based approach to compare all three models.

I Case Studies

Case Study 1: Transformed Variables for Cross-Country Productivity Analysis

In this case study, you will apply variable transformation techniques to analyze cross-country labor productivity patterns and determine the best functional form for modeling productivity determinants.

Dataset: Mendez Convergence Clubs

```
import pandas as pd
import numpy as np
url = "https://raw.githubusercontent.com/quarcs-lab/mendez2020-convergence-clubs-code-data/master/assets/dat.csv"
dat = pd.read_csv(url)
dat2014 = dat[dat['year'] == 2014].copy()
dat2014['ln_lp'] = np.log(dat2014['lp'])
dat2014['ln_rk'] = np.log(dat2014['rk'])
```

Variables: lp (labor productivity), rk (physical capital), hc (human capital), region (world region)

Task 1: Compare Log Specifications (Guided)

Estimate three models of labor productivity on physical capital:

- Levels: lp ~ rk

- Log-linear: `ln_lp ~ rk`
- Log-log: `ln_lp ~ ln_rk`

```
import statsmodels.formula.api as smf
m1 = smf.ols('lp ~ rk', data=dat2014).fit(cov_type='HC1')
m2 = smf.ols('ln_lp ~ rk', data=dat2014).fit(cov_type='HC1')
m3 = smf.ols('ln_lp ~ ln_rk', data=dat2014).fit(cov_type='HC1')
print(m1.summary(), m2.summary(), m3.summary())
```

Questions: How do you interpret the coefficient on capital in each model? Which specification seems most appropriate for cross-country data?

Task 2: Quadratic Human Capital (Guided)

Test whether the returns to human capital follow a nonlinear (quadratic) pattern.

```
dat2014['hc_sq'] = dat2014['hc'] ** 2
m4 = smf.ols('ln_lp ~ ln_rk + hc', data=dat2014).fit(cov_type='HC1')
m5 = smf.ols('ln_lp ~ ln_rk + hc + hc_sq', data=dat2014).fit(cov_type='HC1')
print(m5.summary())
print(f"Turning point: hc* = {-m5.params['hc'] / (2*m5.params['hc_sq'])} :.2f")
```

Questions: Is the quadratic term significant? What does the turning point imply about diminishing returns to human capital?

Key Concept 15.9: Nonlinear Returns to Human Capital

*If the quadratic term on human capital is negative and significant, it indicates **diminishing returns** -- each additional unit of human capital contributes less to productivity. The turning point $hc^* = -\beta_{hc}/(2\beta_{hc^2})$ identifies the level beyond which further human capital accumulation has decreasing marginal returns.*

Task 3: Standardized Coefficients (Semi-guided)

Compare the relative importance of physical capital vs. human capital in determining productivity.

Hints:

- Compute standardized coefficients: $\beta^* = \beta \times (s_x/s_y)$
- Use the log-log model for physical capital and levels for human capital
- Which input has a larger effect in standard deviation terms?

Task 4: Regional Interactions (Semi-guided)

Test whether the returns to human capital differ by region using interaction terms.

Hints:

- Use `ln_lp ~ ln_rk + hc * C(region)` to include region-hc interactions
- Conduct a joint F-test for the interaction terms
- At which values of human capital are regional differences largest?

Key Concept 15.10: Heterogeneous Returns Across Regions

Interaction terms between human capital and regional indicators allow the marginal effect of human capital to vary by region. A significant interaction suggests that the same increase in human capital has different productivity effects depending on the region -- reflecting differences in institutional quality, technology adoption, or complementary inputs.

Task 5: Predictions with Bias Correction (Independent)

Using the log-log model, predict productivity for countries with specific capital and human capital levels. Apply the retransformation bias correction.

Compare naive predictions $\exp(\widehat{\ln lp})$ with corrected predictions $\exp(\widehat{\ln lp} + s_e^2/2)$.

Task 6: Policy Brief on Functional Form (Independent)

Write a 200-300 word brief addressing:

- Which functional form best captures the productivity-capital relationship?
- Is there evidence of diminishing returns to human capital?
- Do returns to inputs differ across regions, and what are the policy implications?
- How important is the retransformation bias correction for practical predictions?

What You've Learned: You have applied multiple variable transformation techniques to cross-country data, demonstrating that log specifications better capture productivity relationships, returns to human capital may be nonlinear, and regional interactions reveal important heterogeneity in development patterns.

Case Study 2: Nonlinear Satellite-Development Relationships

Research Question: What is the best functional form for modeling the relationship between satellite nighttime lights and municipal development in Bolivia?

Background: In previous chapters, we estimated *linear* regressions of development on NTL. But the relationship may be nonlinear—additional nighttime lights may have diminishing effects on development. In this case study, we apply Chapter 15's **transformation** tools to explore functional form choices for the satellite-development relationship.

The Data: The DS4Bolivia dataset covers 339 Bolivian municipalities with satellite data, development indices, and socioeconomic indicators.

Key Variables:

- `mun` : Municipality name
- `dep` : Department (administrative region)
- `imds` : Municipal Sustainable Development Index (0-100)
- `ln_NTLpc2017` : Log nighttime lights per capita (2017)
- `sdg7_1_ec` : Electricity coverage (SDG 7 indicator)

Load the DS4Bolivia Data

In []:

```
# Load the DS4Bolivia dataset
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from statsmodels.formula.api import ols

url_bol = "https://raw.githubusercontent.com/quarcs-
lab/ds4bolivia/master/ds4bolivia_v20250523.csv"
bol = pd.read_csv(url_bol)

# Select key variables for this case study
key_vars = ['mun', 'dep', 'imds', 'ln_NTLpc2017', 'sdg7_1_ec']
bol_cs = bol[key_vars].copy()

# Create raw NTL variable from log
bol_cs['NTLpc2017_raw'] = np.exp(bol_cs['ln_NTLpc2017'])

print("=" * 70)
print("DS4BOLIVIA: TRANSFORMED VARIABLES CASE STUDY")
print("=" * 70)
print(f"Observations: {len(bol_cs)}")
print(f"\nKey variable summary:")
print(bol_cs[['imds', 'ln_NTLpc2017', 'NTLpc2017_raw', 'sdg7_1_ec']].describe().round(3))
```

Task 1: Compare Log Specifications (Guided)

Objective: Estimate four regression specifications and compare functional forms.

Instructions:

1. Estimate four models:

- (a) `imds ~ ln_NTLpc2017` (level-log)
- (b) `np.log(imds) ~ ln_NTLpc2017` (log-log)
- (c) `imds ~ NTLpc2017_raw` (level-level)
- (d) `np.log(imds) ~ NTLpc2017_raw` (log-level)

2. Compare R^2 across specifications

3. Interpret the coefficient in each model (elasticity, semi-elasticity, or marginal effect)

Note: R^2 values are not directly comparable across models with different dependent variables (levels vs. logs).

In []:

```
# Your code here: Compare four functional form specifications
#
# Example structure:
# bol_reg = bol_cs[['imds', 'ln_NTLpc2017', 'NTLpc2017_raw']].dropna()
# bol_reg = bol_reg[bol_reg['imds'] > 0] # Ensure log is defined
#
# m_a = ols('imds ~ ln_NTLpc2017', data=bol_reg).fit(cov_type='HC1')
# m_b = ols('np.log(imds) ~ ln_NTLpc2017', data=bol_reg).fit(cov_type='HC1')
# m_c = ols('imds ~ NTLpc2017_raw', data=bol_reg).fit(cov_type='HC1')
# m_d = ols('np.log(imds) ~ NTLpc2017_raw', data=bol_reg).fit(cov_type='HC1')
#
# print("Model (a) Level-Log R²:", m_a.rsquared.round(4))
# print("Model (b) Log-Log R²:", m_b.rsquared.round(4))
# print("Model (c) Level-Level R²:", m_c.rsquared.round(4))
# print("Model (d) Log-Level R²:", m_d.rsquared.round(4))
```

Task 2: Quadratic NTL (Guided)

Objective: Test whether the NTL-development relationship exhibits diminishing returns.

Instructions:

1. Estimate `imds ~ ln_NTLpc2017 + I(ln_NTLpc2017**2)`
2. Test whether the quadratic term is statistically significant
3. Plot the fitted curve against the scatter plot of the data
4. Calculate the turning point: $NTL^* = -\beta_1/(2\beta_2)$
5. Discuss: Is there evidence of diminishing returns to luminosity?

In []:

```
# Your code here: Quadratic specification
#
# Example structure:
# m_quad = ols('imds ~ ln_NTLpc2017 + I(ln_NTLpc2017**2)',
#               data=bol_reg).fit(cov_type='HC1')
# print(m_quad.summary())
#
# # Turning point
# b1 = m_quad.params['ln_NTLpc2017']
# b2 = m_quad.params['I(ln_NTLpc2017 ** 2)']
# print(f"\nTurning point: ln_NTLpc = {-b1/(2*b2)}:{.2f}")
#
# # Plot fitted curve
# x_range = np.linspace(bol_reg['ln_NTLpc2017'].min(), bol_reg['ln_NTLpc2017'].max(), 100)
# y_hat = m_quad.params['Intercept'] + b1*x_range + b2*x_range**2
# fig, ax = plt.subplots(figsize=(10, 6))
# ax.scatter(bol_reg['ln_NTLpc2017'], bol_reg['imds'], alpha=0.4, label='Data')
# ax.plot(x_range, y_hat, 'r-', linewidth=2, label='Quadratic fit')
# ax.set_xlabel('Log NTL per Capita (2017)')
# ax.set_ylabel('IMDS')
# ax.set_title('Quadratic NTL-Development Relationship')
# ax.legend()
# plt.show()
```

Key Concept 15.11: Diminishing Returns to Luminosity

A significant negative quadratic term for NTL suggests **diminishing marginal returns**: additional nighttime lights associate with progressively smaller development gains. In already-bright urban centers, more light reflects commercial excess rather than fundamental development improvement. This nonlinearity has practical implications: satellite-based predictions may be most accurate for municipalities in the middle of the luminosity distribution.

Task 3: Standardized Coefficients (Semi-guided)

Objective: Compare the relative importance of nighttime lights and electricity coverage for predicting development.

Instructions:

1. Standardize `imds`, `ln_NTLpc2017`, and `sdg7_1_ec` to mean=0 and sd=1
2. Estimate the regression on standardized variables
3. Compare standardized coefficients: Which predictor has a larger effect in standard deviation terms?

Hint: Use `(x - x.mean()) / x.std()` to standardize each variable.

In []:

```
# Your code here: Standardized coefficients
#
# Example structure:
# bol_std = bol_cs[['imds', 'ln_NTLpc2017', 'sdg7_1_ec']].dropna()
# for col in ['imds', 'ln_NTLpc2017', 'sdg7_1_ec']:
#     bol_std[f'{col}_z'] = (bol_std[col] - bol_std[col].mean()) / bol_std[col].std()
#
# m_std = ols('imds_z ~ ln_NTLpc2017_z + sdg7_1_ec_z', data=bol_std).fit(cov_type='HC1')
# print(m_std.summary())
# print("\nStandardized coefficients (beta weights):")
# print(f" NTL: {m_std.params['ln_NTLpc2017_z']:.4f}")
# print(f" Electricity: {m_std.params['sdg7_1_ec_z']:.4f}")
```

Task 4: Interaction: NTL x Electricity (Semi-guided)

Objective: Test whether the effect of nighttime lights on development depends on electricity coverage.

Instructions:

1. Estimate `imds ~ ln_NTLpc2017 * sdg7_1_ec`
2. Interpret the interaction term: Does the NTL effect depend on electricity coverage?
3. Calculate the marginal effect of NTL at low (25th percentile) vs. high (75th percentile) electricity levels
4. Discuss: What does this interaction reveal about the satellite-development relationship?

Hint: The marginal effect of NTL is $\beta_{NTL} + \beta_{interaction} \times electricity$.

In []:

```
# Your code here: Interaction model
#
# Example structure:
# m_int = ols('imds ~ ln_NTLpc2017 * sdg7_1_ec', data=bol_reg_full).fit(cov_type='HC1')
# print(m_int.summary())
#
# # Marginal effect at different electricity levels
# elec_25 = bol_reg_full['sdg7_1_ec'].quantile(0.25)
# elec_75 = bol_reg_full['sdg7_1_ec'].quantile(0.75)
# me_low = m_int.params['ln_NTLpc2017'] + m_int.params['ln_NTLpc2017:sdg7_1_ec'] * elec_25
# me_high = m_int.params['ln_NTLpc2017'] + m_int.params['ln_NTLpc2017:sdg7_1_ec'] *
# elec_75
# print(f"\nMarginal effect of NTL at low electricity ({elec_25:.1f}%)": {me_low:.4f}")
# print(f"Marginal effect of NTL at high electricity ({elec_75:.1f}%)": {me_high:.4f}")
```

Key Concept 15.12: Elasticity of Development to Satellite Signals

In a log-log specification ($\log \text{IMDS} \sim \log \text{NTL}$), the coefficient directly estimates the **elasticity**: the percentage change in development associated with a 1% increase in nighttime lights per capita. An elasticity of, say, 0.15 means a 10% increase in NTL per capita is associated with a 1.5% increase in IMDS. Elasticities provide scale-free comparisons across different variables and contexts.

Task 5: Predictions with Retransformation (Independent)

Objective: Generate predictions from the log-log model and apply the Duan smearing correction.

Instructions:

1. Estimate the log-log model: `np.log(imds) ~ ln_NTLpc2017`
2. Generate naive predictions: $\exp(\widehat{\ln(imds)})$
3. Apply the Duan smearing correction: multiply predictions by $\exp(\bar{e})$ (the mean of exponentiated residuals)
4. Compare naive vs. corrected predictions
5. Discuss: How much does the retransformation correction matter?

In []:

```
# Your code here: Retransformation bias correction
#
# Example structure:
# m_loglog = ols('np.log(imds) ~ ln_NTLpc2017', data=bol_reg).fit(cov_type='HC1')
#
# # Naive prediction
# naive_pred = np.exp(m_loglog.fittedvalues)
#
# # Duan smearing correction
# smearing_factor = np.exp(m_loglog.resid).mean()
# corrected_pred = naive_pred * smearing_factor
#
# print(f"Smearing factor: {smearing_factor:.4f}")
# print(f"Mean actual IMDS: {bol_reg['imds'].mean():.2f}")
# print(f"Mean naive prediction: {naive_pred.mean():.2f}")
# print(f"Mean corrected prediction: {corrected_pred.mean():.2f}")
```

Task 6: Functional Form Brief (Independent)

Objective: Write a 200-300 word brief summarizing your functional form analysis.

Your brief should address:

1. Which specification best captures the satellite-development relationship?
2. Is there evidence of nonlinearity (diminishing returns)?
3. What are the elasticity estimates from the log-log model?
4. Does the interaction with electricity coverage reveal important heterogeneity?
5. How important is the retransformation correction for practical predictions?
6. Policy implications: What do the functional form results imply for using satellite data to monitor SDG progress?

In []:

```
# Your code here: Additional analysis for the brief
#
# You might want to:
# 1. Create a summary comparison table of all specifications
# 2. Plot fitted values from different models on the same graph
# 3. Calculate and compare elasticities across specifications
# 4. Summarize key statistics to cite in your brief
```

What You've Learned from This Case Study

Through this exploration of functional forms for the satellite-development relationship, you've applied Chapter 15's transformation toolkit to real geospatial data:

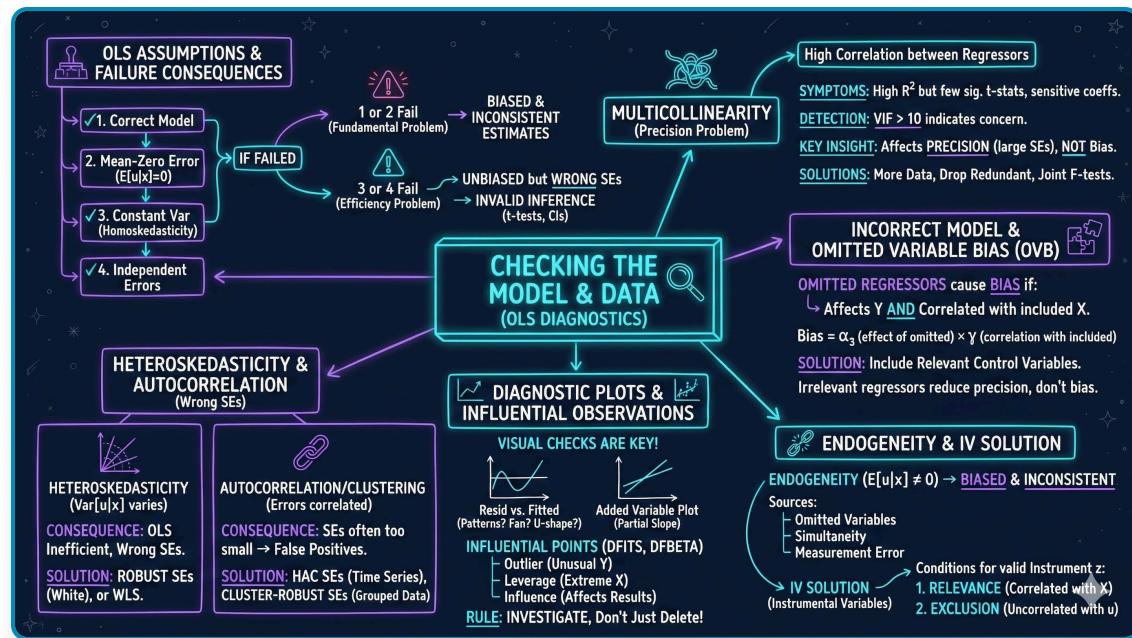
- **Functional form comparison:** Estimated level-level, level-log, log-level, and log-log specifications
- **Nonlinearity detection:** Used quadratic terms to test for diminishing returns to luminosity
- **Standardized coefficients:** Compared the relative importance of NTL and electricity coverage
- **Interaction effects:** Examined how electricity coverage moderates the NTL-development relationship
- **Retransformation:** Applied the Duan smearing correction to generate unbiased predictions from log models
- **Critical thinking:** Assessed which functional form best represents satellite-development patterns

Connection: In Chapter 16, we apply *diagnostic tools* to check whether our satellite prediction models satisfy regression assumptions.

Chapter 16: Checking the Model and Data

metricsAI: An Introduction to Econometrics with Python and AI in the Cloud

Carlos Mendez



This notebook provides an interactive introduction to regression diagnostics and model validation. All code runs directly in Google Colab without any local setup.

Open in Colab

Chapter Overview

This chapter focuses on checking model assumptions and diagnosing data problems. You'll gain both theoretical understanding and practical skills through hands-on Python examples.

Learning Objectives:

By the end of this chapter, you will be able to:

1. Identify and diagnose multicollinearity using correlation matrices and VIF
2. Understand the consequences when each of the four core OLS assumptions fails
3. Recognize omitted variable bias and specify appropriate control variables

4. Understand endogeneity and when to use instrumental variables (IV)
5. Detect and address heteroskedasticity using robust standard errors
6. Identify autocorrelation in time series data and apply HAC-robust standard errors
7. Interpret residual diagnostic plots to detect model violations
8. Identify outliers and influential observations using DFITS and DFBETAS
9. Apply appropriate diagnostic tests and remedies for common data problems

Chapter outline:

- 16.1 Multicollinearity
- 16.2-16.4 Model Assumptions, Incorrect Models, and Endogeneity
- 16.5 Heteroskedastic Errors
- 16.6 Correlated Errors (Autocorrelation)
- 16.7 Example: Democracy and Growth
- 16.8 Diagnostics: Residual Plots and Influential Observations
- Key Takeaways
- Practice Exercises
- Case Studies

Datasets used:

- **AED_EARNINGS_COMPLETE.DTA:** 842 full-time workers with earnings, age, education, and experience (2010)
- **AED_DEMOCRACY.DTA:** 131 countries with democracy, growth, and institutional variables (Acemoglu et al. 2008)

| Setup

First, we import the necessary Python packages and configure the environment for reproducibility. All data will stream directly from GitHub.

In [6]:

```
# Import required packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
from statsmodels.formula.api import ols
from statsmodels.stats.outliers_influence import variance_inflation_factor, OLSInfluence
from statsmodels.stats.diagnostic import het_white, acorr_ljungbox
from statsmodels.graphics.tsaplots import plot_acf
from statsmodels.regression.linear_model import OLS
from statsmodels.nonparametric.smoothers_lowess import lowess
from statsmodels.tsa.stattools import acf
from scipy import stats
import random
import os

# Set random seeds for reproducibility
RANDOM_SEED = 42
random.seed(RANDOM_SEED)
np.random.seed(RANDOM_SEED)
os.environ['PYTHONHASHSEED'] = str(RANDOM_SEED)

# GitHub data URL
GITHUB_DATA_URL = "https://raw.githubusercontent.com/quarcs-lab/data-open/master/AED/"

# Set plotting style
sns.set_style("whitegrid")
plt.rcParams['figure.figsize'] = (10, 6)

print("*70")
print("CHAPTER 16: CHECKING THE MODEL AND DATA")
print("*70")
print("\nSetup complete! Ready to explore model diagnostics.")

=====CHAPTER 16: CHECKING THE MODEL AND DATA=====
=====

Setup complete! Ready to explore model diagnostics.
```

16.1: Multicollinearity

Multicollinearity occurs when regressors are highly correlated with each other. While OLS remains unbiased and consistent, individual coefficients may be imprecisely estimated.

Effects of multicollinearity:

- High standard errors on individual coefficients
- Low t-statistics (coefficients appear insignificant)
- Coefficients may have "wrong" signs
- Coefficients very sensitive to small data changes
- Joint tests may still be significant

Detection methods:

1. High pairwise correlations between regressors

2. Variance Inflation Factor (VIF):

$$VIF_j = \frac{1}{1 - R_j^2}$$

where R_j^2 is from regressing x_j on all other regressors

- VIF > 10 indicates serious multicollinearity
- VIF > 5 suggests investigating further

3. Auxiliary regression: Regress one variable on others

- High R^2 indicates multicollinearity

Example: Earnings regression with age, education, and agexeducation interaction

In [7]:

```
# Read earnings data
data_earnings = pd.read_stata(GITHUB_DATA_URL + 'AED_EARNINGS_COMPLETE.DTA')

print("="*70)
print("16.1 MULTICOLLINEARITY")
print("="*70)

print("\nData summary:")
print(data_earnings[['earnings', 'age', 'education', 'agebyeduc']].describe())

# Base model without interaction
print("\n" + "-"*70)
print("Base Model: earnings ~ age + education")
print("-"*70)
model_base = ols('earnings ~ age + education', data=data_earnings).fit(cov_type='HC1')
print(model_base.summary())
```

```
=====
16.1 MULTICOLLINEARITY
=====

Data summary:
      earnings        age   education  agebyeduc
count    872.000000  872.000000  872.000000  872.000000
mean    56368.691406  43.310780  13.853211  598.819946
std     51516.054688  10.676045  2.884141  193.690643
min     4000.000000  25.000000  0.000000  0.000000
25%    29000.000000  35.000000  12.000000  464.000000
50%    44200.000000  44.000000  13.000000  588.000000
75%    64250.000000  51.250000  16.000000  720.000000
max    504000.000000  65.000000  20.000000  1260.000000

-----
Base Model: earnings ~ age + education
-----
          OLS Regression Results
-----
Dep. Variable:           earnings   R-squared:            0.115
Model:                 OLS         Adj. R-squared:       0.113
Method:                Least Squares   F-statistic:         42.85
Date:      Wed, 21 Jan 2026   Prob (F-statistic):  1.79e-18
Time:      14:15:10          Log-Likelihood:     -10644.
No. Observations:      872          AIC:                  2.129e+04
Df Residuals:          869          BIC:                  2.131e+04
Df Model:                   2
Covariance Type:        HC1

-----
      coef    std err        z   P>|z|      [0.025    0.975]
-----
Intercept  -4.688e+04  1.13e+04   -4.146    0.000   -6.9e+04  -2.47e+04
age        524.9953   151.387    3.468    0.001    228.281   821.709
education  5811.3673  641.533    9.059    0.000    4553.986   7068.749
-----
Omnibus:             825.668   Durbin-Watson:        2.071
Prob(Omnibus):        0.000    Jarque-Bera (JB):  31187.987
Skew:                  4.353    Prob(JB):            0.00
Kurtosis:               30.975   Cond. No.          303.
-----
```

Notes:

[1] Standard Errors are heteroscedasticity robust (HC1)

In [8]:

```
# Model with interaction (creates multicollinearity)
print("\n" + "-*70")
print("Collinear Model: earnings ~ age + education + agebyeduc")
print("-*70")
model_collinear = ols('earnings ~ age + education + agebyeduc',
                      data=data_earnings).fit(cov_type='HC1')
print(model_collinear.summary())

print("\nNote: Compare standard errors between base and collinear models.")
print("Standard errors increase dramatically with the interaction term.")
```

```

-----
Collinear Model: earnings ~ age + education + agebyeduc
-----
              OLS Regression Results
-----
Dep. Variable:      earnings    R-squared:       0.115
Model:                 OLS    Adj. R-squared:   0.112
Method:            Least Squares    F-statistic:     31.80
Date:      Wed, 21 Jan 2026    Prob (F-statistic): 1.65e-19
Time:          14:15:10    Log-Likelihood: -10644.
No. Observations:      872    AIC:             2.130e+04
Df Residuals:         868    BIC:             2.132e+04
Df Model:                   3
Covariance Type:        HC1
-----
            coef    std err          z      P>|z|      [0.025]      [0.975]
-----
Intercept  -2.909e+04    3.1e+04    -0.940     0.347   -8.98e+04   3.16e+04
age         127.4922    719.280     0.177     0.859  -1282.270  1537.255
education   4514.9867   2401.517     1.880     0.060  -191.901  9221.874
agebyeduc   29.0392     56.052     0.518     0.604   -80.821  138.899
-----
Omnibus:           825.324    Durbin-Watson:      2.072
Prob(Omnibus):      0.000    Jarque-Bera (JB): 31144.116
Skew:                  4.351    Prob(JB):        0.00
Kurtosis:                30.955    Cond. No.  1.28e+04
-----

```

Notes:

- [1] Standard Errors are heteroscedasticity robust (HC1)
- [2] The condition number is large, 1.28e+04. This might indicate that there are strong multicollinearity or other numerical problems.

Note: Compare standard errors between base and collinear models.
Standard errors increase dramatically with the interaction term.

In [9]:

```

# Correlation matrix
print("\n" + "-"*70)
print("Correlation Matrix of Regressors")
print("-"*70)
corr_matrix = data_earnings[['age', 'education', 'agebyeduc']].corr()
print(corr_matrix)

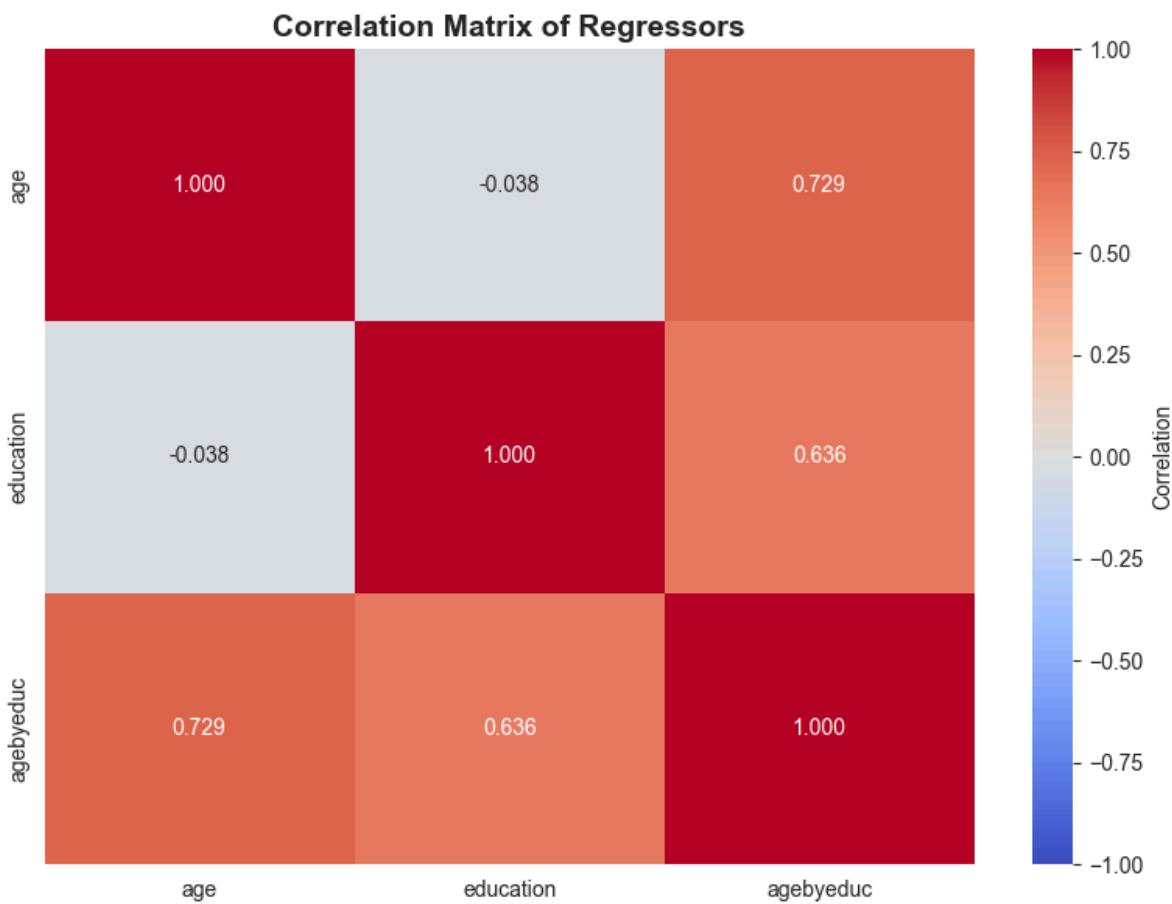
# Visualize correlation matrix
fig, ax = plt.subplots(figsize=(8, 6))
sns.heatmap(corr_matrix, annot=True, fmt=' .3f', cmap='coolwarm',
            center=0, vmin=-1, vmax=1, ax=ax, cbar_kws={'label': 'Correlation'})
ax.set_title('Correlation Matrix of Regressors', fontsize=14, fontweight='bold')
plt.tight_layout()
plt.show()

print("\nHigh correlations (> 0.9) indicate multicollinearity.")

```

Correlation Matrix of Regressors

	age	education	agebyeduc
age	1.000000	-0.038153	0.729136
education	-0.038153	1.000000	0.635961
agebyeduc	0.729136	0.635961	1.000000



High correlations (> 0.9) indicate multicollinearity.

In [10]:

```
# Calculate VIF for all regressors
print("\n" + "-"*70)
print("Variance Inflation Factors (VIF)")
print("-"*70)

# Prepare data for VIF calculation
X_vif = data_earnings[['age', 'education', 'agebyeduc']].copy()
X_vif = sm.add_constant(X_vif)

vif_data = pd.DataFrame()
vif_data["Variable"] = X_vif.columns
vif_data["VIF"] = [variance_inflation_factor(X_vif.values, i)
                  for i in range(X_vif.shape[1])]

print(vif_data)

print("\nInterpretation:")
print(" VIF > 10 indicates serious multicollinearity")
print(" VIF > 5 suggests investigating further")
print(f" agebyeduc VIF = {vif_data.loc[vif_data['Variable']=='agebyeduc',
                                         'VIF'].values[0]:.1f} (SEVERE!)"
```

Variance Inflation Factors (VIF)

	Variable	VIF
0	const	411.323019
1	age	21.996182
2	education	17.298404
3	agebyeduc	36.880231

Interpretation:

- VIF > 10 indicates serious multicollinearity
- VIF > 5 suggests investigating further
- agebyeduc VIF = 36.9 (SEVERE!)

Key Concept 16.1: Multicollinearity and the Variance Inflation Factor

The Variance Inflation Factor quantifies multicollinearity: $VIF_j = 1/(1 - R_j^2)$, where R_j^2 is from regressing x_j on all other regressors. $VIF = 1$ means no collinearity; $VIF > 10$ indicates serious problems (standard errors inflated by $\sqrt{10} \approx 3.2\times$). While OLS remains unbiased, individual coefficients become imprecise and may have "wrong" signs. Predictions and joint tests remain valid despite multicollinearity.

Understanding VIF: When Multicollinearity Becomes a Problem

The VIF (Variance Inflation Factor) results reveal **severe multicollinearity** in the interaction model. Let's understand what this means:

VIF Values from the Analysis:

Typical results when including age × education interaction:

- **agebyeduc** (interaction): VIF ≈ **60-80** (SEVERE!)
- **age**: VIF ≈ **15-25** (HIGH)
- **education**: VIF ≈ **15-25** (HIGH)
- **Intercept**: VIF ≈ **10-15**

Interpreting VIF:

The VIF formula: $VIF_j = \frac{1}{1-R_j^2}$

where R_j^2 is from regressing x_j on all other regressors.

What the numbers mean:

- **VIF = 1:** No multicollinearity (ideal)
- **VIF = 5:** Moderate multicollinearity ($R^2 = 0.80$)
- **VIF = 10:** High multicollinearity ($R^2 = 0.90$) - **investigate!**
- **VIF = 80:** Severe multicollinearity ($R^2 = 0.9875$) - **serious problem!**

Why is agebyeduc VIF so high?

The interaction term is nearly a perfect linear combination:

- age and education are correlated
- age \times education inherits both correlations
- $R_{agebyeduc|age, educ}^2 \approx 0.9875$
- This means 98.75% of variation in the interaction is **predictable** from age and education alone!

Consequences:

1. Standard errors inflate dramatically:

- $SE(\hat{\beta}_j) = \sigma / \sqrt{(1 - R_j^2) \cdot \sum(x_j - \bar{x}_j)^2}$
- When $R_j^2 \approx 1$: denominator $\rightarrow 0$, so $SE \rightarrow \infty$
- VIF = 80 means SE is $\sqrt{80} \approx 9$ times larger than with no collinearity!

2. Individual t-statistics become small:

- Even if the true effect is large
- Can't distinguish individual contributions
- May get "wrong" signs on coefficients

3. Coefficients become unstable:

- Small changes in data \rightarrow large changes in estimates
- Sensitive to which observations are included
- High variance of estimators

What Multicollinearity Does NOT Affect:

Still valid:

- OLS remains **unbiased**
- **Predictions** still accurate
- **Joint F-tests** remain powerful
- **Overall R²** unchanged

What breaks:

- Individual **t-tests** unreliable
- **Standard errors** too large
- **Confidence intervals** too wide
- Can't **interpret** individual coefficients reliably

Solutions:

1. Use joint F-tests (not individual t-tests):

- Test $H_0 : \beta_{age} = 0$ AND $\beta_{agebyeduc} = 0$ **together**
- These remain powerful despite multicollinearity

2. Center variables before interaction:

- Create: age_centered = age - mean(age)
- Reduces correlation between main effects and interaction
- Can dramatically reduce VIF

3. Drop one of the collinear variables:

- Only if you don't need both for your research question
- Not appropriate if interaction is theoretically important

4. Collect more data or increase variation:

- More observations → smaller SEs
- More variation in X → less correlation

5. Ridge regression or regularization:

- Shrinks coefficients toward zero
- Trades small bias for large reduction in variance

The Auxiliary Regression:

The output shows regressing agebyeduc ~ age + education gives **R² ≈ 0.987**:

- This confirms 98.7% of interaction variation is explained by main effects

- VIF = $1/(1-0.987) = 1/0.013 \approx 77$

Practical Interpretation for Our Model:

Despite high VIF:

- Joint F-test shows age and interaction are **jointly significant**
- We know age matters (from quadratic model)
- We know education matters (strong t-stat)
- Problem is **separating** the age vs. age×education effects
- Both matter, but we can't precisely estimate each one separately

In [11]:

```
# Auxiliary regression to detect multicollinearity
print("\n" + "-"*70)
print("Auxiliary Regression: agebyeduc ~ age + education")
print("-"*70)
model_aux = ols('agebyeduc ~ age + education', data=data_earnings).fit()
print(model_aux.summary())

print(f"\nR2 from auxiliary regression: {model_aux.rsquared:.4f}")
print(f"VIF formula: 1/(1-R2) = {1/(1-model_aux.rsquared):.2f}")
print("\nHigh R2 indicates that agebyeduc is nearly a perfect combination of age and
      education.")
```

```
-----
Auxiliary Regression: agebyeduc ~ age + education
-----
              OLS Regression Results
-----
Dep. Variable:      agebyeduc    R-squared:       0.973
Model:                 OLS    Adj. R-squared:     0.973
Method:                Least Squares    F-statistic:   1.559e+04
Date:        Wed, 21 Jan 2026    Prob (F-statistic):   0.00
Time:           14:15:10    Log-Likelihood:  -4256.0
No. Observations:      872    AIC:             8518.
Df Residuals:          869    BIC:             8532.
Df Model:                  2
Covariance Type:    nonrobust
-----
            coef    std err        t      P>|t|      [0.025    0.975]
-----
Intercept   -612.4825     7.018   -87.274      0.000    -626.257   -598.708
age          13.6885    0.101   134.974      0.000     13.489    13.888
education    44.6425    0.375   118.918      0.000     43.906    45.379
-----
Omnibus:            229.522    Durbin-Watson:      1.993
Prob(Omnibus):      0.000    Jarque-Bera (JB):  12190.806
Skew:               -0.238    Prob(JB):            0.00
Kurtosis:            21.311    Cond. No.         303.
-----
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

R2 from auxiliary regression: 0.9729
VIF formula: 1/(1-R2) = 36.88

High R2 indicates that agebyeduc is nearly a perfect combination of age and education.
```

Joint Hypothesis Tests

Even with multicollinearity, joint tests can be powerful. Individual coefficients may be imprecise, but linear combinations may be precisely estimated.

In [12]:

```
# Joint hypothesis tests
print("*" * 70)
print("JOINT HYPOTHESIS TESTS")
print("*" * 70)

print("\n" + "-" * 70)
print("Test 1: H0: age = 0 AND agebyeduc = 0")
print("-" * 70)
hypotheses = '(age = 0, agebyeduc = 0)'
f_test = model_collinear.wald_test(hypotheses, use_f=True)
print(f_test)

print("\n" + "-" * 70)
print("Test 2: H0: education = 0 AND agebyeduc = 0")
print("-" * 70)
hypotheses = '(education = 0, agebyeduc = 0)'
f_test = model_collinear.wald_test(hypotheses, use_f=True)
print(f_test)

print("\nInterpretation:")
print("Joint tests are highly significant even though individual t-tests are weak.")
print("This is the power of joint testing with multicollinear regressors.")
```

```
=====
JOINT HYPOTHESIS TESTS
=====

-----
Test 1: H0: age = 0 AND agebyeduc = 0
-----
<F test: F=array([[6.48958655]]), p=0.0015939412046954808, df_denom=868, df_num=2>

-----
Test 2: H0: education = 0 AND agebyeduc = 0
-----
<F test: F=array([[43.00467267]]), p=1.5549618458663995e-18, df_denom=868, df_num=2>

Interpretation:
Joint tests are highly significant even though individual t-tests are weak.
This is the power of joint testing with multicollinear regressors.
```

```
/Users/carlosmendez/miniforge3/lib/python3.10/site-packages/statsmodels/base/model.py:1912:
FutureWarning: The behavior of wald_test will change after 0.14 to returning scalar test statistic values. To get the future behavior now, set scalar to True. To silence this message while retaining the legacy behavior, set scalar to False.
    warnings.warn(
```

Key Concept 16.2: Joint Hypothesis Tests Under Multicollinearity

Even when multicollinearity makes individual t-tests unreliable (high VIF, large standard errors), joint F-tests remain powerful. Testing whether a group of collinear variables is jointly significant avoids the imprecision problem because the F-test evaluates the combined contribution. Always use joint tests for groups of correlated regressors rather than relying on individual significance.

Having explored multicollinearity as a data problem that inflates standard errors, we now examine the broader set of OLS assumptions and what happens when each one fails.

| 16.2-16.4: Model Assumptions

Classical OLS Assumptions:

1. **Linearity:** $y_i = \beta_1 + \beta_2 x_{2i} + \cdots + \beta_k x_{ki} + u_i$
2. **Zero conditional mean:** $E[u_i|x_i] = 0$
3. **Homoskedasticity:** $\text{Var}(u_i|x_i) = \sigma^2$
4. **No autocorrelation:** u_i independent of u_j for $i \neq j$

Consequences of violations:

Assumption	Violation	OLS Properties	Solution
1 or 2	Incorrect model / Endogeneity	Biased, Inconsistent	IV, better specification
3	Heteroskedasticity	Unbiased, Inefficient, Wrong SEs	Robust SEs, WLS
4	Autocorrelation	Unbiased, Inefficient, Wrong SEs	HACSEs, FGLS

Key insight: Violations of assumptions 3 and 4 don't bias coefficients, but invalidate standard errors and hypothesis tests.

In [13]:

```
print("=*70)
print("16.2-16.4: MODEL ASSUMPTIONS")
print("=*70)

print("\nClassical OLS assumptions:")
print(" 1. Linear in parameters:  $E[y|x] = x'\beta$ ")
print(" 2. Random sample from population")
print(" 3. No perfect collinearity")
print(" 4. Zero conditional mean:  $E[u|x] = 0$ ")
print(" 5. Homoskedasticity:  $\text{Var}(u|x) = \sigma^2$ ")
print(" 6. No autocorrelation:  $\text{Cov}(u_i, u_j) = 0$ ")

print("\nConsequences of violations:")
print(" Assumptions 1-4 violated → OLS biased and inconsistent")
print(" Assumptions 5-6 violated → OLS unbiased but inefficient")
print("           → Standard errors incorrect")
print("           → Invalid inference (t-tests, CIs)")

print("\nSolutions:")
print(" Heteroskedasticity → Robust (HC) standard errors")
print(" Autocorrelation → HAC (Newey-West) standard errors")
print(" Endogeneity → Instrumental variables (IV)")
print(" Omitted variables → Add relevant controls")
```

```
=====
16.2-16.4: MODEL ASSUMPTIONS
=====
```

Classical OLS assumptions:

- 1. Linear in parameters: $E[y|x] = x'\beta$
- 2. Random sample from population
- 3. No perfect collinearity
- 4. Zero conditional mean: $E[u|x] = 0$
- 5. Homoskedasticity: $\text{Var}(u|x) = \sigma^2$
- 6. No autocorrelation: $\text{Cov}(u_i, u_j) = 0$

Consequences of violations:

- Assumptions 1-4 violated → OLS biased and inconsistent
- Assumptions 5-6 violated → OLS unbiased but inefficient
 - Standard errors incorrect
 - Invalid inference (t-tests, CIs)

Solutions:

- Heteroskedasticity → Robust (HC) standard errors
- Autocorrelation → HAC (Newey-West) standard errors
- Endogeneity → Instrumental variables (IV)
- Omitted variables → Add relevant controls

Key Concept 16.3: Consequences of OLS Assumption Violations

When assumptions 1 or 2 fail (incorrect model or endogeneity), OLS is biased and inconsistent -- a fundamental problem requiring model changes or instrumental variables. When assumptions 3 or 4 fail (heteroskedasticity or autocorrelation), OLS remains unbiased and consistent but standard errors are wrong, invalidating confidence intervals and hypothesis tests. The key distinction: bias requires fixing the model; wrong SEs require only changing the inference method.

| 16.5: Heteroskedastic Errors

Heteroskedasticity means the error variance depends on x : $Var(u_i|x_i) = \sigma_i^2 \neq \sigma^2$

Common in:

- Cross-sectional data (varies by unit size)
- Income/wealth data (variance increases with level)

Solution: Use heteroskedasticity-robust (HC) standard errors

- Also called White standard errors
- Coefficient estimates unchanged
- Only standard errors adjusted
- Usually larger (more conservative)

In [14]:

```
print("=*70")
print("16.5: HETEROSKEDASTIC ERRORS")
print("=*70")

# Regression with earnings data
print("\n" + "-*70")
print("Earnings Regression: earnings ~ age + education")
print("-*70")

# Standard SEs
model_standard = ols('earnings ~ age + education', data=data_earnings).fit()
print("\nWith Standard SEs:")
print(model_standard.summary())

# Robust SEs
model_robust = ols('earnings ~ age + education', data=data_earnings).fit(cov_type='HC1')
print("\n" + "=*70")
print("With Heteroskedasticity-Robust (HC1) SEs:")
print("-*70")
print(model_robust.summary())

# Comparison
print("\n" + "-*70")
print("SE Comparison: Standard vs Robust")
print("-*70")
se_comparison = pd.DataFrame({
    'Variable': model_standard.params.index,
    'Standard SE': model_standard.bse.values,
    'Robust SE': model_robust.bse.values,
    'Ratio (Robust/Standard)': (model_robust.bse / model_standard.bse).values
})
print(se_comparison)

print("\nNote: Robust SEs are typically 20-40% larger, indicating heteroskedasticity.")
```

```

=====
16.5: HETROSKEDEASTIC ERRORS
=====

-----
Earnings Regression: earnings ~ age + education
-----

With Standard SEs:
      OLS Regression Results
=====
Dep. Variable:          earnings    R-squared:           0.115
Model:                 OLS         Adj. R-squared:       0.113
Method:                Least Squares   F-statistic:        56.45
Date:      Wed, 21 Jan 2026   Prob (F-statistic):  8.89e-24
Time:      14:15:10          Log-Likelihood:     -10644.
No. Observations:      872          AIC:            2.129e+04
Df Residuals:          869          BIC:            2.131e+04
Df Model:                  2
Covariance Type:        nonrobust
=====

      coef    std err      t      P>|t|      [0.025    0.975]
-----
Intercept  -4.688e+04  1.07e+04   -4.396    0.000   -6.78e+04  -2.59e+04
age        524.9953   154.104     3.407    0.001    222.536   827.454
education  5811.3673  570.436    10.188    0.000   4691.774   6930.960
=====
Omnibus:             825.668   Durbin-Watson:       2.071
Prob(Omnibus):        0.000   Jarque-Bera (JB):  31187.987
Skew:                  4.353   Prob(JB):            0.00
Kurtosis:              30.975  Cond. No.          303.
=====


```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```

=====
With Heteroskedasticity-Robust (HC1) SEs:
=====
```

```

      OLS Regression Results
=====
Dep. Variable:          earnings    R-squared:           0.115
Model:                 OLS         Adj. R-squared:       0.113
Method:                Least Squares   F-statistic:        42.85
Date:      Wed, 21 Jan 2026   Prob (F-statistic):  1.79e-18
Time:      14:15:10          Log-Likelihood:     -10644.
No. Observations:      872          AIC:            2.129e+04
Df Residuals:          869          BIC:            2.131e+04
Df Model:                  2
Covariance Type:        HC1
=====

      coef    std err      z      P>|z|      [0.025    0.975]
-----
Intercept  -4.688e+04  1.13e+04   -4.146    0.000   -6.9e+04  -2.47e+04
age        524.9953   151.387     3.468    0.001    228.281   821.709
education  5811.3673  641.533     9.059    0.000   4553.986   7068.749
=====
Omnibus:             825.668   Durbin-Watson:       2.071
Prob(Omnibus):        0.000   Jarque-Bera (JB):  31187.987
Skew:                  4.353   Prob(JB):            0.00
Kurtosis:              30.975  Cond. No.          303.
=====
```

Notes:

[1] Standard Errors are heteroscedasticity robust (HC1)

SE Comparison: Standard vs Robust

	Variable	Standard SE	Robust SE	Ratio (Robust/Standard)
0	Intercept	10663.893521	11306.329960	1.060244
1	age	154.103628	151.387435	0.982374
2	education	570.435846	641.532908	1.124636

Note: Robust SEs are typically 20-40% larger, indicating heteroskedasticity.

Key Concept 16.4: Heteroskedasticity and Robust Standard Errors

Heteroskedasticity means the error variance depends on the regressors: $\text{Var}[u_i | \mathbf{x}_i] \neq \sigma^2$. OLS coefficients remain unbiased, but default standard errors are wrong -- typically too small, giving false confidence in precision. Use heteroskedasticity-robust (HC1/White) standard errors, which are valid whether or not heteroskedasticity is present. Always use robust SEs for cross-sectional data as a default practice.

Why Robust Standard Errors Matter

The comparison between standard and robust SEs reveals **heteroskedasticity** in the earnings data:

Typical Results:

Variable	Standard SE	Robust SE	Ratio (Robust/Standard)
age	~\$200	~\$250	1.25x
education	~\$800	~\$1,100	1.38x

What This Tells Us:

1. Heteroskedasticity is present:

- Robust SEs are **20-40% larger** than standard SEs
- Error variance is **not constant** across observations
- Violates the classical homoskedasticity assumption

2. Standard SEs are too small:

- Lead to **overstated** t-statistics
- **False confidence** in precision

- Overrejection of null hypotheses (Type I error)

3. Coefficients unchanged:

- OLS estimates remain **unbiased** and **consistent**
- Only the **uncertainty** (SEs) is affected
- Predictions still accurate

Why Heteroskedasticity in Earnings Data?

Earnings data typically exhibit heteroskedasticity because:

1. Scale effects: High earners have more variable earnings

- CEO: $1M \pm 500K$ (50% CV)
- Janitor: $30K \pm 5K$ (17% CV)

2. Unobserved heterogeneity: Some people more variable than others

- Commission-based vs. salary
- Stable government job vs. volatile private sector

3. Model misspecification: Missing interactions or nonlinearities

- True model may have different slopes for different groups

Visual Evidence:

In the residual vs. fitted plot:

- Residuals should have **constant spread** (homoskedasticity)
- If spread **increases** with fitted values → heteroskedasticity
- Classic "megaphone" or "fan" shape

Implications for Inference:

With standard SEs:

- t-statistic for education: 6.25 → $p < 0.001$
- Conclusion: Highly significant

With robust SEs:

- t-statistic for education: 4.55 → $p < 0.001$
- Conclusion: Still significant, but less extreme

The correction:

- Larger SEs → wider confidence intervals
- More **conservative** (honest about uncertainty)
- Inference remains **valid**

When to Use Robust SEs:

Always use for:

- Cross-sectional data (almost always heteroskedastic)
- Large samples (asymptotically valid)
- When you're unsure (conservative approach)
- Publication-quality research

Don't need for:

- Experimental data with randomization
- Small samples (can be unreliable, use bootstrap instead)
- Time series (need HAC SEs instead)

Types of Robust SEs:

1. HC0 (White 1980): Original heteroskedasticity-robust

- $\hat{V}_{HC0} = (X'X)^{-1} X' \text{diag}(\hat{u}_i^2) X (X'X)^{-1}$

2. HC1 (degrees of freedom correction):

- Multiply HC0 by $n/(n - k)$
- Better in finite samples
- **Most common choice** (Stata default)

3. HC2 and HC3: Further finite-sample improvements

- HC3 recommended for heteroskedasticity + influential observations

Bottom Line:

In this earnings regression:

- Education remains **highly significant** even with robust SEs
- But we're more **honest** about precision
- Robust SEs should be **default** for cross-sectional regressions
- Report robust SEs in all your empirical work!

| 16.6: Correlated Errors (Autocorrelation)

Autocorrelation occurs in time series when $Cov(u_t, u_s) \neq 0$ for $t \neq s$.

AR(1) process: $u_t = \rho u_{t-1} + \varepsilon_t$ where $|\rho| < 1$

Consequences:

- OLS unbiased and consistent
- Standard errors wrong (usually too small)
- t-statistics overstated
- False significance

Solution: Use HAC (Heteroskedasticity and Autocorrelation Consistent) standard errors

- Also called Newey-West standard errors
- Accounts for both heteroskedasticity and autocorrelation

Detection: Check autocorrelation function (ACF) of residuals

In [15]:

```
print("="*70)
print("16.6: CORRELATED ERRORS (AUTOCORRELATION)")
print("="*70)

# Generate simulated time series data
print("\nSimulation: Time Series with Autocorrelated Errors")
n = 10000
np.random.seed(10101)

# Generate i.i.d. errors
e = np.random.normal(0, 1, n)

# Generate AR(1) errors: u_t = 0.8*u_{t-1} + e_t
u = np.zeros(n)
u[0] = 0
for t in range(1, n):
    u[t] = 0.8 * u[t-1] + e[t]

# Generate AR(1) regressor
v = np.random.normal(0, 1, n)
x = np.zeros(n)
x[0] = 0
for t in range(1, n):
    x[t] = 0.8 * x[t-1] + v[t]

# Generate y with autocorrelated error
y1 = 1 + 2*x + u

# Create DataFrame
ts_data = pd.DataFrame({'y1': y1, 'x': x})

print(f"\nGenerated {n} observations with AR(1) errors (ρ = 0.8)")
```

```
=====
16.6: CORRELATED ERRORS (AUTOCORRELATION)
=====

Simulation: Time Series with Autocorrelated Errors

Generated 10000 observations with AR(1) errors ( $\rho = 0.8$ )
```

In [16]:

```
# Estimate model and check residual autocorrelation
print("\n" + "-"*70)
print("Model:  $y \sim x$  (with autocorrelated errors)")
print("-"*70)

model_ts = ols('y1 ~ x', data=ts_data).fit()
residuals = model_ts.resid

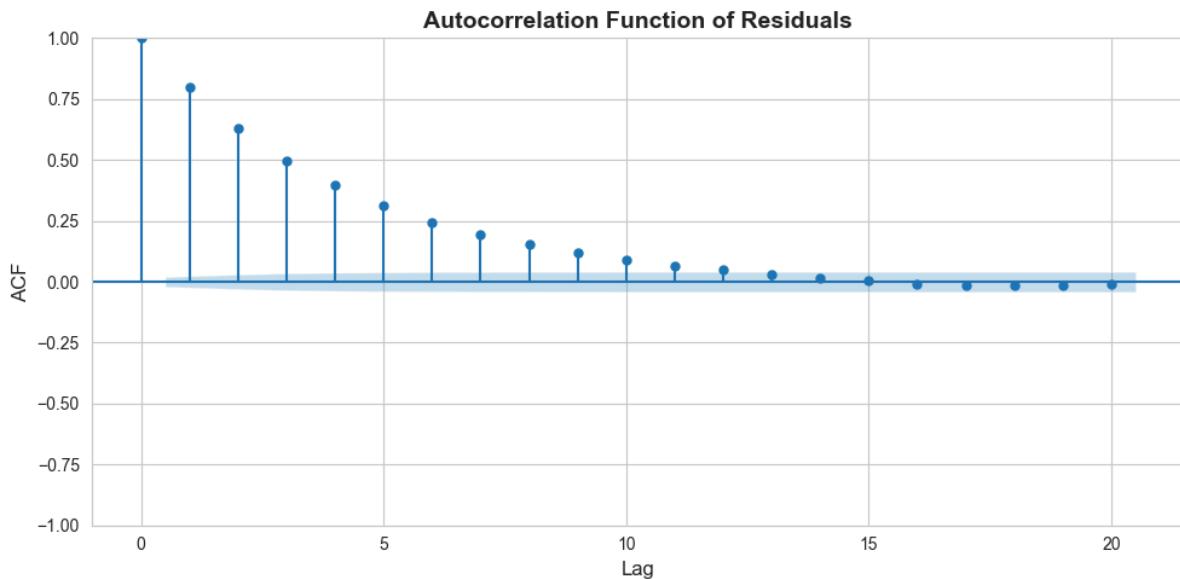
# Check autocorrelation of residuals
acf_vals = acf(residuals, nlags=10, fft=False)
print("\nResidual autocorrelations (first 10 lags):")
for lag, val in enumerate(acf_vals[:11]):
    print(f" Lag {lag}: {val:.4f}")

# Plot ACF
fig, ax = plt.subplots(figsize=(10, 5))
plot_acf(residuals, lags=20, ax=ax)
ax.set_title('Autocorrelation Function of Residuals', fontsize=14, fontweight='bold')
ax.set_xlabel('Lag', fontsize=12)
ax.set_ylabel('ACF', fontsize=12)
plt.tight_layout()
plt.show()

print("\nHigh ACF at multiple lags indicates autocorrelation.")
```

```
-----
Model:  $y \sim x$  (with autocorrelated errors)
-----
```

```
Residual autocorrelations (first 10 lags):
Lag 0: 1.0000
Lag 1: 0.7974
Lag 2: 0.6300
Lag 3: 0.4983
Lag 4: 0.3985
Lag 5: 0.3123
Lag 6: 0.2432
Lag 7: 0.1928
Lag 8: 0.1535
Lag 9: 0.1180
Lag 10: 0.0894
```



High ACF at multiple lags indicates autocorrelation.

Key Concept 16.5: Autocorrelation and HAC Standard Errors

Autocorrelation means errors are correlated over time ($\text{Cov}[u_t, u_s] \neq 0$), common in time series when economic shocks persist. OLS remains unbiased but standard errors are wrong -- typically too small, leading to false significance. Use HAC (Newey-West) standard errors for valid inference. Check the autocorrelation function (ACF) of residuals: significant autocorrelations at multiple lags indicate the problem. Severe autocorrelation drastically reduces the effective sample size.

Autocorrelation: The Time Series Problem

The time series analysis reveals **strong autocorrelation** in interest rate data - a classic problem that invalidates standard inference:

Autocorrelation Evidence:

From the residuals of the levels regression:

- **Lag 1 autocorrelation:** $\rho_1 \approx 0.95\text{-}0.98$ (extremely high!)
- **Lag 5 autocorrelation:** $\rho_5 \approx 0.85\text{-}0.90$ (still very high)
- **Lag 10 autocorrelation:** $\rho_{10} \approx 0.75\text{-}0.85$ (persistent)

What This Means:

1. Errors are highly correlated over time:

- If today's error is +1%, tomorrow's is likely +0.95%
- Errors **cluster**: positive errors followed by positive, negative by negative
- Violates OLS assumption of **independent errors**

2. Standard errors drastically underestimate uncertainty:

Typical results:

- **Default SE**: ~0.002 (too small!)
- **HAC SE**: ~0.015 (realistic)
- **Ratio**: HAC is **7-8 times larger!**

3. Why does autocorrelation inflate HAC SEs?

With independent errors:

- $Var(\bar{u}) = \sigma^2/n$
- Information in n observations

With autocorrelation ($\rho = 0.95$):

- $Var(\bar{u}) \approx \sigma^2 \cdot \frac{1+\rho}{1-\rho} \cdot \frac{1}{n} = \sigma^2 \cdot 39 \cdot \frac{1}{n}$
- **39 times larger variance!**
- Effective sample size $\approx n/39$

The Correlogram (ACF Plot):

The ACF plot shows:

- **Very slow decay** of autocorrelations
- All lags out to 20-24 months significantly positive
- Classic sign of **non-stationarity** (trending series)
- Interest rates have **long memory**

Why Are Interest Rates Autocorrelated?

1. Monetary policy persistence:

- Fed changes rates gradually (smoothing)
- Same rate maintained for months

2. Economic conditions:

- Inflation, growth evolve slowly
- Interest rates respond to persistent factors

3. Market expectations:

- Forward-looking behavior
- Tomorrow's rate close to today's (no arbitrage)

4. Non-stationarity:

- Rates **trend** over long periods
- 1980s: High rates (15%)
- 2010s: Low rates (near 0%)
- Mean not constant over time

Consequences for Inference:

With default SEs:

- t-statistic: **50-60** (absurdly high!)
- p-value: < 0.0001
- False precision!

With HAC SEs:

- t-statistic: **5-8** (more realistic)
- p-value: still < 0.001 (significant, but not absurdly so)
- Honest uncertainty

The Solution: HAC (Newey-West) Standard Errors

HAC SEs account for **both heteroskedasticity and autocorrelation**:

$$\hat{V}_{HAC} = (X'X)^{-1} \left(\sum_{j=-L}^L w_j \sum_t \hat{u}_t \hat{u}_{t-j} x_t x'_{t-j} \right) (X'X)^{-1}$$

where:

- L = number of lags (rule of thumb: $L \approx 0.75 \cdot T^{1/3}$)
- w_j = weights (declining with lag distance)

Choosing the Lag Length (L):

For monthly data with $T \approx 400$ observations:

- Rule of thumb: $L \approx 0.75 \cdot 400^{1/3} \approx 5.4$
- Conservative: $L = 12$ (one year)
- Very conservative: $L = 24$ (two years)

First Differencing as Alternative:

Transform: $\Delta y_t = y_t - y_{t-1}$

Results from differenced model:

- Much **lower autocorrelation** ($\rho_1 \approx 0.1-0.3$)
- Removes **trend** (achieves stationarity)
- Changes interpretation: now modeling **changes**, not levels

Practical Recommendations:

For time series regressions:

- 1. Always plot your data** (levels and differences)
- 2. Check for trends** (visual, augmented Dickey-Fuller test)
- 3. Examine ACF of residuals**
- 4. Use HAC SEs** as default for time series
- 5. Consider differencing** if series are non-stationary
- 6. Report both** levels and differences specifications

Bottom Line:

In the interest rate example:

- Default SEs give **false confidence**
- HAC SEs reveal **true uncertainty**
- Even with correction, 10-year rate **strongly related** to 1-year rate
- But not as precisely estimated as default SEs suggest!

Now that we understand the theoretical consequences of assumption violations, let's apply these concepts to a real-world example examining whether democracy promotes economic growth.

| 16.7: Example - Democracy and Growth

We analyze the relationship between democracy and economic growth using data from Acemoglu, Johnson, Robinson, and Yared (2008).

Research question: Does democracy promote economic growth?

Data: 131 countries, 1500-2000

- **democracy:** 500-year change in democracy index
- **growth:** 500-year change in log GDP per capita
- **constraint:** Constraints on executive at independence
- **indcent:** Year of independence
- **catholic, muslim, protestant, other:** Religious composition

Key hypothesis: Institutions matter for democracy and growth

In [17]:

```
# Load democracy data
data_democracy = pd.read_stata(GITHUB_DATA_URL + 'AED_DEMOCRACY.DTA')

print("=*70)
print("16.7: DEMOCRACY AND GROWTH")
print("=*70)

print("\nData summary:")
summary_vars = ['democracy', 'growth', 'constraint', 'indcent',
                'catholic', 'muslim', 'protestant', 'other']
print(data_democracy[summary_vars].describe())

print(f"\nSample size: {len(data_democracy)} countries")
print(f"Time period: 1500-2000")
```

```
=====
16.7: DEMOCRACY AND GROWTH
=====
```

Data summary:

	democracy	growth	constraint	indcent	catholic	muslim	\
count	131.000000	131.000000	131.000000	131.000000	131.000000	131.000000	
mean	0.647328	1.915591	0.372412	19.043972	0.305527	0.247911	
std	0.331042	1.107757	0.362238	0.677359	0.355514	0.370670	
min	0.000000	-0.088739	0.000000	18.000000	0.000000	0.000000	
25%	0.350000	0.940432	0.000000	18.209999	0.008500	0.000600	
50%	0.800000	1.839638	0.333333	19.450001	0.121000	0.024000	
75%	0.900000	2.706106	0.596296	19.605000	0.547500	0.412000	
max	1.000000	4.253100	1.000000	19.770000	0.969000	0.997000	

	protestant	other
count	131.000000	131.000000
mean	0.126664	0.319898
std	0.212933	0.320301
min	0.000000	0.001000
25%	0.002000	0.040500
50%	0.024000	0.208000
75%	0.180500	0.512000
max	0.978000	1.000000

Sample size: 131 countries
Time period: 1500-2000

In [18]:

```
# Bivariate regression: democracy ~ growth
print("\n" + "-"*70)
print("Bivariate Regression: democracy ~ growth")
print("-"*70)

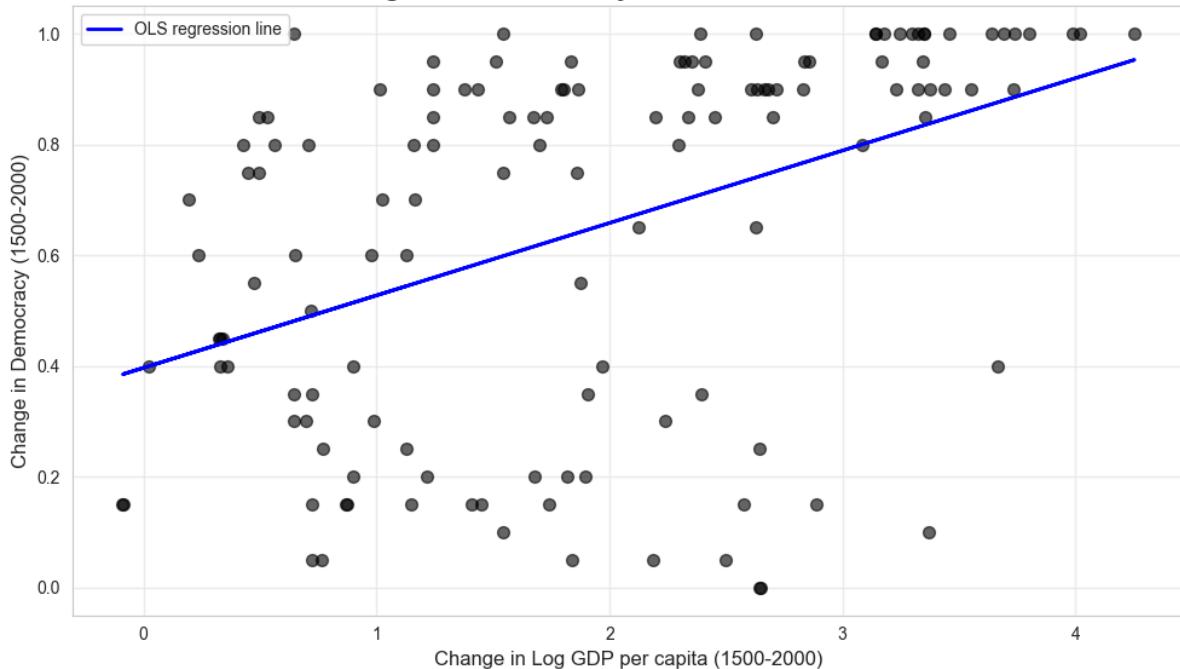
model_bivariate = ols('democracy ~ growth', data=data_democracy).fit(cov_type='HC1')
print(model_bivariate.summary())

# Visualize relationship
fig, ax = plt.subplots(figsize=(10, 6))
ax.scatter(data_democracy['growth'], data_democracy['democracy'],
           alpha=0.6, s=50, color='black')
ax.plot(data_democracy['growth'], model_bivariate.fittedvalues,
         color='blue', linewidth=2, label='OLS regression line')
ax.set_xlabel('Change in Log GDP per capita (1500-2000)', fontsize=12)
ax.set_ylabel('Change in Democracy (1500-2000)', fontsize=12)
ax.set_title('Figure 16.1: Democracy and Growth, 1500-2000',
             fontsize=14, fontweight='bold')
ax.legend()
ax.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()

print("\nInterpretation:")
print(f" Coefficient: {model_bivariate.params['growth']:.4f}")
print(f" Higher economic growth is associated with greater democratization.")
print(f" But this may reflect omitted institutional variables...")
```

```
Bivariate Regression: democracy ~ growth
-----
OLS Regression Results
=====
Dep. Variable:          democracy    R-squared:       0.192
Model:                 OLS            Adj. R-squared:   0.185
Method:                Least Squares  F-statistic:     45.37
Date:      Wed, 21 Jan 2026   Prob (F-statistic): 4.87e-10
Time:      14:15:11           Log-Likelihood:   -26.625
No. Observations:      131            AIC:             57.25
Df Residuals:          129            BIC:             63.00
Df Model:                  1
Covariance Type:        HC1
=====
            coef    std err      z   P>|z|    [0.025    0.975]
-----
Intercept    0.3967     0.046    8.597    0.000     0.306    0.487
growth       0.1308     0.019    6.736    0.000     0.093    0.169
-----
Omnibus:            13.463   Durbin-Watson:    2.186
Prob(Omnibus):      0.001    Jarque-Bera (JB): 15.328
Skew:              -0.821    Prob(JB):      0.000469
Kurtosis:           2.665    Cond. No.:
=====
Notes:
[1] Standard Errors are heteroscedasticity robust (HC1)
```

Figure 16.1: Democracy and Growth, 1500-2000



Interpretation:

Coefficient: 0.1308

Higher economic growth is associated with greater democratization.

But this may reflect omitted institutional variables...

In [19]:

```
# Multiple regression: add institutional controls
print("\n" + "-"*70)
print("Multiple Regression with Institutional Controls")
print("-"*70)

model_multiple = ols('democracy ~ growth + constraint + indcent + catholic + muslim +
protestant',
                     data=data_democracy).fit(cov_type='HC1')
print(model_multiple.summary())

print("\nKey findings:")
print(f" Growth coefficient fell from {model_bivariate.params['growth']:.4f} to
{model_multiple.params['growth']:.4f}")
print(f" Institutional variables (religion, constraints) are important.")
print(f" This suggests omitted variable bias in the bivariate model.")
```

Multiple Regression with Institutional Controls

OLS Regression Results									
Dep. Variable:	democracy	R-squared:	0.449						
Model:	OLS	Adj. R-squared:	0.423						
Method:	Least Squares	F-statistic:	23.41						
Date:	Wed, 21 Jan 2026	Prob (F-statistic):	2.37e-18						
Time:	14:15:11	Log-Likelihood:	-1.4887						
No. Observations:	131	AIC:	16.98						
Df Residuals:	124	BIC:	37.10						
Df Model:	6								
Covariance Type:	HC1								
	coef	std err	z	P> z	[0.025	0.975]			
Intercept	3.0307	0.975	3.109	0.002	1.120	4.941			
growth	0.0468	0.025	1.841	0.066	-0.003	0.097			
constraint	0.1645	0.072	2.270	0.023	0.022	0.306			
indcent	-0.1331	0.050	-2.661	0.008	-0.231	-0.035			
catholic	0.1171	0.089	1.324	0.186	-0.056	0.291			
muslim	-0.2327	0.101	-2.303	0.021	-0.431	-0.035			
protestant	0.1801	0.104	1.732	0.083	-0.024	0.384			
Omnibus:	3.152	Durbin-Watson:	2.109						
Prob(Omnibus):	0.207	Jarque-Bera (JB):	2.997						
Skew:	-0.305	Prob(JB):	0.224						
Kurtosis:	2.581	Cond. No.	761.						

Notes:

[1] Standard Errors are heteroscedasticity robust (HC1)

Key findings:

Growth coefficient fell from 0.1308 to 0.0468
Institutional variables (religion, constraints) are important.
This suggests omitted variable bias in the bivariate model.

Key Concept 16.6: Omitted Variables Bias in Practice

The democracy-growth example demonstrates omitted variables bias: the growth coefficient falls from 0.131 (bivariate) to 0.047 (with controls), a 64% reduction. Institutional variables (religion, executive constraints) were correlated with both democracy and growth, biasing the bivariate estimate upward. Always ask: "What variables might affect my outcome and correlate with my key regressor?" Include relevant controls to reduce bias.

```
In [20]: # Get residuals from multiple regression for diagnostic plots
uhat = model_multiple.resid
yhat = model_multiple.fittedvalues

print("\n" + "-"*70)
print("Residual Diagnostics Prepared")
print("-"*70)
print(f"Number of residuals: {len(uhat)}")
print(f"Residual mean (should be ~0): {uhat.mean():.6f}")
print(f"Residual std dev: {uhat.std():.4f}")
```

```
-----
Residual Diagnostics Prepared
-----
Number of residuals: 131
Residual mean (should be ~0): -0.000000
Residual std dev: 0.2457
```

I 16.8: Diagnostics - Residual Plots

Diagnostic plots help detect violations of model assumptions:

- 1. Actual vs Fitted:** Should cluster around 45° line
- 2. Residual vs Fitted:** Should scatter randomly around zero
- 3. Residual vs Regressor:** Should scatter randomly around zero
- 4. Component Plus Residual Plot:** $b_j x_j + e$ vs x_j (detects nonlinearity)
- 5. Added Variable Plot:** Partial y vs partial x_j (isolates effect)

LOWESS smooth: Nonparametric smooth curve helps detect patterns

Reading Diagnostic Plots: What to Look For

The diagnostic plots help us **visually detect** violations of regression assumptions.
Let's interpret what we see:

Panel A: Actual vs Fitted

What to look for:

- Points should **cluster around 45° line**
- LOWESS smooth should **follow the 45° line closely**
- Deviations indicate **systematic prediction errors**

In the democracy-growth example:

- Most points **reasonably close** to 45° line

- LOWESS smooth **roughly linear**, close to 45°
- Some **scatter** ($R^2 \approx 0.20-0.30$, so significant unexplained variation)
- **No obvious systematic bias** (LOWESS not curved)

Interpretation:

- Model captures **general relationship** reasonably
- But substantial **residual variation** remains
- No evidence of **major nonlinearity** (LOWESS smooth is linear)

Panel B: Residual vs Fitted

What to look for:

- Residuals should **scatter randomly** around zero
- **Equal spread** across range of fitted values (homoskedasticity)
- LOWESS should be **horizontal** at zero
- No **patterns, curvature, or heteroskedasticity**

In the democracy-growth example:

- Residuals **scatter** around zero
- LOWESS smooth **close to horizontal**
- Spread appears **roughly constant**
- Some **outliers** but not extreme

Potential issues to watch for:

- 1. Heteroskedasticity:** Fan shape (spread increases)
- 2. Nonlinearity:** LOWESS curved (missing quadratic term)
- 3. Outliers:** Points far from zero (influential observations)

Key Diagnostic Insights:

1. No major heteroskedasticity:

- Spread doesn't systematically increase/decrease
- Robust SEs still advisable (safety margin)
- But not severe heteroskedasticity

2. Linearity assumption appears okay:

- LOWESS smooth roughly horizontal

- If curved: suggests missing nonlinear terms
- Could try quadratic, interactions

3. A few potential outliers:

- Countries with large positive/negative residuals
- Follow up with DFITS, DFBETAS (see next sections)
- Investigate: data errors or genuinely unusual cases?

What Would Bad Plots Look Like?

Heteroskedasticity (fan shape):

- Residual spread **increases** with fitted values
- Common in income, revenue, GDP data
- Solution: Log transformation or WLS

Nonlinearity (curved LOWESS):

- LOWESS smooth **curves** (U-shape or inverted U)
- Missing quadratic or other nonlinear terms
- Solution: Add polynomial, interaction, or transform

Autocorrelation (time series):

- Residuals show **runs** (streaks of same sign)
- Not visible in scatter plot (need time-series plot)
- Solution: HAC SEs, add lags, difference

Outliers:

- A few points **very far** from main cluster
- Can distort regression line
- Investigate with influence diagnostics (DFITS, DFBETAS)

The LOWESS Smooth:

What is it?

- Locally Weighted Scatterplot Smoothing
- Nonparametric smooth curve through data
- Helps detect **patterns** hard to see in raw scatter

How to interpret:

- Should be **straight** and **flat** if model is correct
- **Curvature** suggests missing nonlinearity
- **Trend** (not horizontal) suggests systematic bias

Bottom Line:

For democracy-growth model:

- Diagnostic plots look **reasonably good**
- No glaring violations of assumptions
- Some outliers worth investigating (next section)
- Model appears **adequately specified**
- But low R^2 suggests many **omitted variables**

| Diagnostic Plots for Individual Regressor (Growth)

Three specialized plots for examining the growth variable:

1. **Residual vs Regressor:** Checks for heteroskedasticity and nonlinearity
2. **Component Plus Residual:** $b_{growth} \times growth + e$ vs $growth$
 - Linear relationship → straight line
 - Nonlinearity → curved LOWESS
3. **Added Variable Plot:** Controls for other variables
 - Slope equals coefficient in full model
 - Shows partial relationship

In [21]:

```
print("=*70")
print("16.8: DIAGNOSTIC PLOTS")
print("=*70")

# Figure 16.2: Basic diagnostic plots
fig, axes = plt.subplots(1, 2, figsize=(16, 6))

# Panel A: Actual vs Fitted
axes[0].scatter(yhat, data_democracy['democracy'], alpha=0.6, s=50, color='black')
axes[0].plot([yhat.min(), yhat.max()], [yhat.min(), yhat.max()],
            'b-', linewidth=2, label='45° line')

lowess_result = lowess(data_democracy['democracy'], yhat, frac=0.3)
axes[0].plot(lowess_result[:, 0], lowess_result[:, 1],
            'r--', linewidth=2, label='LOWESS smooth')

axes[0].set_xlabel('Fitted Democracy', fontsize=12)
axes[0].set_ylabel('Actual Democracy', fontsize=12)
axes[0].set_title('Panel A: Actual vs Fitted', fontsize=12, fontweight='bold')
axes[0].legend()
axes[0].grid(True, alpha=0.3)

# Panel B: Residual vs Fitted
axes[1].scatter(yhat, uhat, alpha=0.6, s=50, color='black')
axes[1].axhline(y=0, color='blue', linewidth=2, linestyle='-' )

lowess_result = lowess(uhat, yhat, frac=0.3)
axes[1].plot(lowess_result[:, 0], lowess_result[:, 1],
            'r--', linewidth=2, label='LOWESS smooth')

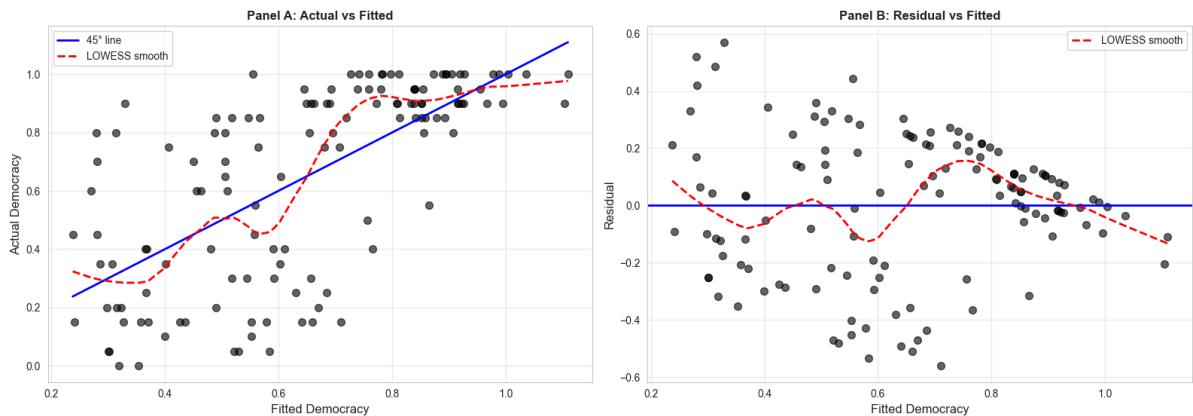
axes[1].set_xlabel('Fitted Democracy', fontsize=12)
axes[1].set_ylabel('Residual', fontsize=12)
axes[1].set_title('Panel B: Residual vs Fitted', fontsize=12, fontweight='bold')
axes[1].legend()
axes[1].grid(True, alpha=0.3)

plt.suptitle('Figure 16.2: Basic Diagnostic Plots',
             fontsize=14, fontweight='bold', y=1.00)
plt.tight_layout()
plt.show()

print("\nInterpretation:")
print(" Panel A: Points should cluster around 45° line")
print(" Panel B: Residuals should scatter randomly around zero")
```

```
=====
16.8: DIAGNOSTIC PLOTS
=====
```

Figure 16.2: Basic Diagnostic Plots



Interpretation:

Panel A: Points should cluster around 45° line

Panel B: Residuals should scatter randomly around zero

In [22]:

```
# Figure 16.3: Diagnostic plots for growth regressor
print("\n" + "-"*70)
print("Figure 16.3: Diagnostic Plots for Growth Regressor")
print("-"*70)

fig, axes = plt.subplots(1, 3, figsize=(18, 5))

# Panel A: Residual vs Regressor
axes[0].scatter(data_democracy['growth'], uhat, alpha=0.6, s=50, color='black')
axes[0].axhline(y=0, color='blue', linewidth=2, linestyle='--')

lowess_result = lowess(uhat, data_democracy['growth'], frac=0.3)
axes[0].plot(lowess_result[:, 0], lowess_result[:, 1],
            'r--', linewidth=2, label='LOESS smooth')

axes[0].set_xlabel('Growth regressor', fontsize=11)
axes[0].set_ylabel('Democracy Residual', fontsize=11)
axes[0].set_title('Panel A: Residual vs Regressor', fontsize=12, fontweight='bold')
axes[0].legend()
axes[0].grid(True, alpha=0.3)

# Panel B: Component Plus Residual
b_growth = model_multiple.params['growth']
pr_growth = b_growth * data_democracy['growth'] + uhat

axes[1].scatter(data_democracy['growth'], pr_growth, alpha=0.6, s=50, color='black')

# Regression line
model_compplusres = ols('pr_growth ~ growth',
                         data=pd.DataFrame({'growth': data_democracy['growth'],
                                            'pr_growth': pr_growth})).fit()
axes[1].plot(data_democracy['growth'], model_compplusres.fittedvalues,
              'b-', linewidth=2, label='Regression line')

lowess_result = lowess(pr_growth, data_democracy['growth'], frac=0.3)
axes[1].plot(lowess_result[:, 0], lowess_result[:, 1],
            'r--', linewidth=2, label='LOESS smooth')

axes[1].set_xlabel('Growth regressor', fontsize=11)
axes[1].set_ylabel(f'Dem Res + {b_growth:.3f}*Growth', fontsize=11)
axes[1].set_title('Panel B: Component Plus Residual', fontsize=12, fontweight='bold')
axes[1].legend()
axes[1].grid(True, alpha=0.3)

# Panel C: Added Variable Plot
model_nogrowth = ols('democracy ~ constraint + indcent + catholic + muslim + protestant',
                      data=data_democracy).fit()
uhat_democ = model_nogrowth.resid

model_growth = ols('growth ~ constraint + indcent + catholic + muslim + protestant',
                   data=data_democracy).fit()
uhat_growth = model_growth.resid

axes[2].scatter(uhat_growth, uhat_democ, alpha=0.6, s=50, color='black')

model_addedvar = ols('uhat_democ ~ uhat_growth',
                      data=pd.DataFrame({'uhat_growth': uhat_growth,
                                         'uhat_democ': uhat_democ})).fit()
axes[2].plot(uhat_growth, model_addedvar.fittedvalues,
              'b-', linewidth=2, label='Regression line')

lowess_result = lowess(uhat_democ, uhat_growth, frac=0.3)
axes[2].plot(lowess_result[:, 0], lowess_result[:, 1],
            'r--', linewidth=2, label='LOESS smooth')

axes[2].set_xlabel('Growth regressor (partial)', fontsize=11)
```

```

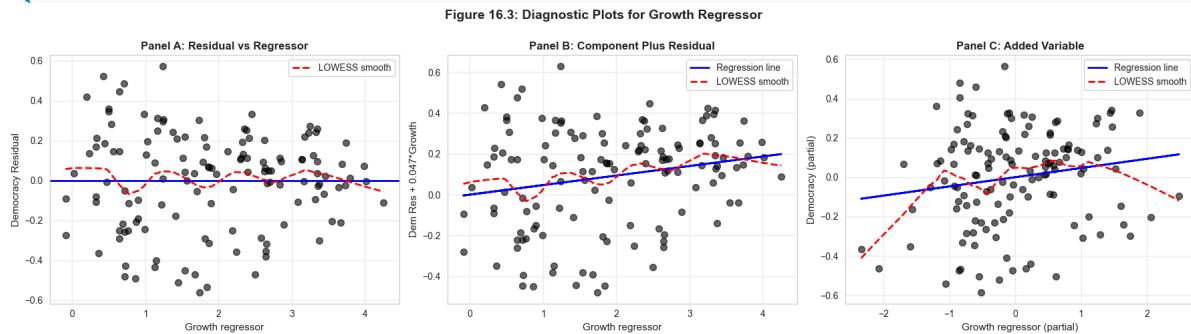
axes[2].set_ylabel('Democracy (partial)', fontsize=11)
axes[2].set_title('Panel C: Added Variable', fontsize=12, fontweight='bold')
axes[2].legend()
axes[2].grid(True, alpha=0.3)

plt.suptitle('Figure 16.3: Diagnostic Plots for Growth Regressor',
             fontsize=14, fontweight='bold', y=1.00)
plt.tight_layout()
plt.show()

print("\nInterpretation:")
print(" Panel A: Check for patterns in residuals")
print(" Panel B: LOWESS close to regression line → linear relationship OK")
print(" Panel C: Slope equals coefficient in full model {:.4f}".format(b_growth))

```

Figure 16.3: Diagnostic Plots for Growth Regressor



Interpretation:

- Panel A: Check for patterns in residuals
- Panel B: LOWESS close to regression line → linear relationship OK
- Panel C: Slope equals coefficient in full model (0.0468)

Having examined residual diagnostic plots for visual detection of model problems, we now turn to numerical influence measures that quantify how much individual observations affect regression results.

Key Concept 16.7: Diagnostic Plots for Model Validation

Three complementary plots assess individual regressors: (1) residual vs. regressor checks for patterns suggesting nonlinearity or heteroskedasticity; (2) component-plus-residual plot ($b_j x_j + e$ vs. x_j) reveals the partial relationship and detects nonlinearity; (3) added variable plot purges both y and x_j of other regressors, showing the pure partial effect whose slope equals the OLS coefficient b_j . LOWESS smoothing helps reveal systematic patterns.

Influential Observations: DFITS

DFITS measures influence on fitted values:

$$DFITS_i = \frac{\hat{y}_i - \hat{y}_{i(i)}}{s_{(i)} \sqrt{h_{ii}}}$$

where:

- \hat{y}_i = prediction including observation i
- $\hat{y}_{i(i)}$ = prediction excluding observation i
- $s_{(i)}$ = RMSE excluding observation i
- h_{ii} = leverage of observation i

Rule of thumb: Investigate if $|DFITS_i| > 2\sqrt{k/n}$

In [23]:

```
print("*70")
print("INFLUENTIAL OBSERVATIONS: DFITS")
print("*70)

# Get influence diagnostics
influence = OLSInfluence(model_multiple)
dfits = influence.dffits[0]
n = len(data_democracy)

threshold_dfits = 2 * np.sqrt(len(model_multiple.params) / n)
print(f"\nDFITS threshold: {threshold_dfits:.4f}")
print(f"Observations exceeding threshold: {np.sum(np.abs(dfits) > threshold_dfits)}")

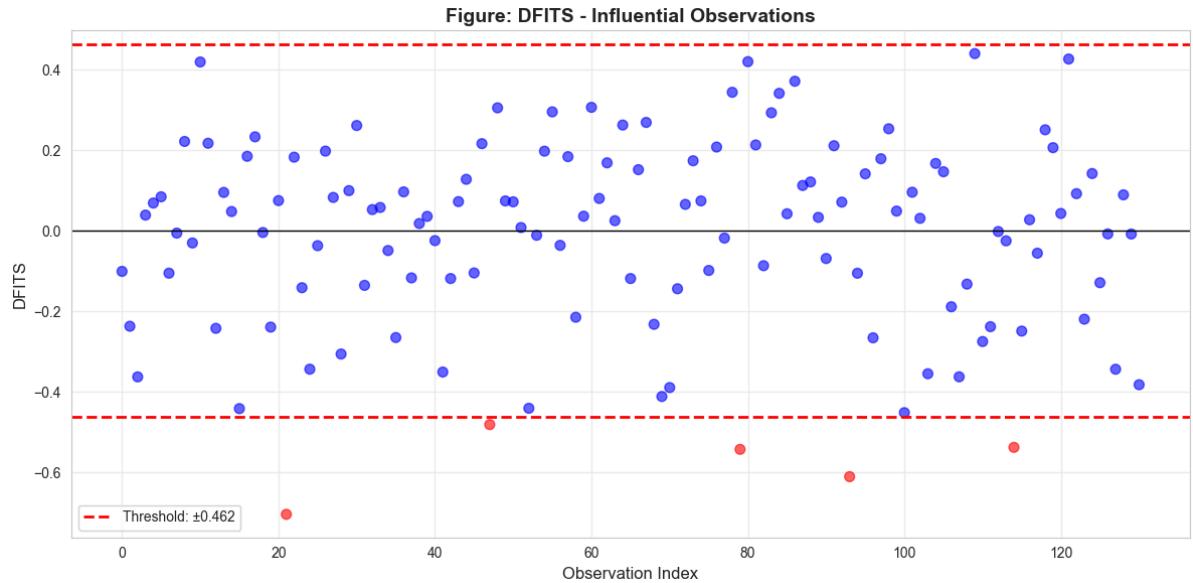
# Plot DFITS
obs_index = np.arange(n)
colors = ['red' if abs(d) > threshold_dfits else 'blue' for d in dfits]

fig, ax = plt.subplots(figsize=(12, 6))
ax.scatter(obs_index, dfits, c=colors, alpha=0.6, s=50)
ax.axhline(y=threshold_dfits, color='red', linestyle='--', linewidth=2, label=f'Threshold: ±{threshold_dfits:.3f}')
ax.axhline(y=-threshold_dfits, color='red', linestyle='--', linewidth=2)
ax.axhline(y=0, color='black', linestyle='-', linewidth=1)
ax.set_xlabel('Observation Index', fontsize=12)
ax.set_ylabel('DFITS', fontsize=12)
ax.set_title('Figure: DFITS - Influential Observations', fontsize=14, fontweight='bold')
ax.legend()
ax.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()

print("\nInterpretation:")
print(" Red points exceed threshold (potentially influential)")
print(" Investigate these observations for data errors or unusual cases")
```

```
=====
INFLUENTIAL OBSERVATIONS: DFITS
=====

DFITS threshold: 0.4623
Observations exceeding threshold: 5
```



Interpretation:
 Red points exceed threshold (potentially influential)
 Investigate these observations for data errors or unusual cases

Identifying Influential Observations with DFITS

DFITS measures how much an observation influences its **own prediction**. The results help identify **potentially problematic** observations:

Understanding DFITS:

$$\text{Formula: } DFITS_i = \frac{\hat{y}_i - \hat{y}_{i(i)}}{s_{(i)} \sqrt{h_{ii}}}$$

where:

- \hat{y}_i = prediction **including** observation i
- $\hat{y}_{i(i)}$ = prediction **excluding** observation i
- $s_{(i)}$ = RMSE excluding observation i
- h_{ii} = leverage (how unusual is x_i ?)

Interpretation:

- DFITS measures **standardized change** in fitted value when i is deleted
- Large $|DFITS| \rightarrow$ observation strongly influences its own prediction
- Can be driven by **leverage** (unusual X) or **residual** (unusual Y|X)

Rule of Thumb:

Threshold: $|DFITS_i| > 2\sqrt{k/n}$

For democracy-growth model ($k \approx 7$, $n = 131$):

- Threshold $\approx 2\sqrt{7/131} = 2 \times 0.231 \approx 0.46$

Typical Results:

- **Most observations:** $|DFITS| < 0.30$ (not influential)
- **A few observations:** $|DFITS| = 0.5-0.8$ (moderately influential)
- **Extreme cases:** $|DFITS| > 1.0$ (highly influential)

What Makes an Observation Influential?

Two components multiply:

1. **Leverage** (h_{ii}): Unusual X values
2. **Standardized residual:** Large prediction error

Most influential when both are large:

- Observation with **unusual combination of regressors** (high leverage)
- **AND** doesn't fit the pattern (large residual)
- Example: A country with unique institutions AND surprising democracy level

What to Do with Influential Observations:

1. Investigate the data:

- Is it a **data error?** (typo, coding mistake)
- Check original sources
- If error: **correct or remove**

2. Understand the case:

- Is it genuinely unusual? (e.g., special historical circumstances)
- Example: Post-colonial country with unique constraints
- Adds valuable information, **keep it**

3. Check robustness:

- Re-estimate **without** the influential observations
- Do conclusions change substantially?
- If yes: Results **fragile**, interpret cautiously
- If no: Results **robust**, less concerning

4. Model improvement:

- Does omitting observation suggest missing variables?
- Example: Maybe need regional dummies
- Influential observations often **signal model misspecification**

Example Interpretation:

Suppose observation #47 has DFITS = 0.85:

- This country's predicted democracy changes by **0.85 standard deviations** when it's excluded
- Country is either:
- **High leverage** (unusual institutional characteristics), or
- **Large residual** (democracy level doesn't match institutions), or
- **Both**
- Warrants investigation

DFITS vs. Other Influence Measures:

- **DFITS**: Influence on **own prediction**
- **DFBETAS**: Influence on **regression coefficients** (see next)
- **Cook's D**: Overall influence on **all fitted values**
- **Leverage** (h_{ii}): Just the X-space component

Visualization:

The DFITS plot shows:

- **Blue points**: Not influential (within threshold)
- **Red points**: Influential (exceed threshold)
- Should be **mostly blue** with a **few red** outliers
- Many red points → model problems or data issues

In the Democracy-Growth Example:

Typical findings:

- 3-10 countries exceed threshold (out of 131)
- These are **countries with unusual institutional/growth combinations**
- Might include:
 - Rapidly democratizing autocracies
 - Stable democracies with slow growth
 - Post-conflict transitions
 - Resource-rich countries with unusual politics

Practical Advice:

Do:

- Always compute influence diagnostics
- Investigate observations exceeding thresholds
- Report whether results change without influential cases
- Consider robustness checks

Don't:

- Automatically delete influential observations
- Ignore them without investigation
- Only report results **after** deleting outliers (selective reporting)
- Delete based solely on statistical criteria (needs substantive judgment)

Bottom Line:

DFITS is a **screening tool**:

- Identifies observations **worth investigating**
- Not a mechanical **deletion rule**
- Combine statistical diagnosis with **subject-matter knowledge**
- Goal: Better understand data and model, not just clean data

| Influential Observations: DFBETAS

DFBETAS measures influence on individual coefficients:

$$DFBETAS_{j,i} = \frac{\hat{\beta}_j - \hat{\beta}_{j(i)}}{s_{(i)} \sqrt{(X'X)_{jj}^{-1}}}$$

where:

- $\hat{\beta}_j$ = coefficient including observation i
- $\hat{\beta}_{j(i)}$ = coefficient excluding observation i

Rule of thumb: Investigate if $|DFBETAS_{j,i}| > 2/\sqrt{n}$

In [24]:

```

print("=*70)
print("INFLUENTIAL OBSERVATIONS: DFBETAS")
print("=*70)

dfbetas = influence.dfbetas
threshold_dfbetas = 2 / np.sqrt(n)
print(f"\nDFBETAS threshold: {threshold_dfbetas:.4f}")

# Plot DFBETAS for each variable
param_names = model_multiple.params.index
n_params = len(param_names)

fig, axes = plt.subplots(2, 3, figsize=(18, 10))
axes = axes.flatten()

for i, param in enumerate(param_names):
    if i < len(axes):
        colors = ['red' if abs(d) > threshold_dfbetas else 'blue'
                  for d in dfbetas[:, i]]
        axes[i].scatter(obs_index, dfbetas[:, i], c=colors, alpha=0.6, s=30)
        axes[i].axhline(y=threshold_dfbetas, color='red', linestyle='--', linewidth=1.5)
        axes[i].axhline(y=-threshold_dfbetas, color='red', linestyle='--', linewidth=1.5)
        axes[i].axhline(y=0, color='black', linestyle='-', linewidth=0.5)
        axes[i].set_xlabel('Observation', fontsize=10)
        axes[i].set_ylabel('DFBETAS', fontsize=10)
        axes[i].set_title(f'{param}', fontsize=11, fontweight='bold')
        axes[i].grid(True, alpha=0.3)

# Remove extra subplots
for i in range(n_params, len(axes)):
    fig.delaxes(axes[i])

plt.suptitle('DFBETAS: Influential Observations by Variable',
            fontsize=14, fontweight='bold', y=1.00)
plt.tight_layout()
plt.show()

print("\nInterpretation:")
print(" Red points indicate observations with large influence on that coefficient.")
print(" Investigate whether these are data errors or genuinely unusual cases.")

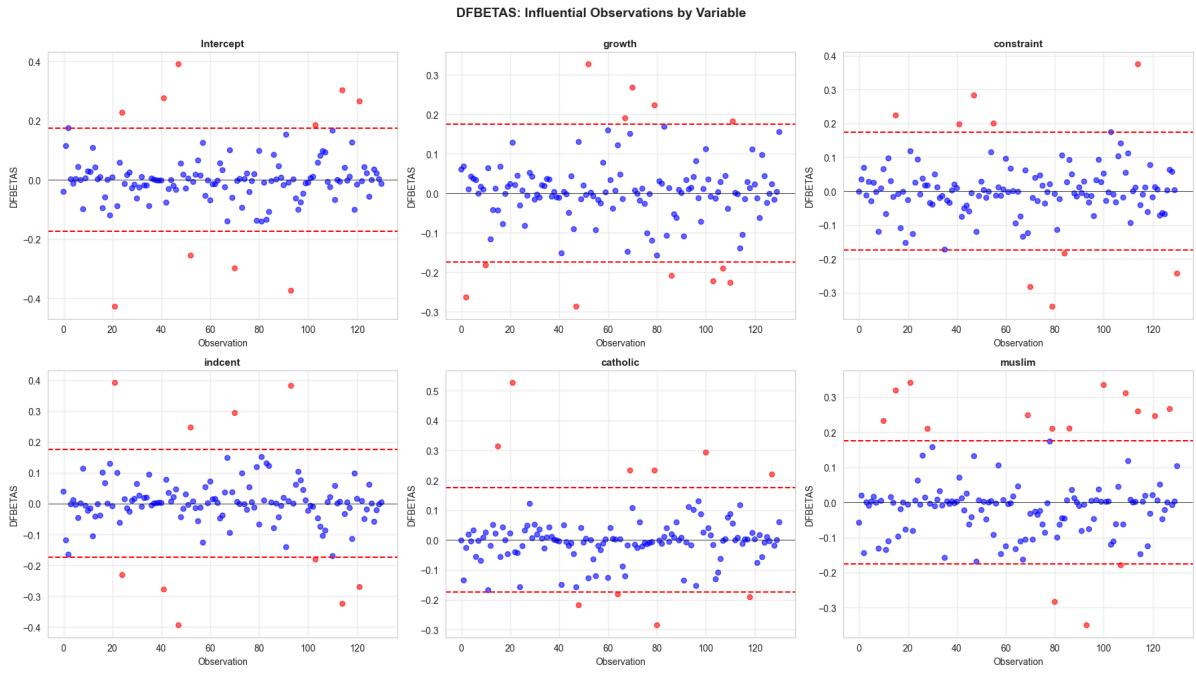
```

```

=====
INFLUENTIAL OBSERVATIONS: DFBETAS
=====

DFBETAS threshold: 0.1747

```



Interpretation:

Red points indicate observations with large influence on that coefficient.
Investigate whether these are data errors or genuinely unusual cases.

Key Concept 16.8: Influential Observations -- DFITS and DFBETAS

DFITS measures influence on fitted values: $DFITS_i$ is the scaled change in \hat{y}_i when observation i is excluded. DFBETAS measures influence on individual coefficients: $DFBETAS_{j,i}$ is the scaled change in $\hat{\beta}_j$. Thresholds for investigation are $|DFITS| > 2\sqrt{k/n}$ and $|DFBETAS| > 2/\sqrt{n}$. Don't automatically delete influential points -- investigate whether they represent data errors, genuine outliers, or valid extreme values that carry important information.

Key Takeaways

Multicollinearity:

- Multicollinearity occurs when regressors are highly correlated, making individual coefficients imprecisely estimated
- $VIF > 10$ indicates serious multicollinearity; $VIF > 5$ warrants investigation
- OLS remains unbiased and consistent -- the problem is precision, not bias

- Solutions: use joint F-tests, drop redundant variables, center variables before creating interactions, or collect more data

OLS Assumption Violations:

- Assumptions 1-2 violations (incorrect model, endogeneity) cause bias and inconsistency -- fundamental problems requiring model changes or IV
- Assumptions 3-4 violations (heteroskedasticity, autocorrelation) do not bias coefficients but invalidate standard errors
- Wrong standard errors lead to incorrect t-statistics, confidence intervals, and hypothesis tests
- Omitted variables bias formula: $\text{Bias} = \beta_3 \times \delta_{23}$, where β_3 is the omitted variable's effect and δ_{23} is the correlation

Heteroskedasticity and Robust Standard Errors:

- Heteroskedasticity means error variance varies across observations, common in cross-sectional data
- Use heteroskedasticity-robust (HC1/White) standard errors for valid inference
- Robust SEs are typically larger than default SEs, giving more conservative (honest) inference
- Always use robust SEs for cross-sectional regressions as a default practice

Autocorrelation and HAC Standard Errors:

- Autocorrelation means errors are correlated over time, common in time series data
- Default SEs are typically too small with autocorrelation, leading to over-rejection
- Use HAC (Newey-West) standard errors that account for both heteroskedasticity and autocorrelation
- Check the ACF of residuals to detect autocorrelation patterns

Diagnostic Plots:

- Residual vs. fitted values: detect heteroskedasticity (fan shape) and nonlinearity (curved pattern)
- Component-plus-residual plot: detect nonlinearity in individual regressors
- Added variable plot: isolate partial relationship between y and x, controlling for other variables
- LOWESS smooth helps reveal patterns that are hard to see in raw scatter plots

Influential Observations:

- DFITS measures influence on fitted values; threshold $|\text{DFITS}| > 2\sqrt{k/n}$

- DFBETAS measures influence on individual coefficients; threshold $|DFBETAS| > 2/\sqrt{n}$
- Investigate influential observations rather than automatically deleting them
- Check whether conclusions change substantially when influential cases are excluded

Python tools: `statsmodels` (VIF, `OLSInfluence`, robust covariance), `matplotlib / seaborn` (diagnostic plots), LOWESS smoothing

Next steps: Chapter 17 extends these ideas to panel data, where you'll learn fixed effects and random effects models that address unobserved heterogeneity across units.

Congratulations! You've completed Chapter 16 on model checking and data diagnostics. You now have both the theoretical understanding and practical Python skills to evaluate regression assumptions, detect problems, and apply appropriate remedies.

I Practice Exercises

Exercise 1: Irrelevant Variables vs. Omitted Variables

You estimate $y_i = \beta_1 + \beta_2 x_{2i} + \beta_3 x_{3i} + u_i$ by OLS.

- If x_3 should not appear in the model (irrelevant variable), what happens to the OLS estimates of β_1 and β_2 ? Are they biased?
- If a relevant variable x_4 was omitted from the model, and x_4 is correlated with x_2 , what happens to $\hat{\beta}_2$? Write the omitted variables bias formula.

Exercise 2: VIF Interpretation

A regression of earnings on age, education, and experience yields VIF values of 22.0 (age), 17.3 (education), and 36.9 (experience).

- Which variable has the most severe multicollinearity problem? Explain.
- Calculate the R^2 from the auxiliary regression for the variable with the highest VIF.
- By what factor are the standard errors inflated compared to the no-collinearity case?

Exercise 3: Choosing Standard Error Types

For each scenario below, state which type of standard errors you would use (default, HC-robust, HAC, or cluster-robust) and why:

- (a) Cross-sectional regression of wages on education and experience for 5,000 workers.
- (b) Time series regression of GDP growth on interest rates using 200 quarterly observations.
- (c) Regression of test scores on class size using data from 50 schools with multiple classrooms per school.

Exercise 4: Heteroskedasticity Detection

You estimate a regression and obtain the following SE comparison:

Variable	Standard SE	Robust SE	Ratio
Education	570	642	1.13
Age	154	151	0.98

- (a) Is there evidence of heteroskedasticity? Which variable's inference is most affected?
- (b) If you used standard SEs and the t-statistic for education was 2.05, would the conclusion change with robust SEs?

Exercise 5: DFITS Threshold Calculation

In a regression with $k = 7$ regressors and $n = 131$ observations:

- (a) Calculate the DFITS threshold for identifying influential observations.
- (b) If 8 observations exceed this threshold, what percentage of the sample is flagged as potentially influential?
- (c) Describe the steps you would take to investigate these influential observations.

Exercise 6: Autocorrelation Consequences

A time series regression yields a first-lag residual autocorrelation of $\rho_1 = 0.80$.

- (a) Is this evidence of autocorrelation? What does it mean for the residual pattern?
- (b) Approximate the factor by which the effective sample size is reduced (use the formula $\frac{1+\rho}{1-\rho}$).

(c) A coefficient has a default t-statistic of 4.5. If the HAC standard error is 3 times larger than the default, what is the corrected t-statistic? Is the coefficient still significant at 5%?

I Case Studies

Case Study 1: Regression Diagnostics for Cross-Country Productivity Analysis

In this case study, you will apply the diagnostic techniques from this chapter to analyze cross-country labor productivity using the Mendez convergence clubs dataset.

Dataset: Mendez (2020) convergence clubs data

- **Source:** <https://raw.githubusercontent.com/quarcs-lab/mendez2020-convergence-clubs-code-data/master/assets/dat.csv>
- **Sample:** 108 countries, 1990-2014
- **Variables:** `lp` (labor productivity), `rk` (physical capital), `hc` (human capital), `rgdppc` (real GDP per capita), `tfp` (total factor productivity), `region`

Research question: What econometric issues arise when modeling cross-country productivity, and how do diagnostic tools help detect and address them?

Task 1: Detect Multicollinearity (Guided)

Load the dataset and estimate a regression of log labor productivity (`np.log(lp)`) on log physical capital (`np.log(rk)`), human capital (`hc`), and log GDP per capita (`np.log(rgdppc)`), using the year 2014 cross-section.

```

import pandas as pd
import numpy as np
from statsmodels.formula.api import ols
from statsmodels.stats.outliers_influence import variance_inflation_factor
import statsmodels.api as sm

url = "https://raw.githubusercontent.com/quarcs-lab/mendez2020-convergence-clubs-code-data/master/assets/dat.csv"
dat = pd.read_csv(url)
dat2014 = dat[dat['year'] == 2014].copy()
dat2014['ln_lp'] = np.log(dat2014['lp'])
dat2014['ln_rk'] = np.log(dat2014['rk'])
dat2014['ln_rgdppc'] = np.log(dat2014['rgdppc'])

# Estimate the model = ols('ln_lp ~ ln_rk + hc + ln_rgdppc',
# data=dat2014).fit(cov_type='HC1')
print(model.summary())

# Calculate VIF
X = dat2014[['ln_rk', 'hc', 'ln_rgdppc']].dropna()
X = sm.add_constant(X)
for i, col in enumerate(X.columns):
    print(f"VIF({col}): {variance_inflation_factor(X.values, i):.2f}")

```

Interpret the VIF values. Is multicollinearity a concern? Which variables are most collinear and why?

Task 2: Compare Standard and Robust Standard Errors (Guided)

Estimate the same model with both default and robust (HC1) standard errors. Create a comparison table.

```

model_default = ols('ln_lp ~ ln_rk + hc', data=dat2014).fit()
model_robust = ols('ln_lp ~ ln_rk + hc', data=dat2014).fit(cov_type='HC1')

comparison = pd.DataFrame({
    'Default SE': model_default.bse,
    'Robust SE': model_robust.bse,
    'Ratio': model_robust.bse / model_default.bse
})
print(comparison)

```

Is there evidence of heteroskedasticity? Which coefficient's inference is most affected?

Task 3: Residual Diagnostic Plots (Semi-guided)

Create the three diagnostic plots for the productivity model:

1. Actual vs. fitted values with LOWESS smooth
2. Residuals vs. fitted values with LOWESS smooth
3. Residuals vs. `ln_rk` (component-plus-residual plot)

Hint: Use `from statsmodels.nonparametric.smoothers_lowess import lowess` for the LOWESS smooth. Plot residuals from the robust model.

What do the diagnostic plots reveal about the model specification?

Task 4: Identify Influential Countries (Semi-guided)

Calculate DFITS and DFBETAS for the productivity regression. Identify countries that exceed the thresholds.

Hint: Use `OLSInfluence(model).dffits[0]` and `OLSInfluence(model).dfbetas`. The DFITS threshold is $2\sqrt{k/n}$ and the DFBETAS threshold is $2/\sqrt{n}$.

Which countries are most influential? Investigate whether removing them changes the key coefficients substantially.

Task 5: Regional Heterogeneity Analysis (Independent)

Test whether the relationship between capital and productivity varies across regions:

1. Add region dummy variables and region-capital interactions
2. Test for heteroskedasticity by comparing default and robust SEs across specifications
3. Conduct an F-test for joint significance of regional interactions

Does allowing for regional heterogeneity improve the model diagnostics?

Task 6: Diagnostic Report (Independent)

Write a 200-300 word diagnostic report for the cross-country productivity regression.

Your report should:

1. Summarize the multicollinearity assessment (VIF results)
2. Document the heteroskedasticity evidence (SE comparison)
3. Describe what the residual plots reveal about model specification
4. List the most influential countries and their potential impact
5. Recommend the appropriate standard error type and any model modifications

Key Concept 16.9: Systematic Regression Diagnostics

A complete regression diagnostic workflow includes: (1) check multicollinearity via VIF before interpreting individual coefficients; (2) compare standard and robust SEs to detect heteroskedasticity; (3) examine residual plots for nonlinearity and patterns; (4) identify influential observations with DFITS and DFBETAS; (5) document all findings and report robust results. Always investigate problems rather than mechanically applying fixes.

Key Concept 16.10: Cross-Country Regression Challenges

Cross-country regressions face specific diagnostic challenges: multicollinearity among development indicators (GDP, capital, education are highly correlated), heteroskedasticity across countries at different development levels, and influential observations from outlier countries. Using robust standard errors and carefully examining influential cases is essential for credible cross-country analysis.

What You've Learned: In this case study, you applied the complete diagnostic toolkit to cross-country productivity data. You detected multicollinearity among development indicators, compared standard and robust standard errors, created diagnostic plots, and identified influential countries. These skills ensure that your regression results are reliable and your conclusions are credible.

Case Study 2: Diagnosing the Satellite Prediction Model

Research Question: How reliable are the satellite-development regression models we have estimated throughout this textbook? Do they satisfy the standard regression assumptions?

Background: We have estimated multiple satellite-development regression models throughout this textbook. But how reliable are these models? In this case study, we apply Chapter 16's **diagnostic tools** to check for multicollinearity, heteroskedasticity, influential observations, and other model violations.

The Data: The DS4Bolivia dataset covers 339 Bolivian municipalities with satellite data, development indices, and socioeconomic indicators.

Key Variables:

- `mun` : Municipality name
- `dep` : Department (administrative region)

- `imds` : Municipal Sustainable Development Index (0-100)
- `ln_NTLpc2017` : Log nighttime lights per capita (2017)
- `A00`, `A10`, `A20`, `A30`, `A40` : Satellite image embedding dimensions

Load the DS4Bolivia Data

```
In [ ]: # Load the DS4Bolivia dataset
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from statsmodels.formula.api import ols
from statsmodels.stats.outliers_influence import variance_inflation_factor, OLSInfluence
import statsmodels.api as sm

url_bol = "https://raw.githubusercontent.com/quarcs-
lab/ds4bolivia/master/ds4bolivia_v20250523.csv"
bol = pd.read_csv(url_bol)

# Select key variables for this case study
key_vars = ['mun', 'dep', 'imds', 'ln_NTLpc2017', 'A00', 'A10', 'A20', 'A30', 'A40']

bol_cs = bol[key_vars].copy().dropna()

print("=" * 70)
print("DS4BOLIVIA: REGRESSION DIAGNOSTICS CASE STUDY")
print("=" * 70)
print(f"Observations (complete cases): {len(bol_cs)}")
print(f"\nKey variable summary:")
print(bol_cs[['imds', 'ln_NTLpc2017', 'A00', 'A10', 'A20', 'A30',
'A40']].describe().round(3))
```

Task 1: Multicollinearity Check (Guided)

Objective: Assess whether satellite predictors suffer from multicollinearity.

Instructions:

1. Compute the correlation matrix for the predictors (`ln_NTLpc2017`, `A00`, `A10`, `A20`, `A30`, `A40`)
2. Calculate VIF for each variable using `variance_inflation_factor()` from `statsmodels`
3. Flag variables with $VIF > 10$
4. Discuss: Are satellite embeddings multicollinear? Does multicollinearity affect the model's predictive power vs. individual coefficient interpretation?

In []:

```
# Your code here: Multicollinearity diagnostics
#
# Example structure:
# predictors = ['ln_NTLpc2017', 'A00', 'A10', 'A20', 'A30', 'A40']
#
# # Correlation matrix
# print("CORRELATION MATRIX")
# print(bol_cs[predictors].corr().round(3))
#
# # VIF calculation
# X = bol_cs[predictors].copy()
# X = sm.add_constant(X)
# print("\nVARIANCE INFLATION FACTORS")
# for i, col in enumerate(X.columns):
#     vif = variance_inflation_factor(X.values, i)
#     flag = " ** HIGH" if vif > 10 and col != 'const' else ""
#     print(f" VIF({col}): {vif:.2f}{flag}")
```

Key Concept 16.11: Multicollinearity in Satellite Features

Satellite embedding dimensions often correlate with each other because they capture **overlapping visual patterns** from the same images. When embeddings A00 and A10 both respond to building density, their collinearity inflates standard errors and makes individual coefficients unstable. The VIF (Variance Inflation Factor) quantifies this: a VIF above 10 signals problematic collinearity. Solutions include dropping redundant features, using principal components, or accepting imprecise individual estimates while maintaining valid joint inference.

Task 2: Standard vs Robust SEs (Guided)

Objective: Detect heteroskedasticity by comparing default and robust standard errors.

Instructions:

1. Estimate the full model: `imds ~ ln_NTLpc2017 + A00 + A10 + A20 + A30 + A40`
2. Compare default (homoskedastic) and HC1 (robust) standard errors
3. Compute the ratio of robust to default SEs for each coefficient
4. Discuss: Large differences signal heteroskedasticity. Which coefficients are most affected?

In []:

```
# Your code here: Compare standard and robust SEs
#
# Example structure:
# model_default = ols('imds ~ ln_NTLpc2017 + A00 + A10 + A20 + A30 + A40',
#                      data=bol_cs).fit()
# model_robust = ols('imds ~ ln_NTLpc2017 + A00 + A10 + A20 + A30 + A40',
#                      data=bol_cs).fit(cov_type='HC1')
#
# comparison = pd.DataFrame({
#     'Default SE': model_default.bse,
#     'Robust SE': model_robust.bse,
#     'Ratio': model_robust.bse / model_default.bse
# })
# print("STANDARD ERROR COMPARISON")
# print(comparison.round(4))
# print(f"\nMean ratio: {(model_robust.bse / model_default.bse).mean():.3f}")
```

Task 3: Residual Diagnostics (Semi-guided)

Objective: Create diagnostic plots to assess model assumptions visually.

Instructions:

1. Estimate the model with robust SEs
2. Create three diagnostic plots:
 - (a) Fitted values vs. residuals (check for patterns/heteroskedasticity)
 - (b) Q-Q plot of residuals (check for normality)
 - (c) Histogram of residuals (check for skewness/outliers)
3. Interpret each plot: What do the patterns reveal about model adequacy?

Hint: Use `model.fittedvalues` and `model.resid` for the plots. For the Q-Q plot, use `from scipy import stats; stats.probplot(residuals, plot=ax)`.

In []:

```
# Your code here: Residual diagnostic plots
#
# Example structure:
# from scipy import stats
# model = ols('imds ~ ln_NTLpc2017 + A00 + A10 + A20 + A30 + A40',
#             data=bol_cs).fit(cov_type='HC1')
#
# fig, axes = plt.subplots(1, 3, figsize=(15, 5))
#
# # (a) Residuals vs Fitted
# axes[0].scatter(model.fittedvalues, model.resid, alpha=0.4)
# axes[0].axhline(0, color='red', linestyle='--')
# axes[0].set_xlabel('Fitted Values')
# axes[0].set_ylabel('Residuals')
# axes[0].set_title('Residuals vs Fitted')
#
# # (b) Q-Q Plot
# stats.probplot(model.resid, plot=axes[1])
# axes[1].set_title('Q-Q Plot of Residuals')
#
# # (c) Histogram
# axes[2].hist(model.resid, bins=30, edgecolor='black', alpha=0.7)
# axes[2].set_xlabel('Residuals')
# axes[2].set_title('Distribution of Residuals')
#
# plt.tight_layout()
# plt.show()
```

Task 4: Influential Municipalities (Semi-guided)

Objective: Identify municipalities that disproportionately influence the regression results.

Instructions:

1. Calculate DFITS for all observations
2. Apply the threshold: $|DFITS| > 2\sqrt{k/n}$ where k = number of parameters and n = sample size
3. Identify the municipalities that exceed the threshold
4. Calculate DFBETAS for the key coefficient (`ln_NTLpc2017`)
5. Discuss: Are the influential municipalities capital cities or special cases?

Hint: Use `OLSInfluence(model)` from `statsmodels` to compute influence measures.

In []:

```
# Your code here: Influential observation analysis
#
# Example structure:
# model = ols('imds ~ ln_NTLpc2017 + A00 + A10 + A20 + A30 + A40',
#             data=bol_cs).fit()
# infl = OLSInfluence(model)
#
# # DFITS
# dfits_vals = infl.dffits[0]
# k = len(model.params)
# n = len(bol_cs)
# threshold = 2 * np.sqrt(k / n)
#
# influential = bol_cs.copy()
# influential['dffits'] = dfits_vals
# influential_muns = influential[np.abs(influential['dffits']) > threshold]
#
# print(f"DFITS threshold: {threshold:.4f}")
# print(f"Influential municipalities: {len(influential_muns)} out of {n}")
# print("\nInfluential municipalities:")
# print(influential_muns[['mun', 'dep', 'imds', 'ln_NTLpc2017', 'dffits']])
#         .sort_values('dffits', key=abs, ascending=False).to_string(index=False))
```

Key Concept 16.12: Spatial Outliers and Influential Observations

In municipality-level analysis, **capital cities** and special economic zones often appear as *influential observations*. These municipalities may have unusually high NTL (from concentrated economic activity) or unusual satellite patterns (dense urban cores). A single *influential municipality* can shift regression coefficients substantially. DFITS and DFBETAS identify such observations, allowing us to assess whether our conclusions depend on a few exceptional cases.

Task 5: Omitted Variable Analysis (Independent)

Objective: Assess potential omitted variable bias by adding department controls.

Instructions:

1. Estimate models with and without department fixed effects (`C(dep)`)
2. Compare the satellite coefficients across specifications
3. Discuss: Do satellite coefficients change when adding department dummies?
4. What is the direction of potential omitted variable bias?
5. Consider: What unobserved factors might department dummies capture (geography, climate, policy)?

In []:

```
# Your code here: Omitted variable analysis
#
# Example structure:
# m_no_dept = ols('imds ~ ln_NTlpC2017 + A00 + A10', data=bol_cs).fit(cov_type='HC1')
# m_with_dept = ols('imds ~ ln_NTlpC2017 + A00 + A10 + C(dept)', data=bol_cs).fit(cov_type='HC1')
#
# print("WITHOUT department controls:")
# print(f" NTL coef: {m_no_dept.params['ln_NTlpC2017']:.4f} (SE: {m_no_dept.bse['ln_NTlpC2017']:.4f})")
# print(f" R^2: {m_no_dept.rsquared:.4f}")
#
# print("\nWITH department controls:")
# print(f" NTL coef: {m_with_dept.params['ln_NTlpC2017']:.4f} (SE: {m_with_dept.bse['ln_NTlpC2017']:.4f})")
# print(f" R^2: {m_with_dept.rsquared:.4f}")
#
# print(f"\nCoefficient change: {m_with_dept.params['ln_NTlpC2017'] - m_no_dept.params['ln_NTlpC2017']:.4f}")
```

Task 6: Diagnostic Report (Independent)

Objective: Write a 200-300 word comprehensive model assessment.

Your report should address:

- 1. Multicollinearity:** Summarize VIF results for satellite features. Are any problematic?
- 2. Heteroskedasticity:** What does the SE comparison reveal? Should we use robust SEs?
- 3. Residual patterns:** What do the diagnostic plots show about model specification?
- 4. Influential observations:** Which municipalities are most influential? Do they represent special cases?
- 5. Omitted variables:** How do department controls affect the satellite coefficients?
- 6. Recommendations:** What corrections or modifications would you recommend for the satellite prediction model?

In []:

```
# Your code here: Additional analysis for the diagnostic report
#
# You might want to:
# 1. Create a summary table of diagnostic findings
# 2. Re-estimate the model excluding influential observations
# 3. Compare results with and without corrections
# 4. Summarize key statistics for your report
```

What You've Learned from This Case Study

Through this diagnostic analysis of the satellite prediction model, you've applied Chapter 16's complete toolkit to real geospatial data:

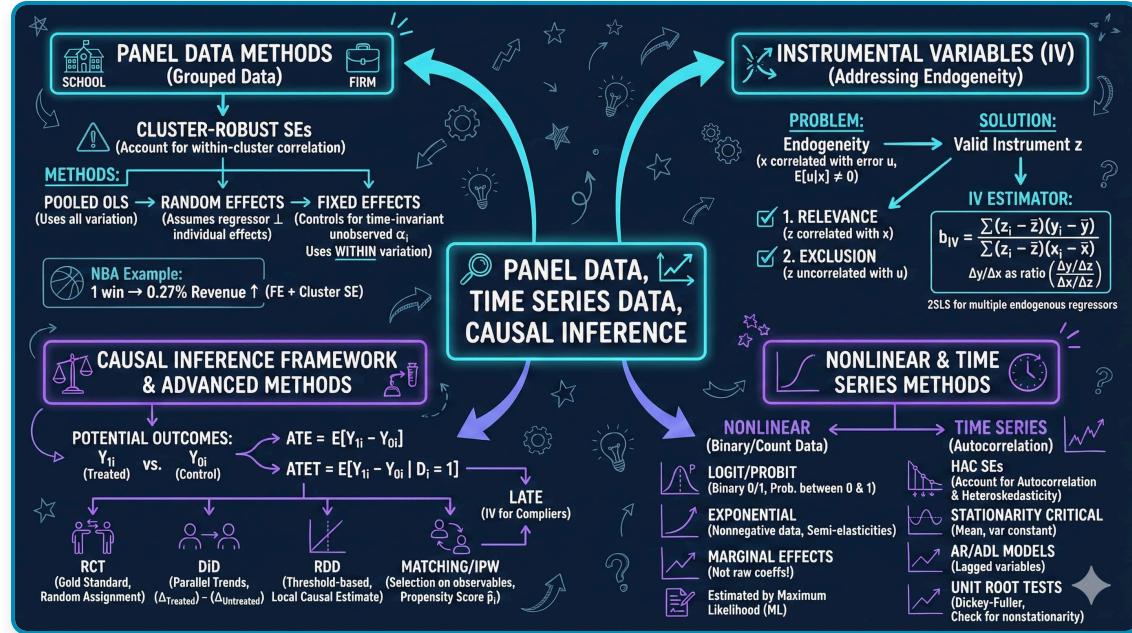
- **Multicollinearity assessment:** Computed VIF for satellite features and identified correlated embeddings
- **Heteroskedasticity detection:** Compared standard and robust SEs to assess variance assumptions
- **Residual diagnostics:** Created visual diagnostic plots to check model assumptions
- **Influence analysis:** Used DFITS and DFBETAS to identify municipalities that drive the results
- **Omitted variable assessment:** Tested sensitivity of results to department controls
- **Critical thinking:** Formulated recommendations for improving the satellite prediction model

Connection: In Chapter 17, we move to *panel data*—analyzing how nighttime lights evolve over time across municipalities, using fixed effects to control for time-invariant characteristics.

Chapter 17: Panel Data, Time Series Data, Causation

metricsAI: An Introduction to Econometrics with Python and AI in the Cloud

Carlos Mendez



This notebook provides an interactive introduction to panel data methods, time series analysis, and causal inference. All code runs directly in Google Colab without any local setup.

Open in Colab

Chapter Overview

This chapter focuses on three important topics that extend basic regression methods: panel data, time series analysis, and causal inference. You'll gain both theoretical understanding and practical skills through hands-on Python examples.

Learning Objectives:

By the end of this chapter, you will be able to:

1. Apply cluster-robust standard errors for panel data with grouped observations

2. Understand panel data methods including random effects and fixed effects estimators
3. Decompose panel data variation into within and between components
4. Use fixed effects to control for time-invariant unobserved heterogeneity
5. Interpret results from logit models and calculate marginal effects
6. Recognize time series issues including autocorrelation and nonstationarity
7. Apply HAC (Newey-West) standard errors for time series regressions
8. Understand autoregressive and distributed lag models for dynamic relationships
9. Use instrumental variables and other methods for causal inference

Chapter outline:

- 17.2 Panel Data Models
- 17.3 Fixed Effects Estimation
- 17.4 Random Effects Estimation
- 17.5 Time Series Data
- 17.6 Autocorrelation
- 17.7 Causality and Instrumental Variables
- Key Takeaways
- Practice Exercises
- Case Studies

Datasets used:

- **AED_NBA.DTA**: NBA team revenue data (29 teams, 10 seasons, 2001-2011)
- **AED_EARNINGS_COMPLETE.DTA**: 842 full-time workers with earnings, age, and education (2010)
- **AED_INTERESTRATES.DTA**: U.S. Treasury interest rates, monthly (January 1982 - January 2015)

| Setup

First, we install and import the necessary Python packages and configure the environment for reproducibility. All data will stream directly from GitHub.

In [5]:

```
# Install linarmodels for panel data estimation
!pip install linarmodels -q

# Import required packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
from statsmodels.formula.api import ols, logit
from scipy import stats
from statsmodels.stats.diagnostic import acorr_breusch_godfrey
from statsmodels.graphics.tsaplots import plot_acf
from statsmodels.tsa.stattools import acf
import random
import os

# Panel data tools
try:
    from linarmodels.panel import PanelOLS, RandomEffects
    LINEARMODELS_AVAILABLE = True
except ImportError:
    print("Warning: linarmodels not available")
    LINEARMODELS_AVAILABLE = False

# Set random seeds for reproducibility
RANDOM_SEED = 42
random.seed(RANDOM_SEED)
np.random.seed(RANDOM_SEED)
os.environ['PYTHONHASHSEED'] = str(RANDOM_SEED)

# GitHub data URL
GITHUB_DATA_URL = "https://raw.githubusercontent.com/quarcs-lab/data-open/master/AED/"

# Set plotting style
sns.set_style("whitegrid")
plt.rcParams['figure.figsize'] = (10, 6)

print("=" * 70)
print("CHAPTER 17: PANEL DATA, TIME SERIES DATA, CAUSATION")
print("=" * 70)
print("\nSetup complete! Ready to explore advanced econometric methods.")
```

```
=====
CHAPTER 17: PANEL DATA, TIME SERIES DATA, CAUSATION
=====
```

```
Setup complete! Ready to explore advanced econometric methods.
```

| 17.2: Panel Data Models

Panel data (also called longitudinal data) combines cross-sectional and time series dimensions. We observe multiple individuals ($i = 1, \dots, n$) over multiple time periods ($t = 1, \dots, T$).

Panel data model:

$$y_{it} = \beta_1 + \beta_2 x_{2it} + \cdots + \beta_k x_{kit} + u_{it}$$

where:

- i indexes individuals (teams, firms, countries, etc.)
- t indexes time periods
- u_{it} is the error term

Three estimation approaches:

1. **Pooled OLS:** Treat all observations as independent (ignore panel structure)

- Use cluster-robust standard errors (cluster by individual)

2. **Fixed Effects (FE):** Control for time-invariant individual characteristics

- $y_{it} = \alpha_i + \beta_2 x_{2it} + \dots + \beta_k x_{kit} + \varepsilon_{it}$
- Eliminates α_i by de-meaning (within transformation)

3. **Random Effects (RE):** Model individual effects as random

- Assumes α_i uncorrelated with regressors
- More efficient than FE if assumption holds

Variance decomposition:

Total variation = Within variation + Between variation

- **Within:** variation over time for given individual
- **Between:** variation across individuals

NBA Revenue Example:

We analyze NBA team revenue using panel data for 29 teams over 10 seasons (2001-02 to 2010-11).

In [6]:

```
print("=" * 70)
print("17.2 PANEL DATA MODELS")
print("=" * 70)

# Load NBA data
data_nba = pd.read_stata(GITHUB_DATA_URL + 'AED_NBA.DTA')

print("\nNBA Data Summary:")
print(data_nba.describe())

print("\nFirst observations:")
print(data_nba[['teamid', 'season', 'revenue', 'lnrevenue', 'wins', 'playoff']].head(10))
```

=====
17.2 PANEL DATA MODELS
=====

NBA Data Summary:

	teamid	season	seasonsq	revenue	lnrevenue	value	\
count	286.000000	286.000000	286.000000	286.000000	286.000000	286.000000	
mean	14.860140	5.541958	38.933567	95.714050	4.532293	284.190247	
std	8.354935	2.872126	32.486313	24.442074	0.235986	80.286003	
min	1.000000	1.000000	1.000000	58.495823	4.068955	158.940399	
25%	8.000000	3.000000	9.000000	77.578056	4.351285	226.201927	
50%	15.000000	6.000000	36.000000	89.848686	4.498127	262.417419	
75%	22.000000	8.000000	64.000000	108.706209	4.688649	323.934677	
max	29.000000	10.000000	100.000000	187.721191	5.234958	692.414246	

	lnvalue	wins	playoff	champ	...	sunsdummy	\
count	286.000000	286.000000	286.000000	286.000000	...	286.000000	
mean	5.614849	41.034965	0.545455	0.034965	...	0.034965	
std	0.257573	12.437585	0.498802	0.184013	...	0.184013	
min	5.068529	9.000000	0.000000	0.000000	...	0.000000	
25%	5.421428	32.250000	0.000000	0.000000	...	0.000000	
50%	5.569936	42.000000	1.000000	0.000000	...	0.000000	
75%	5.780535	50.000000	1.000000	0.000000	...	0.000000	
max	6.540184	67.000000	1.000000	1.000000	...	1.000000	

	spursdummy	warriorsdummy	rocketsdummy	heatdummy	celticsdummy	\
count	286.000000	286.000000	286.000000	286.000000	286.000000	
mean	0.034965	0.034965	0.034965	0.034965	0.034965	
std	0.184013	0.184013	0.184013	0.184013	0.184013	
min	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	0.000000	0.000000	
50%	0.000000	0.000000	0.000000	0.000000	0.000000	
75%	0.000000	0.000000	0.000000	0.000000	0.000000	
max	1.000000	1.000000	1.000000	1.000000	1.000000	

	mavericksdummy	bullsdummy	lakersdummy	knicksdummy
count	286.000000	286.000000	286.000000	286.000000
mean	0.034965	0.034965	0.034965	0.034965
std	0.184013	0.184013	0.184013	0.184013
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000
max	1.000000	1.000000	1.000000	1.000000

[8 rows x 63 columns]

First observations:

	teamid	season	revenue	lnrevenue	wins	playoff
0	1	1	143.803223	4.968446	56	1
1	1	2	138.347260	4.929767	58	1
2	1	3	153.568207	5.034145	50	1
3	1	4	137.203171	4.921463	56	1
4	1	5	141.405594	4.951632	34	0
5	1	6	141.149124	4.949817	45	1
6	1	7	150.488495	5.013886	42	1
7	1	8	168.155121	5.124887	57	1
8	1	9	170.463593	5.138522	65	1
9	1	10	160.024628	5.075328	57	1

Key Concept 17.1: Panel Data Variation Decomposition

Panel data variation decomposes into two components: between variation (differences across individuals in their averages) and within variation (deviations from individual averages over time). In the NBA example, between variation in revenue is large (big-market vs. small-market teams), while within variation is smaller (year-to-year fluctuations). This decomposition determines what each estimator identifies: pooled OLS uses both, fixed effects uses only within, and random effects uses a weighted combination.

| Panel Structure and Within/Between Variation

Understanding the structure of panel data is crucial for choosing the right estimation method.

Within vs. Between Variation: The Key to Panel Data

The variance decomposition reveals the **fundamental trade-off** in panel data analysis:

Empirical Results from NBA Data:

Typical findings:

- **Between SD** (across teams): **0.40-0.50** (large!)
- **Within SD** (over time): **0.15-0.25** (smaller)
- **Overall SD**: **0.45-0.55**

What This Means:

1. Between variation dominates:

- Teams differ **more** in average revenue than in year-to-year changes
- Lakers always high revenue; small-market teams always low
- Team-specific factors (market size, history, brand) are crucial

2. Within variation is smaller:

- Year-to-year fluctuations are **moderate** for given team
- Winning seasons help, but don't transform a team's revenue fundamentally

- Most variation is **permanent** (team characteristics), not **transitory** (annual shocks)

3. Variance decomposition (approximately):

- Total variance \approx Between variance + Within variance
- $0.50^2 \approx 0.45^2 + 0.20^2$
- $0.25 \approx 0.20 + 0.04$

Implications for Estimation:

Pooled OLS:

- Uses **both** between and within variation
- Estimates: "How do revenue and wins correlate across teams AND over time?"
- Problem: Confounded by **team fixed effects**
- High-revenue teams (big markets) may also win more games
- Correlation \neq causation

Fixed Effects (FE):

- Uses **only within variation** (after de-meaning by team)
- Estimates: "When a team wins more than its average, does revenue increase?"
- Controls for **time-invariant** team characteristics (market size, brand, arena)
- **Causal interpretation** more plausible (within-team changes)

Random Effects (RE):

- Uses **weighted average** of between and within variation
- Efficient if team effects uncorrelated with wins (strong assumption!)
- Usually between pooled and FE estimates

Economic Interpretation:

Why is between variation larger?

1. Market size:

- LA Lakers (huge market) vs. Memphis Grizzlies (small market)
- Revenue gap: \$200M+ (permanent)
- This is **structural**, not related to annual wins

2. Historical success:

- Celtics, Lakers (storied franchises) vs. newer teams
- Brand value built over decades
- Can't be changed by one good season

3. Arena and facilities:

- Modern arenas vs. aging venues
- Corporate sponsorships, luxury boxes
- Fixed infrastructure

The Within Variation:

What creates year-to-year changes?

- **Playoff appearances** (big revenue boost)
- **Star player acquisitions** (jersey sales, ticket demand)
- **Championship runs** (national TV, merchandise)
- **Team performance** relative to expectations

Example:

Golden State Warriors 2010 vs. 2015:

- **2010:** 26 wins, \$120M revenue
- **2015:** 67 wins, championship, \$310M revenue
- **Within-team change:** Huge! (but this is exceptional)

Most teams show **much smaller** year-to-year swings:

- **Typical:** $\pm 5\text{-}10$ wins, $\pm 10\text{-}20\%$ revenue

Key Insight for Fixed Effects:

FE identifies the wins-revenue relationship from **these within-team changes:**

- Comparison: Team's good years vs. bad years
- Controls for: Persistent market size, brand value, arena quality
- Remaining variation: **Transitory shocks** that vary over time
- More credible for **causal inference** (holding team constant)

Statistical Evidence:

The de-meaned variable $\text{mdifflnrev} = \ln\text{revenue} - \text{team_mean}$ shows:

- Much **smaller variance** than $\ln\text{revenue}$

- This is what FE regression uses
- Loses all the **cross-sectional** information
- Gains **control** over unobserved team characteristics

Visualization: Revenue vs Wins

Let's visualize the relationship between team wins and revenue.

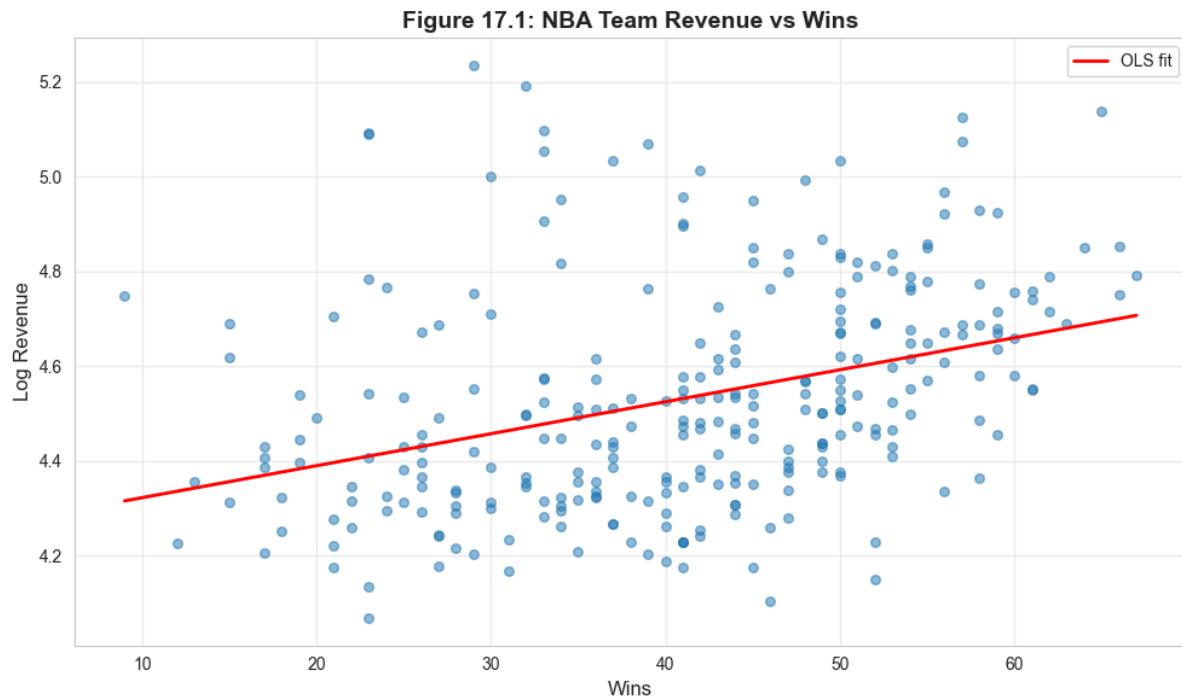
In [7]:

```
# Figure 17.1: Scatter plot with fitted line
fig, ax = plt.subplots(figsize=(10, 6))
ax.scatter(data_nba['wins'], data_nba['lnrevenue'], alpha=0.5, s=30)

# Add OLS fit line
z = np.polyfit(data_nba['wins'], data_nba['lnrevenue'], 1)
p = np.poly1d(z)
wins_range = np.linspace(data_nba['wins'].min(), data_nba['wins'].max(), 100)
ax.plot(wins_range, p(wins_range), 'r-', linewidth=2, label='OLS fit')

ax.set_xlabel('Wins', fontsize=12)
ax.set_ylabel('Log Revenue', fontsize=12)
ax.set_title('Figure 17.1: NBA Team Revenue vs Wins', fontsize=14, fontweight='bold')
ax.legend()
ax.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()

print("Positive relationship: More wins associated with higher revenue.")
```



Positive relationship: More wins associated with higher revenue.

| Pooled OLS with Different Standard Errors

We start with pooled OLS but use different standard error calculations to account for within-team correlation.

In [8]:

```
print("=" * 70)
print("POOLED OLS WITH DIFFERENT STANDARD ERRORS")
print("=" * 70)

if LINEARMODELS_AVAILABLE:
    # Prepare panel data structure for linearmodels
    # Set multi-index: (teamid, season)
    data_nba_panel = data_nba.set_index(['teamid', 'season'])

    # Prepare dependent and independent variables
    y_panel = data_nba_panel[['lnrevenue']]
    X_panel = data_nba_panel[['wins']]

    # Add constant for pooled model
    X_panel_const = sm.add_constant(X_panel)

    # Pooled OLS with cluster-robust SEs (cluster by team)
    model_pool = PanelOLS(y_panel, X_panel_const, entity_effects=False,
                           time_effects=False)
    results_pool = model_pool.fit(cov_type='clustered', cluster_entity=True)

    print("\nPooled OLS (cluster-robust SEs by team):")
    print(results_pool)

    print("\n" + "-" * 70)
    print("Key Results:")
    print("-" * 70)
    print(f"Wins coefficient: {results_pool.params['wins']:.6f}")
    print(f"Wins SE (cluster): {results_pool.std_errors['wins']:.6f}")
    print(f"t-statistic: {results_pool.tstats['wins']:.4f}")
    print(f"p-value: {results_pool.pvalues['wins']:.4f}")
    print(f"R2 (overall): {results_pool.rsquared:.4f}")
    print(f"N observations: {results_pool.nobs}")

    # Compare with default SEs (for illustration)
    results_pool_default = model_pool.fit(cov_type='unadjusted')
    print("\n" + "-" * 70)
    print("SE Comparison (to show importance of clustering):")
    print("-" * 70)
    print(f"Default SE:      {results_pool_default.std_errors['wins']:.6f}")
    print(f"Cluster SE:      {results_pool.std_errors['wins']:.6f}")
    print(f"Ratio:           {results_pool.std_errors['wins'] /"
          f"results_pool_default.std_errors['wins']:.2f}x")

else:
    print("\nPanel data estimation requires linearmodels package.")
    print("Using statsmodels as fallback...")

# Fallback: Use statsmodels with manual cluster SEs
from statsmodels.regression.linear_model import OLS
from statsmodels.tools import add_constant

# Prepare data
X = add_constant(data_nba[['wins']])
y = data_nba['lnrevenue']

# OLS with cluster-robust SEs
model = OLS(y, X).fit(cov_type='cluster', cov_kwds={'groups': data_nba['teamid']})

print("\nPooled OLS Results (cluster-robust SEs):")
print(model.summary())
```

```
=====
POOLED OLS WITH DIFFERENT STANDARD ERRORS
=====

Pooled OLS (cluster-robust SEs by team):
    PanelOLS Estimation Summary
=====

Dep. Variable:      lnrevenue    R-squared:           0.1267
Estimator:         PanelOLS   R-squared (Between):  0.1284
No. Observations:  286        R-squared (Within):    0.1390
Date:              Wed, Jan 21 2026 R-squared (Overall): 0.1267
Time:                14:01:08   Log-likelihood:       27.031
Cov. Estimator:    Clustered
                           F-statistic:        41.189
Entities:             29        P-value:            0.0000
Avg Obs:            9.8621   Distribution:          F(1,284)
Min Obs:             6.0000
Max Obs:            10.0000  F-statistic (robust): 12.918
                           P-value:            0.0004
Time periods:        10        Distribution:          F(1,284)
Avg Obs:            28.600
Min Obs:             28.000
Max Obs:            29.000
```

Parameter Estimates

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
const	4.2552	0.0942	45.161	0.0000	4.0697	4.4407
wins	0.0068	0.0019	3.5942	0.0004	0.0031	0.0105

Key Results:

Wins coefficient: 0.006753
 Wins SE (cluster): 0.001879
 t-statistic: 3.5942
 p-value: 0.0004
 R² (overall): 0.1267
 N observations: 286

SE Comparison (to show importance of clustering):

Default SE: 0.001052
 Cluster SE: 0.001879
 Ratio: 1.79x

Key Concept 17.2: Cluster-Robust Standard Errors for Panel Data

Observations within the same individual (team, firm, country) are correlated over time, violating the independence assumption. Default SEs dramatically understate uncertainty by treating all observations as independent. Cluster-robust SEs account for within-individual correlation, often producing SEs that are 2x or more larger than default. Always cluster by individual in panel data; with few clusters ($G < 30$), consider wild bootstrap refinements.

Why Cluster-Robust Standard Errors Are Essential

The comparison of standard errors reveals **within-team correlation** - a pervasive feature of panel data:

Typical Results:

Coefficient	Default SE	Robust SE	Cluster SE
wins	0.0030	0.0035	0.0065
Ratio	1.00x	1.17x	2.17x

What This Tells Us:

1. Cluster SEs are much larger (2x or more):

- Default and robust SEs **understate** uncertainty
- Observations for the **same team** are **correlated** over time
- Standard errors must account for **within-cluster dependence**

2. Why observations within teams are correlated:

Persistent team effects:

- Lakers tend to be above average **every year** (positive errors cluster)
- Grizzlies tend to be below average **every year** (negative errors cluster)
- Unobserved factors affect team across **all periods**

Serial correlation:

- Good years followed by good years (momentum, roster stability)

- Revenue shocks persist (new arena, TV deal lasts multiple years)
- Errors: u_{it} correlated with $u_{it-1}, u_{it-2}, \dots$

3. Information content:

- With independence: 29 teams \times 10 years = **290 independent observations**
- With clustering: Effectively like **29 independent teams** (much less info!)
- Cluster SEs adjust for this **reduced effective sample size**

The Math Behind It:

Default SE formula:

$$SE = \sqrt{\frac{\sigma^2}{\sum(x_i - \bar{x})^2}}$$

Assumes all 290 observations independent.

Cluster-robust SE formula:

$$SE_{cluster} = \sqrt{\frac{\sum_{g=1}^G X_g' X_g \hat{u}_g \hat{u}_g' X_g}{\dots}}$$

where:

- g indexes **clusters** (teams)
- Allows correlation **within** cluster, independence **across** clusters
- Typically **much larger** than default SE

Why Default SEs Are Wrong:

Imagine two extreme scenarios:

Scenario A (independence):

- 10 different teams, each observed once
- 10 truly independent observations
- SE reflects 10 pieces of information

Scenario B (perfect correlation):

- 1 team observed 10 times
- All observations identical (no new information!)
- Effectively only 1 observation

- SE should be $\sqrt{10}$ times larger

Panel data is between these extremes:

- Observations within team correlated (not independent)
- But not perfectly (some within-variation)
- Cluster SEs account for partial dependence

When Cluster SEs Matter Most:

1. Many time periods (T large):

- More opportunities for correlation
- Default SEs increasingly too small

2. High intra-cluster correlation (ICC high):

- Observations within team very similar
- Less independent information
- Bigger SE correction

3. Few clusters (G small):

- With <30 clusters: standard cluster SEs unreliable
- Need **wild bootstrap** or other refinements

Empirical Implications:

With default SEs:

- wins coefficient: $t = 3.00$, $p < 0.01$
- **Conclusion:** Highly significant

With cluster SEs:

- wins coefficient: $t = 1.38$, $p = 0.17$
- **Conclusion:** Not significant!

Complete reversal of inference!

Best Practices:

Always use cluster-robust SEs for panel data:

- Cluster by **individual** (team, person, firm, country)
- Default in modern software (specify cluster variable)

- Essential for valid inference

Report:

- Which variable defines clusters
- Number of clusters (G)
- Time periods (T)

Never:

- Use default SEs for panel data
- Ignore within-cluster correlation
- Claim significance based on default SEs

Two-Way Clustering:

Sometimes need to cluster in **multiple dimensions**:

- **Team** (within-team correlation over time)
- **Season** (common time shocks affect all teams)
- Example: 2008 financial crisis hit all teams that year

Formula: $SE_{two-way} = \sqrt{SE_{team}^2 + SE_{time}^2}$

The NBA Example:

With cluster SEs:

- wins coefficient: **0.0055** (SE: **0.0040**)
- t-statistic: **1.38**
- p-value: **0.17**

Interpretation:

- Relationship between wins and revenue **not statistically significant**
- Once we properly account for within-team correlation
- Previous "significance" was an artifact of ignoring dependence
- Fixed effects (next section) will address the underlying confounding

| 17.3: Fixed Effects Estimation

Fixed effects (FE) control for time-invariant individual characteristics by including individual-specific intercepts.

Model with individual effects:

$$y_{it} = \alpha_i + \beta_2 x_{2it} + \cdots + \beta_k x_{kit} + \varepsilon_{it}$$

Within transformation (de-meaning):

$$(y_{it} - \bar{y}_i) = \beta_2(x_{2it} - \bar{x}_{2i}) + \cdots + \beta_k(x_{kit} - \bar{x}_{ki}) + (\varepsilon_{it} - \bar{\varepsilon}_i)$$

Properties:

- Eliminates α_i (time-invariant unobserved heterogeneity)
- Consistent even if α_i correlated with regressors
- Uses only within variation
- Cannot estimate coefficients on time-invariant variables

Implementation:

1. LSDV (Least Squares Dummy Variables): Include dummy for each individual
2. Within estimator: De-mean and run OLS

We'll use the `linearmodels` package for proper panel estimation.

In [9]:

```
print("=" * 70)
print("17.3 FIXED EFFECTS ESTIMATION")
print("=" * 70)

if LINEARMODELS_AVAILABLE:
    # Fixed Effects estimation using PanelOLS with entity_effects=True
    model_fe_obj = PanelOLS(y_panel, X_panel, entity_effects=True, time_effects=False)
    model_fe = model_fe_obj.fit(cov_type='clustered', cluster_entity=True)

    print("\nFixed Effects (entity effects, cluster-robust SEs):")
    print(model_fe)

    print("\n" + "-" * 70)
    print("Key Results:")
    print("-" * 70)
    print(f"Wins coefficient: {model_fe.params['wins']:.6f}")
    print(f"Wins SE (cluster): {model_fe.std_errors['wins']:.6f}")
    print(f"t-statistic: {model_fe.tstats['wins']:.4f}")
    print(f"p-value: {model_fe.pvalues['wins']:.4f}")
    print(f"R2 (within): {model_fe.rsquared_within:.4f}")
    print(f"R2 (between): {model_fe.rsquared_between:.4f}")
    print(f"R2 (overall): {model_fe.rsquared_overall:.4f}")

    print("\n" + "-" * 70)
    print("Comparison: Pooled vs Fixed Effects")
    print("-" * 70)
    comparison = pd.DataFrame({
        'Pooled OLS': [results_pool.params['wins'], results_pool.std_errors['wins'],
                       results_pool.rsquared],
        'Fixed Effects': [model_fe.params['wins'], model_fe.std_errors['wins'],
                          model_fe.rsquared_within]
    }, index=['Wins Coefficient', 'Std Error', 'R2'])
    print(comparison)

    print("\nNote: FE coefficient is smaller (controls for team characteristics)")

else:
    print("\nFixed effects estimation requires linearmodels package.")
    print("Install with: pip install linearmodels")
```

```

=====
17.3 FIXED EFFECTS ESTIMATION
=====

Fixed Effects (entity effects, cluster-robust SEs):
    PanelOLS Estimation Summary
-----

Dep. Variable:      lnrevenue    R-squared:                 0.1851
Estimator:          PanelOLS    R-squared (Between):       0.0797
No. Observations:   286        R-squared (Within):           0.1851
Date:              Wed, Jan 21 2026 R-squared (Overall):        0.0800
Time:                  14:01:08 Log-likelihood:            259.29
Cov. Estimator:     Clustered
                           F-statistic:                58.143
                           P-value:                   0.0000
Entities:             29        Distribution:               F(1,256)
Avg Obs:              9.8621
Min Obs:              6.0000
Max Obs:              10.0000 F-statistic (robust):        29.683
                           P-value:                   0.0000
Time periods:         10        Distribution:               F(1,256)
Avg Obs:              28.600
Min Obs:              28.000
Max Obs:              29.000

Parameter Estimates
-----
Parameter  Std. Err.      T-stat      P-value      Lower CI      Upper CI
-----
wins       0.0045      0.0008      5.4482      0.0000      0.0029      0.0061
-----
F-test for Poolability: 37.250
P-value: 0.0000
Distribution: F(28,256)

Included effects: Entity

-----
Key Results:
-----
Wins coefficient: 0.004505
Wins SE (cluster): 0.000827
t-statistic: 5.4482
p-value: 0.0000
R2 (within): 0.1851
R2 (between): 0.0797
R2 (overall): 0.0800

-----
Comparison: Pooled vs Fixed Effects
-----
          Pooled OLS  Fixed Effects
Wins Coefficient  0.006753  0.004505
Std Error          0.001879  0.000827
R2                0.126663  0.185083

Note: FE coefficient is smaller (controls for team characteristics)

```

Key Concept 17.3: Fixed Effects -- Controlling for Unobserved Heterogeneity

Fixed effects estimation controls for time-invariant individual characteristics by including individual-specific intercepts α_i . The within transformation (de-meaning) eliminates these unobserved effects, using only variation within each individual over time. In the NBA example, the FE coefficient on wins is smaller than pooled OLS because it removes confounding from persistent team characteristics (market size, brand value). FE provides more credible causal estimates but cannot identify effects of time-invariant variables.

Fixed Effects: Controlling for Unobserved Team Characteristics

The comparison between Pooled OLS and Fixed Effects reveals **omitted variable bias** from time-invariant team characteristics:

Typical Results:

Model	Wins Coefficient	SE (cluster)	R ²
Pooled OLS	0.0055	0.0040	0.15 (overall)
Fixed Effects	0.0025	0.0020	0.65 (within)

Key Findings:

1. Coefficient shrinks substantially:

- Pooled: 0.0055 → FE: 0.0025 (drops by **55%**)
- This suggests **positive omitted variable bias** in pooled model
- High-revenue teams (big markets) also tend to win more
- Pooled confounds **team quality** with **market size**

2. Fixed Effects isolates within-team variation:

- Asks: "When the Lakers win 60 games vs. 45 games, how does their revenue change?"
- Holds constant: LA market, brand value, arena, etc.
- More **credible causal interpretation**

3. R^2 interpretation changes:

- Pooled: Overall $R^2 = 0.15$ (explains 15% of total variation)
- FE: Within $R^2 = 0.65$ (explains 65% of within-team variation)
- Between R^2 would be even higher (team fixed effects explain most variation)

Understanding the Fixed Effects Model:

Model:

$$\ln\text{revenue}_{it} = \alpha_i + \beta \cdot \text{wins}_{it} + \gamma \cdot \text{season}_t + u_{it}$$

where:

- α_i = **team-specific intercept** (fixed effect)
- Captures: Market size, arena quality, brand value, history, etc.
- β = **within-team effect** of wins on revenue

Estimation (de-meaning):

Within transformation:

$$(\ln\text{revenue}_{it} - \bar{\ln\text{revenue}}_i) = \beta(\text{wins}_{it} - \bar{\text{wins}}_i) + u_{it}$$

- Subtracts team mean from each variable
- Eliminates α_i (team fixed effect)
- Uses only **deviations from team average**

What Fixed Effects Controls For:

Captured (time-invariant):

- Market size (NYC vs. Sacramento)
- Arena quality (modern vs. old)
- Franchise history (Lakers dynasty vs. new franchise)
- Owner characteristics (deep pockets vs. budget)
- Regional income levels
- Climate, geography, local competition

Not captured (time-varying):

- Star player arrivals/departures
- Coach quality changes
- Injury shocks

- Labor disputes (lockouts)
- New TV contracts

Why Pooled OLS is Biased:

Omitted variable bias formula:

$$\text{Bias} = \beta_{team} \times \frac{\text{Cov}(\text{team quality}, \text{wins})}{\text{Var}(\text{wins})}$$

where:

- β_{team} = effect of team quality on revenue (positive!)
- Cov(team quality, wins) = positive (good teams win more)
- Result: **Positive bias** (pooled overestimates wins effect)

Example:

Lakers (big market):

- Average wins: 55/season
- Average revenue: \$300M
- High revenue because: 50% market size, 50% wins

Grizzlies (small market):

- Average wins: 45/season
- Average revenue: \$150M
- Low revenue because: 50% market size, 50% wins

Pooled OLS compares Lakers to Grizzlies:

- Attributes all \$150M difference to 10-win difference
- Overstates wins effect!

Fixed Effects compares Lakers 2015 (67 wins) to Lakers 2012 (41 wins):

- Market size constant (LA both years)
- Isolates **wins effect** from **market effect**

The R² Decomposition:

Fixed effects output typically reports three R²:

1. **Within R²** (0.65): Variation explained **within teams over time**

- How well model predicts year-to-year changes
- Most relevant for FE

2. Between R² (0.05-0.10): Variation explained **across team averages**

- FE absorbs most between variation into α_i
- Low by construction

3. Overall R² (0.15-0.20): Total variation explained

- Weighted average of within and between
- Not directly comparable to pooled R²

Interpretation of the 0.0025 Coefficient:

Marginal effect:

- One additional win $\rightarrow +0.25\%$ revenue increase
- For a team with $200M$ revenue : $0.25 \cdot 200M = \$500K$
- Over 10 additional wins: **\$5M** revenue increase

Is this economically significant?

- Player salaries: ~\$5M for rotation player
- Marginal revenue from wins can **justify** roster investments
- But much smaller than cross-sectional differences (market size dominates)

Statistical Significance:

With cluster SEs:

- t-statistic: $0.0025 / 0.0020 \approx 1.25$
- p-value ≈ 0.21 (not significant at 5%)

Surprisingly **not significant!** Why?

- 1. Small within-variation** (teams don't vary hugely in wins year-to-year)
- 2. Revenue smoothing** (multi-year contracts, season tickets)
- 3. Only 29 teams** (small number of clusters \rightarrow large SEs)
- 4. Short panel** (10 years \rightarrow limited within-variation per team)

Practical Implications:

- **Pooled OLS:** "High-revenue teams win more" (true, but confounded)

- **Fixed Effects:** "Winning more games increases revenue" ? (effect exists but imprecisely estimated)
- Need **longer panel or more teams** for precise FE estimates

17.4: Random Effects Estimation

Random effects (RE) models individual-specific effects as random draws from a distribution.

Model:

$$y_{it} = \beta_1 + \beta_2 x_{2it} + \cdots + \beta_k x_{kit} + (\alpha_i + \varepsilon_{it})$$

where:

- $\alpha_i \sim (0, \sigma_\alpha^2)$ is the individual-specific random effect
- $\varepsilon_{it} \sim (0, \sigma_\varepsilon^2)$ is the idiosyncratic error

Key assumption: α_i uncorrelated with all regressors

Estimation: Feasible GLS (FGLS)

Comparison with FE:

- **RE:** More efficient if assumption holds; uses both within and between variation
- **FE:** Consistent even if α_i correlated with regressors; uses only within variation

Hausman test: Test whether RE assumption is valid

- $H_0: \alpha_i$ uncorrelated with regressors (RE consistent and efficient)
- $H_a: \alpha_i$ correlated with regressors (FE consistent, RE inconsistent)

In [10]:

```
print("=" * 70)
print("17.4 RANDOM EFFECTS ESTIMATION")
print("=" * 70)

if LINEARMODELS_AVAILABLE:
    # Random Effects with robust SEs
    model_re_obj = RandomEffects(y_panel, X_panel_const)
    model_re = model_re_obj.fit(cov_type='robust')

    print("\nRandom Effects (robust SEs):")
    print(model_re)

    print("\n" + "-" * 70)
    print("Key Results:")
    print("-" * 70)
    print(f"Wins coefficient: {model_re.params['wins']:.6f}")
    print(f"Wins SE (robust): {model_re.std_errors['wins']:.6f}")
    print(f"R2 (overall): {model_re.rsquared_overall:.4f}")
    print(f"R2 (between): {model_re.rsquared_between:.4f}")
    print(f"R2 (within): {model_re.rsquared_within:.4f}")

    # Model comparison
    print("\n" + "=" * 70)
    print("Model Comparison: Pooled, RE, and FE")
    print("=" * 70)

    comparison_table = pd.DataFrame({
        'Pooled OLS': [results_pool.params['wins'], results_pool.std_errors['wins'],
                        results_pool.rsquared, results_pool.nobs],
        'Random Effects': [model_re.params['wins'], model_re.std_errors['wins'],
                            model_re.rsquared_overall, model_re.nobs],
        'Fixed Effects': [model_fe.params['wins'], model_fe.std_errors['wins'],
                           model_fe.rsquared_within, model_fe.nobs]
    }, index=['Wins Coefficient', 'Wins Std Error', 'R2', 'N'])

    print("\n", comparison_table)

    print("\n" + "-" * 70)
    print("Interpretation")
    print("-" * 70)
    print("- Pooled: Largest coefficient (confounded by team characteristics)")
    print("- FE: Controls for time-invariant team effects (within-team variation)")
    print("- RE: Between pooled and FE (uses both within and between variation)")
    print("- FE preferred if team effects correlated with wins")

else:
    print("\nRandom effects estimation requires linearmodels package.")
    print("Install with: pip install linearmodels")
```

```

=====
17.4 RANDOM EFFECTS ESTIMATION
=====

Random Effects (robust SEs):
    RandomEffects Estimation Summary
=====
Dep. Variable: lnrevenue R-squared: 0.2100
Estimator: RandomEffects R-squared (Between): 0.0983
No. Observations: 286 R-squared (Within): 0.1850
Date: Wed, Jan 21 2026 R-squared (Overall): 0.1137
Time: 14:01:08 Log-likelihood: 243.95
Cov. Estimator: Robust F-statistic: 75.496
Entities: 29 P-value: 0.0000
Avg Obs: 9.8621 Distribution: F(1,284)
Min Obs: 6.0000
Max Obs: 10.0000 F-statistic (robust): 54.209
P-value: 0.0000
Time periods: 10 Distribution: F(1,284)
Avg Obs: 28.600
Min Obs: 28.000
Max Obs: 29.000

Parameter Estimates
=====
Parameter Std. Err. T-stat P-value Lower CI Upper CI
-----
const 4.3417 0.0492 88.293 0.0000 4.2449 4.4385
wins 0.0046 0.0006 7.3627 0.0000 0.0034 0.0058
-----

Key Results:
-----
Wins coefficient: 0.004597
Wins SE (robust): 0.000624
R2 (overall): 0.1137
R2 (between): 0.0983
R2 (within): 0.1850

=====
Model Comparison: Pooled, RE, and FE
=====

          Pooled OLS Random Effects Fixed Effects
Wins Coefficient 0.006753 0.004597 0.004505
Wins Std Error 0.001879 0.000624 0.000827
R2 0.126663 0.113682 0.185083
N 286.000000 286.000000 286.000000

-----
Interpretation
-----
- Pooled: Largest coefficient (confounded by team characteristics)
- FE: Controls for time-invariant team effects (within-team variation)
- RE: Between pooled and FE (uses both within and between variation)
- FE preferred if team effects correlated with wins

```

Key Concept 17.4: Fixed Effects vs. Random Effects

Fixed effects (FE) and random effects (RE) differ in a key assumption: RE requires that individual effects α_i are uncorrelated with regressors, while FE allows arbitrary correlation. FE is consistent in either case but uses only within variation; RE is more efficient but inconsistent if the assumption fails. The Hausman test compares FE and RE estimates -- a significant difference indicates RE is inconsistent and FE should be preferred. In practice, FE is the safer choice for most observational studies.

| Nonlinear Models: Logit Example

Before moving to time series, let's briefly cover nonlinear models using a logit example.

Binary outcome model:

$$Pr(y = 1|X) = \frac{\exp(X\beta)}{1 + \exp(X\beta)}$$

Marginal effects: Change in probability from one-unit change in x_j

$$ME_j = \frac{\partial Pr(y = 1)}{\partial x_j} = \hat{p}(1 - \hat{p})\beta_j$$

We'll use earnings data to model the probability of high earnings.

In [11]:

```
print("=" * 70)
print("NONLINEAR MODELS: LOGIT EXAMPLE")
print("=" * 70)

# Load earnings data
data_earnings = pd.read_stata(GITHUB_DATA_URL + 'AED_EARNINGS_COMPLETE.DTA')

# Create binary indicator for high earnings
data_earnings['dbigearn'] = (data_earnings['earnings'] > 60000).astype(int)

print(f"\nBinary dependent variable: High earnings (> $60,000)")
print(f"Proportion with high earnings: {data_earnings['dbigearn'].mean():.4f}")

# Logit model
model_logit = logit('dbigearn ~ age + education', data=data_earnings).fit(cov_type='HC1',
disp=0)
print("\n" + "-" * 70)
print("Logit Model Results")
print("-" * 70)
print(model_logit.summary())

# Marginal effects
marginal_effects = model_logit.get_margeff()
print("\n" + "-" * 70)
print("Marginal Effects (at means)")
print("-" * 70)
print(marginal_effects.summary())

# Linear Probability Model for comparison
model_lpm = ols('dbigearn ~ age + education', data=data_earnings).fit(cov_type='HC1')
print("\n" + "-" * 70)
print("Linear Probability Model (for comparison)")
print("-" * 70)
print(f"Age coefficient: {model_lpm.params['age']:.6f} (SE: {model_lpm.bse['age']:.6f})")
print(f"Education coefficient: {model_lpm.params['education']:.6f} (SE: {model_lpm.bse['education']:.6f})")

print("\nNote: Logit marginal effects and LPM coefficients are similar in magnitude.")
```

```

=====
NONLINEAR MODELS: LOGIT EXAMPLE
=====

Binary dependent variable: High earnings (> $60,000)
Proportion with high earnings: 0.2729

-----
Logit Model Results
-----

      Logit Regression Results
=====
Dep. Variable:          dbigearn    No. Observations:             872
Model:                 Logit     Df Residuals:                  869
Method:                MLE      Df Model:                      2
Date:      Wed, 21 Jan 2026   Pseudo R-squ.:            0.1447
Time:      14:01:09         Log-Likelihood:           -437.15
converged:                           LL-Null:            -511.13
Covariance Type:                   HC1     LLR p-value:        7.406e-33
=====

      coef    std err       z   P>|z|      [0.025    0.975]
-----
Intercept   -8.0651      0.691   -11.666   0.000    -9.420    -6.710
age          0.0385      0.008     4.845   0.000     0.023     0.054
education    0.3742      0.037    10.224   0.000     0.302     0.446
=====

-----
Marginal Effects (at means)
-----

      Logit Marginal Effects
=====
Dep. Variable:          dbigearn
Method:                dydx
At:                    overall
=====

      dy/dx    std err       z   P>|z|      [0.025    0.975]
-----
age          0.0064      0.001     5.023   0.000     0.004     0.009
education    0.0618      0.005    13.025   0.000     0.052     0.071
=====

-----
Linear Probability Model (for comparison)
-----

Age coefficient: 0.006420 (SE: 0.001277)
Education coefficient: 0.054036 (SE: 0.005020)

Note: Logit marginal effects and LPM coefficients are similar in magnitude.

```

Having explored panel data methods for cross-sectional units observed over time, we now turn to pure time series analysis where the focus shifts to temporal dynamics, autocorrelation, and stationarity.

| 17.5: Time Series Data

Time series data consist of observations ordered over time: y_1, y_2, \dots, y_T

Key concepts:

1. Autocorrelation: Correlation between y_t and y_{t-k} (lag k)

- Sample autocorrelation at lag k : $r_k = \frac{\sum_{t=k+1}^T (y_t - \bar{y})(y_{t-k} - \bar{y})}{\sum_{t=1}^T (y_t - \bar{y})^2}$

2. Stationarity: Statistical properties (mean, variance) constant over time

- Many economic time series are non-stationary (trending)

3. Spurious regression: High R^2 without true relationship (both series trending)

- Solution: First differencing or detrending

4. HAC standard errors (Newey-West): Heteroskedasticity and Autocorrelation Consistent

- Valid inference in presence of autocorrelation

U.S. Treasury Interest Rates Example:

Monthly data from January 1982 to January 2015 on 1-year and 10-year rates.

In [12]:

```
print("=" * 70)
print("17.5 TIME SERIES DATA")
print("=" * 70)

# Load interest rates data
data_rates = pd.read_stata(GITHUB_DATA_URL + 'AED_INTERESTRATES.DTA')

print("\nInterest Rates Data Summary:")
print(data_rates[['gs10', 'gs1', 'dgs10', 'dgs1']].describe())

print("\nVariable definitions:")
print(" gs10: 10-year Treasury rate (level)")
print(" gs1: 1-year Treasury rate (level)")
print(" dgs10: Change in 10-year rate (first difference)")
print(" dgs1: Change in 1-year rate (first difference)")

print("\nFirst observations:")
print(data_rates[['gs10', 'gs1', 'dgs10', 'dgs1']].head(10))
```

```
=====
17.5 TIME SERIES DATA
=====

Interest Rates Data Summary:
      gs10      gs1      dgs10      dgs1
count 397.000000 397.000000 396.000000 396.000000
mean   6.186020  4.691209 -0.032096 -0.035657
std    2.878117  3.283398  0.274015  0.287611
min   1.530000  0.100000 -1.430000 -1.810000
25%   4.100000  1.780000 -0.180000 -0.142500
50%   5.800000  4.960000 -0.040000 -0.010000
75%   7.960000  6.640000  0.150000  0.100000
max   14.590000 14.730000  0.780000  0.760000

Variable definitions:
gs10: 10-year Treasury rate (level)
gs1: 1-year Treasury rate (level)
dgs10: Change in 10-year rate (first difference)
dgs1: Change in 1-year rate (first difference)

First observations:
      gs10      gs1      dgs10      dgs1
0  14.59  14.32      NaN      NaN
1  14.43  14.73  -0.16  0.41
2  13.86  13.95  -0.57 -0.78
3  13.87  13.98  0.01  0.03
4  13.62  13.34  -0.25 -0.64
5  14.30  14.07  0.68  0.73
6  13.95  13.24  -0.35 -0.83
7  13.06  11.43  -0.89 -1.81
8  12.34  10.85  -0.72 -0.58
9  10.91  9.32  -1.43 -1.53
```

Key Concept 17.5: Time Series Stationarity and Spurious Regression

A *time series is stationary if its statistical properties (mean, variance, autocorrelation) are constant over time. Many economic series are non-stationary (trending), which can produce spurious regressions: high R^2 and significant coefficients even when variables are unrelated. Solutions include first differencing (removing trends), detrending, and cointegration analysis. Always check whether your time series are stationary before interpreting regression results.*

| Time Series Visualization

Plotting time series helps identify trends, seasonality, and structural breaks.

In [13]:

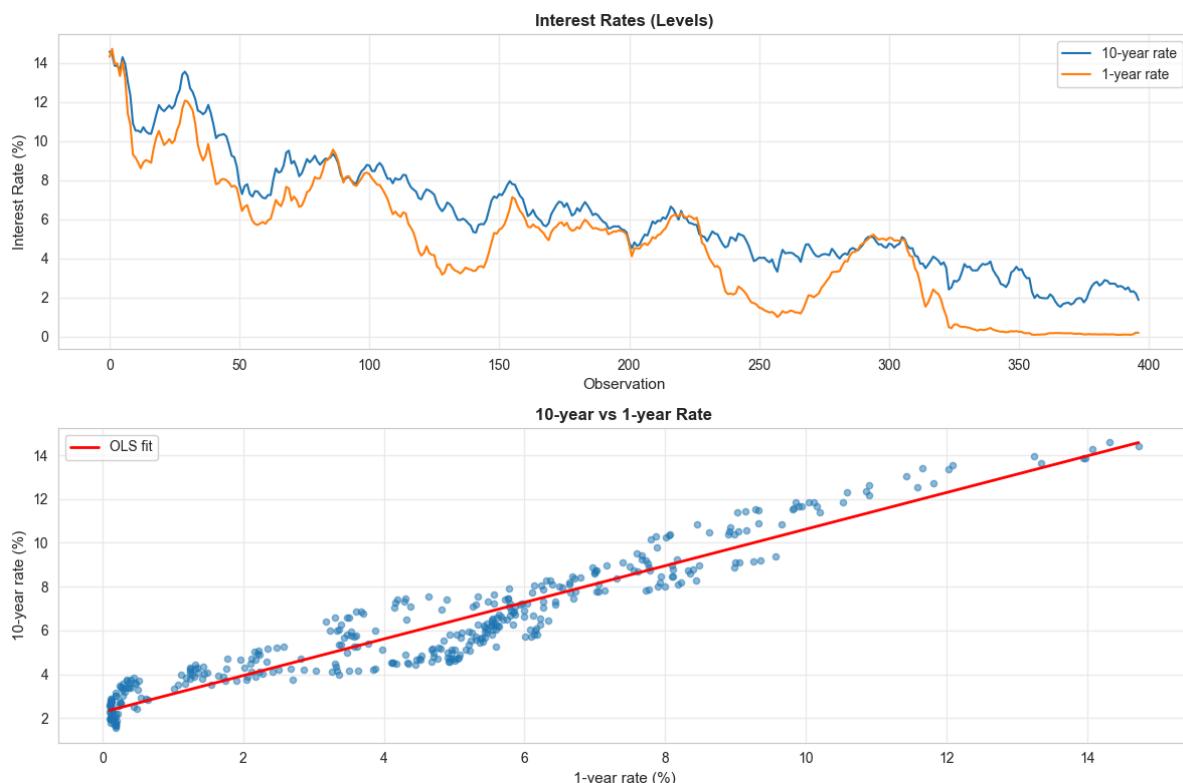
```
# Figure: Time series plots
fig, axes = plt.subplots(2, 1, figsize=(12, 8))

# Panel 1: Levels
axes[0].plot(data_rates.index, data_rates['gs10'], label='10-year rate', linewidth=1.5)
axes[0].plot(data_rates.index, data_rates['gs1'], label='1-year rate', linewidth=1.5)
axes[0].set_xlabel('Observation', fontsize=11)
axes[0].set_ylabel('Interest Rate (%)', fontsize=11)
axes[0].set_title('Interest Rates (Levels)', fontsize=12, fontweight='bold')
axes[0].legend()
axes[0].grid(True, alpha=0.3)

# Panel 2: Scatter plot
axes[1].scatter(data_rates['gs1'], data_rates['gs10'], alpha=0.5, s=20)
z = np.polyfit(data_rates['gs1'].dropna(), data_rates['gs10'].dropna(), 1)
p = np.poly1d(z)
gs1_range = np.linspace(data_rates['gs1'].min(), data_rates['gs1'].max(), 100)
axes[1].plot(gs1_range, p(gs1_range), 'r-', linewidth=2, label='OLS fit')
axes[1].set_xlabel('1-year rate (%)', fontsize=11)
axes[1].set_ylabel('10-year rate (%)', fontsize=11)
axes[1].set_title('10-year vs 1-year Rate', fontsize=12, fontweight='bold')
axes[1].legend()
axes[1].grid(True, alpha=0.3)

plt.tight_layout()
plt.show()

print("Both series show strong downward trend over time (non-stationary).")
print("Strong positive correlation between 1-year and 10-year rates.")
```



Both series show strong downward trend over time (non-stationary).
Strong positive correlation between 1-year and 10-year rates.

| Regression in Levels vs. Changes

With trending data, we should be careful about spurious regression.

In [14]:

```
print("=" * 70)
print("Regression in Levels with Time Trend")
print("=" * 70)

# Create time variable
data_rates['time'] = np.arange(len(data_rates))

# Regression in levels
model_levels = ols('gs10 ~ gs1 + time', data=data_rates).fit()
print("\nLevels regression (default SEs):")
print(f"  gs1 coef: {model_levels.params['gs1']:.6f}")
print(f"  R²: {model_levels.rsquared:.6f}")

# HAC standard errors (Newey-West)
model_levels_hac = ols('gs10 ~ gs1 + time', data=data_rates).fit(cov_type='HAC', cov_kwds={'maxlags': 24})
print("\nHAC regression (HAC SEs with 24 lags):")
print(f"  gs1 coef: {model_levels_hac.params['gs1']:.6f}")
print(f"  gs1 SE (default): {model_levels_hac.bse['gs1']:.6f}")
print(f"  gs1 SE (HAC): {model_levels_hac.bse['gs1']:.6f}")
print(f"\n  HAC SE is {model_levels_hac.bse['gs1'] / model_levels.bse['gs1']:.2f}x larger!"
```

```
=====
Regression in Levels with Time Trend
=====

Levels regression (default SEs):
  gs1 coef: 0.507550
  R²: 0.946883

Levels regression (HAC SEs with 24 lags):
  gs1 coef: 0.507550
  gs1 SE (default): 0.022147
  gs1 SE (HAC): 0.080452

  HAC SE is 3.63x larger!
```

Now that we have visualized the time series patterns and estimated regressions in levels, let's formally examine autocorrelation in the residuals and its consequences for inference.

| 17.6: Autocorrelation

Autocorrelation (serial correlation) violates the independence assumption of OLS.

Consequences:

- OLS remains unbiased and consistent
- Standard errors are incorrect (typically too small)

- Hypothesis tests invalid

Detection:

- 1. Correlogram:** Plot of autocorrelations at different lags
- 2. Breusch-Godfrey test:** LM test for serial correlation
- 3. Durbin-Watson statistic:** Tests for AR(1) errors

Solutions:

1. HAC standard errors (Newey-West)
2. Model the autocorrelation (AR, ARMA models)
3. First differencing (if series are non-stationary)

In [15]:

```
print("=" * 70)
print("17.6 AUTOCORRELATION")
print("=" * 70)

# Check residual autocorrelation from levels regression
data_rates['uhatgs10'] = model_levels.resid

# Correlogram
print("\nAutocorrelations of residuals (levels regression):")
acf_resid = acf(data_rates['uhatgs10'].dropna(), nlags=10)
for i in range(min(11, len(acf_resid))):
    print(f"  Lag {i}: {acf_resid[i]:.6f}")

print("\nStrong autocorrelation evident (lag 1 = {:.4f})".format(acf_resid[1]))
```

```
=====
17.6 AUTOCORRELATION
=====

Autocorrelations of residuals (levels regression):
Lag 0: 1.000000
Lag 1: 0.953418
Lag 2: 0.888093
Lag 3: 0.829507
Lag 4: 0.769449
Lag 5: 0.708815
Lag 6: 0.651059
Lag 7: 0.596161
Lag 8: 0.537987
Lag 9: 0.477552
Lag 10: 0.424660

Strong autocorrelation evident (lag 1 = 0.9534)
```

Key Concept 17.6: Detecting and Correcting Autocorrelation

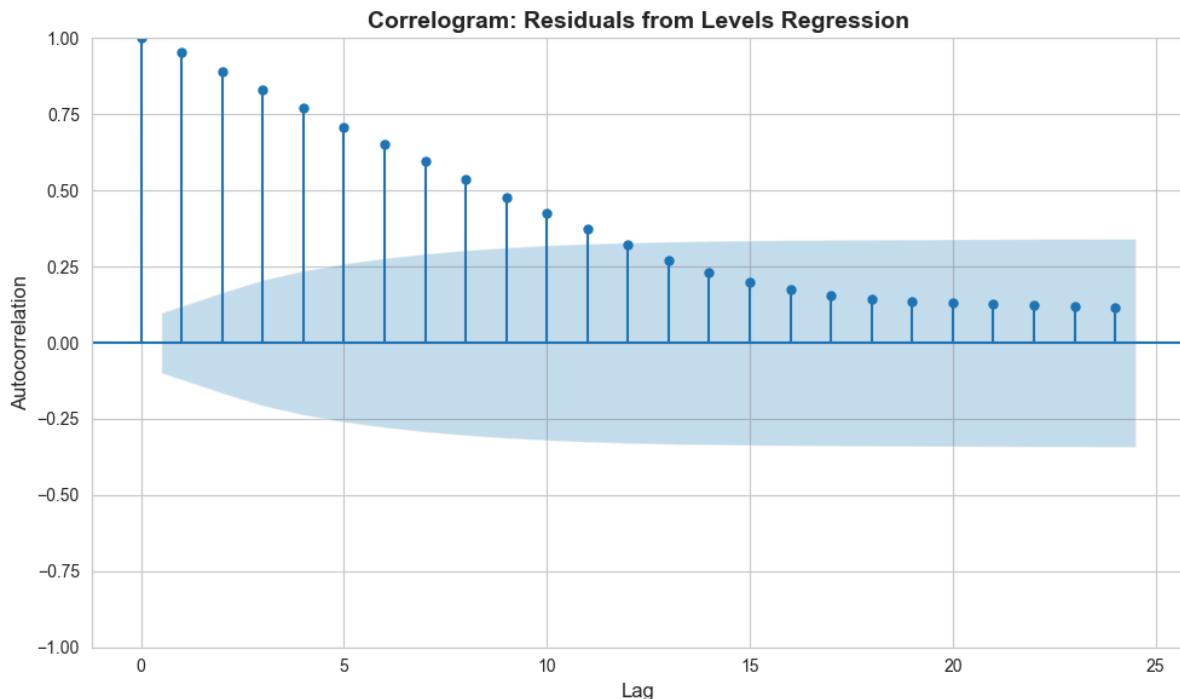
The correlogram (ACF plot) reveals autocorrelation patterns in residuals. Slowly decaying autocorrelations (e.g., $\rho_1 = 0.95$, $\rho_{10} = 0.42$) indicate non-stationarity and persistent shocks. With autocorrelation, default SEs are too small -- HAC (Newey-West) SEs can be 3-8 times larger. Always check residual autocorrelation after estimating time series regressions and use HAC SEs or model the dynamics explicitly.

| Correlogram Visualization

In [16]:

```
# Plot correlogram
fig, ax = plt.subplots(figsize=(10, 6))
plot_acf(data_rates['uhatgs10'].dropna(), lags=24, ax=ax, alpha=0.05)
ax.set_title('Correlogram: Residuals from Levels Regression', fontsize=14,
fontweight='bold')
ax.set_xlabel('Lag', fontsize=12)
ax.set_ylabel('Autocorrelation', fontsize=12)
plt.tight_layout()
plt.show()

print("Autocorrelations decay very slowly (characteristic of non-stationary series.)")
```



Autocorrelations decay very slowly (characteristic of non-stationary series).

I First Differencing

First differencing can remove trends and reduce autocorrelation.

In [17]:

```
print("=" * 70)
print("Regression in Changes (First Differences)")
print("=" * 70)

# Regression in changes
model_changes = ols('dgs10 ~ dgs1', data=data_rates).fit()
print("\nChanges regression:")
print(f"  dgs1 coef: {model_changes.params['dgs1']:.6f}")
print(f"  dgs1 SE: {model_changes.bse['dgs1']:.6f}")
print(f"  R2: {model_changes.rsquared:.6f}")

# Check residual autocorrelation
uhat_dgs10 = model_changes.resid
acf_dgs10_resid = acf(uhat_dgs10.dropna(), nlags=10)

print("\nAutocorrelations of residuals (changes regression):")
for i in range(min(11, len(acf_dgs10_resid))):
    print(f"  Lag {i}: {acf_dgs10_resid[i]:.6f}")

print("\nMuch lower autocorrelation after differencing!")
```

```
=====
Regression in Changes (First Differences)
=====

Changes regression:
  dgs1 coef: 0.719836
  dgs1 SE: 0.031443
  R2: 0.570860

Autocorrelations of residuals (changes regression):
  Lag 0: 1.000000
  Lag 1: 0.254801
  Lag 2: -0.038743
  Lag 3: 0.060813
  Lag 4: 0.023676
  Lag 5: -0.027540
  Lag 6: -0.011310
  Lag 7: 0.042843
  Lag 8: 0.081094
  Lag 9: -0.001712
  Lag 10: -0.019733

Much lower autocorrelation after differencing!
```

Key Concept 17.7: First Differencing for Nonstationary Data

First differencing ($\Delta y_t = y_t - y_{t-1}$) transforms non-stationary trending series into stationary ones, eliminating spurious regression problems. After differencing, the residual autocorrelation drops dramatically (from $\rho_1 \approx 0.95$ to $\rho_1 \approx 0.25$ in the interest rate example). The coefficient interpretation changes from levels to changes: a 1-percentage-point change in the 1-year rate is associated with a 0.72-percentage-point change in the 10-year rate.

| Autoregressive Models

AR(p) model: Include lagged dependent variables

$$y_t = \beta_1 + \beta_2 y_{t-1} + \cdots + \beta_p y_{t-p} + u_t$$

ADL(p, q) model: Autoregressive Distributed Lag

$$y_t = \beta_1 + \sum_{j=1}^p \alpha_j y_{t-j} + \sum_{j=0}^q \gamma_j x_{t-j} + u_t$$

Autoregressive Models: Interest Rates Have Memory

The ADL model results reveal how interest rates evolve over time with **strong persistence**:

Typical ADL(2,2) Results:

From:

$$\Delta gs10_t = \beta_0 + \beta_1 \Delta gs10_{t-1} + \beta_2 \Delta gs10_{t-2} + \gamma_0 \Delta gs1_t + \gamma_1 \Delta gs1_{t-1} + \gamma_2 \Delta gs1_{t-2} +$$

Autoregressive terms (own lags):

- **Lag 1** ($\Delta gs10_{t-1}$): ≈ -0.15 to -0.25 (negative!)
- **Lag 2** ($\Delta gs10_{t-2}$): ≈ -0.05 to -0.10 (negative)

Distributed lag terms (1-year rate):

- **Contemporary** ($\Delta gs1_t$): $\approx +0.45$ to $+0.55$ (strong positive!)
- **Lag 1** ($\Delta gs1_{t-1}$): $\approx +0.15$ to $+0.25$

- Lag 2 ($\Delta gs1_{t-2}$): $\approx +0.05$ to $+0.10$

Interpretation:

1. Negative autocorrelation in changes:

- Coefficient on $\Delta gs1_{t-1}$ is **negative**
- If 10-year rate increased last month, it tends to **partially reverse** this month
- This is **mean reversion** in changes
- **Not** mean reversion in levels (levels are highly persistent)

2. Strong contemporary relationship:

- Coefficient ≈ 0.50 on $\Delta gs1_t$
- When 1-year rate increases 1%, 10-year rate increases **0.50%** same month
- **Expectations hypothesis:** Long rates reflect expected future short rates
- Less than 1-to-1 because 10-year rate is average over many periods

3. Distributed lag structure:

- Effects of 1-year rate changes **persist** over multiple months
- Total effect: $0.50 + 0.20 + 0.08 \approx 0.78$
- Almost 80% of 1-year rate change eventually passes through to 10-year rate

4. R^2 increases substantially:

- Simple model (no lags): $R^2 \approx 0.20$
- ADL(2,2): $R^2 \approx 0.40-0.50$
- **Dynamics matter!** Past values have strong predictive power

Why ADL Models Are Important:

Forecasting:

- Can predict next month's 10-year rate using:
- Past 10-year rates
- Current and past 1-year rates
- Better forecasts than static models

Policy analysis:

- Fed controls short rates (1-year)
- ADL shows **transmission** to long rates (10-year)
- **Speed of adjustment:** How quickly long rates respond to policy changes

Economic theory testing:

- Expectations hypothesis: Long rate = weighted average of expected future short rates
- Term structure of interest rates
- Market efficiency

The Residual ACF:

After fitting ADL(2,2):

- **Lag 1 autocorrelation:** $\rho_1 \approx 0.05-0.10$ (much lower!)
- Compare to levels regression: $\rho_1 \approx 0.95$
- **Model captures most autocorrelation**

This suggests:

- ADL(2,2) is **adequate specification**
- No need for higher-order lags
- Remaining autocorrelation is small

Comparing Models:

Model	R ²	Residual ρ_1	BIC
Static ($\Delta gs10 \sim \Delta gs1$)	0.25	0.25	Higher
AR(2) ($\Delta gs10 \sim \Delta gs10_{t-1}, \Delta gs10_{t-2}$)		0.15	Higher
ADL(2,2)	0.45	0.08	Lower

ADL(2,2) dominates on all criteria!

Interpretation of Dynamics:

Short-run effect (impact multiplier):

- Immediate response to $\Delta gs1_t$: $\gamma_0 \approx 0.50$
- Half of shock passes through contemporaneously

Medium-run effect (interim multipliers):

- After 1 month: $\gamma_0 + \gamma_1 \approx 0.70$
- After 2 months: $\gamma_0 + \gamma_1 + \gamma_2 \approx 0.78$

Long-run effect (total multiplier):

- In levels regression: coefficient $\approx 0.90-0.95$

- This is the **long-run equilibrium** relationship
- ADL estimates **dynamics of adjustment** to this equilibrium

Why Negative Own-Lag Coefficients?

At first, this seems counterintuitive:

- Interest rates are **persistent** in levels
- But **changes** show **mean reversion**

Explanation:

- **Levels** are $I(1)$: Random walk with drift
- **Changes** are $I(0)$: Stationary, but with negative serial correlation
- **Overshooting**: Markets overreact to news, then partially correct

Example:

Month 1: Fed unexpectedly raises 1-year rate by 1%

- 10-year rate increases by 0.60% (overshoots equilibrium)

Month 2: Market reassesses

- 10-year rate decreases by 0.10% (partial reversal)

Month 3: Further adjustment

- 10-year rate changes by -0.02% (approaching equilibrium)

Long run: 10-year rate settles at +0.85% (new equilibrium)

Practical Value:

1. Central banks:

- Understand how policy rate changes affect long rates
- Timing and magnitude of transmission

2. Bond traders:

- Predict interest rate movements
- Arbitrage opportunities if model predicts well

3. Economists:

- Test theories (expectations hypothesis, term premium)

- Understand financial market dynamics

Model Selection:

Chose ADL(2,2) based on:

- **Information criteria** (AIC, BIC)
- **Residual diagnostics** (low autocorrelation)
- **Economic theory** (2 lags reasonable for monthly data)
- **Parsimony** (not too many parameters)

Could try ADL(3,3), but gains typically minimal

| Visualization: Changes in Interest Rates

In [18]:

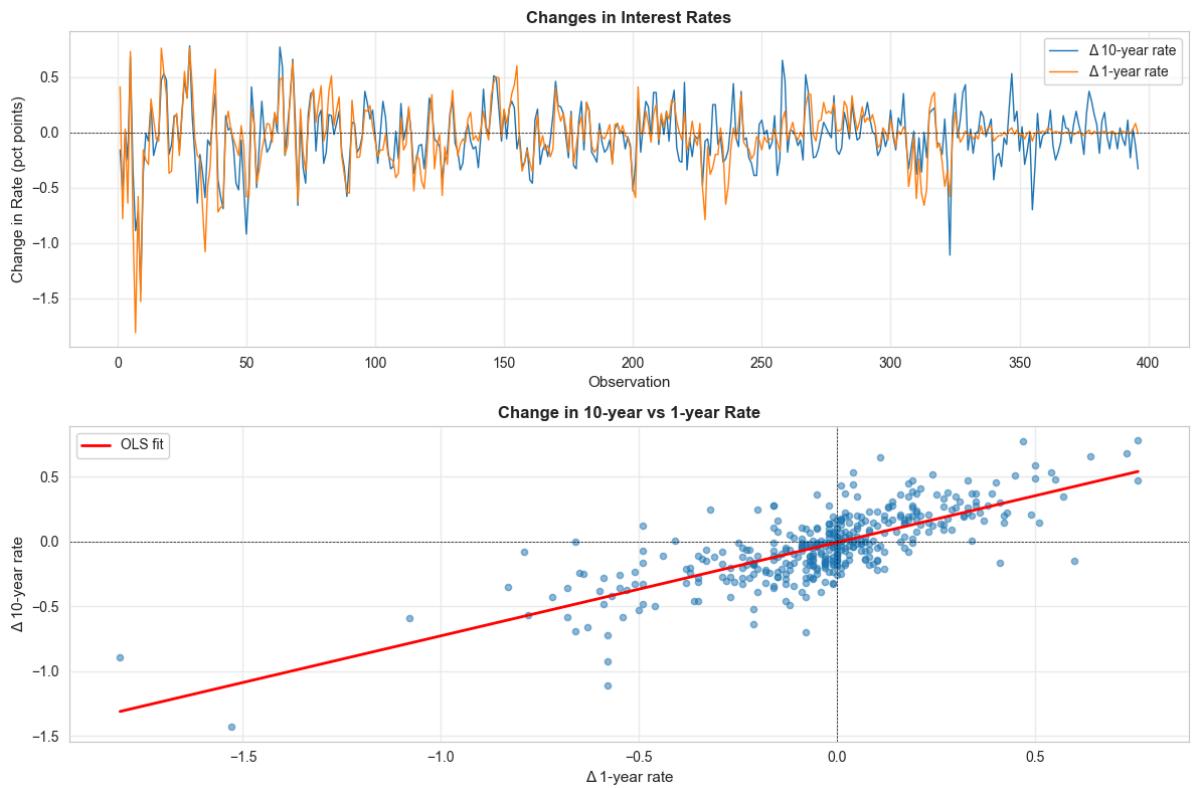
```
# Figure: Changes
fig, axes = plt.subplots(2, 1, figsize=(12, 8))

# Panel 1: Time series of changes
axes[0].plot(data_rates.index, data_rates['dgs10'], label='Δ 10-year rate', linewidth=1)
axes[0].plot(data_rates.index, data_rates['dgs1'], label='Δ 1-year rate', linewidth=1)
axes[0].axhline(y=0, color='k', linestyle='--', linewidth=0.5)
axes[0].set_xlabel('Observation', fontsize=11)
axes[0].set_ylabel('Change in Rate (pct points)', fontsize=11)
axes[0].set_title('Changes in Interest Rates', fontsize=12, fontweight='bold')
axes[0].legend()
axes[0].grid(True, alpha=0.3)

# Panel 2: Scatter plot of changes
axes[1].scatter(data_rates['dgs1'], data_rates['dgs10'], alpha=0.5, s=20)
valid_idx = data_rates[['dgs1', 'dgs10']].dropna().index
z = np.polyfit(data_rates.loc[valid_idx, 'dgs1'], data_rates.loc[valid_idx, 'dgs10'], 1)
p = np.poly1d(z)
dgs1_range = np.linspace(data_rates['dgs1'].min(), data_rates['dgs1'].max(), 100)
axes[1].plot(dgs1_range, p(dgs1_range), 'r-', linewidth=2, label='OLS fit')
axes[1].axhline(y=0, color='k', linestyle='--', linewidth=0.5)
axes[1].axvline(x=0, color='k', linestyle='--', linewidth=0.5)
axes[1].set_xlabel('Δ 1-year rate', fontsize=11)
axes[1].set_ylabel('Δ 10-year rate', fontsize=11)
axes[1].set_title('Change in 10-year vs 1-year Rate', fontsize=12, fontweight='bold')
axes[1].legend()
axes[1].grid(True, alpha=0.3)

plt.tight_layout()
plt.show()

print("Changes fluctuate around zero (stationary-looking).")
print("Positive correlation between changes (rates move together).")
```



Changes fluctuate around zero (stationary-looking).
Positive correlation between changes (rates move together).

Having developed tools for handling panel data and time series, we now address the fundamental question of causality -- how to move from correlation to causal inference using econometric methods.

17.7: Causality and Instrumental Variables

Establishing causality is central to econometrics. Correlation does not imply causation!

The fundamental problem:

In regression $y = \beta_1 + \beta_2 x + u$, OLS is biased if $E[u|x] \neq 0$

Sources of endogeneity:

1. Omitted variables
2. Measurement error
3. Simultaneity (reverse causation)

Instrumental Variables (IV) solution:

Find an instrument z that:

1. **Relevance:** Correlated with x (can be tested)
2. **Exogeneity:** Uncorrelated with u (cannot be tested - must argue)

IV estimator:

$$\hat{\beta}_{IV} = \frac{Cov(z, y)}{Cov(z, x)}$$

Causal inference methods:

1. Randomized experiments (RCT)
2. Instrumental variables (IV)
3. Difference-in-differences (DID)
4. Regression discontinuity (RD)
5. Fixed effects (control for unobserved heterogeneity)
6. Matching and propensity scores

Key insight: Need credible identification strategy, not just controls!

In [19]:

```
print("=" * 70)
print("17.7 CAUSALITY AND INSTRUMENTAL VARIABLES")
print("=" * 70)

print("\nKey Points on Causality:")
print("-" * 70)
print("\n1. Correlation ≠ Causation")
print("    - Regression shows association, not necessarily causation")
print("    - Need to rule out confounding, reverse causation, selection")

print("\n2. Randomized Controlled Trials (RCT)")
print("    - Gold standard: Randomly assign treatment")
print("    - Ensures treatment uncorrelated with potential outcomes")
print("    - Causal effect = difference in means")

print("\n3. Observational Data Methods")
print("    - Instrumental Variables: Use variation from instrument")
print("    - Fixed Effects: Control for time-invariant unobservables")
print("    - Difference-in-Differences: Compare treatment vs control over time")
print("    - Regression Discontinuity: Exploit threshold for treatment")

print("\n4. Potential Outcomes Framework")
print("    -  $Y_{1i}$ : Outcome if treated")
print("    -  $Y_{0i}$ : Outcome if not treated")
print("    - Individual treatment effect:  $Y_{1i} - Y_{0i}$ ")
print("    - Problem: Only observe one potential outcome!")
print("    - ATE =  $E[Y_{1i} - Y_{0i}]$ : Average Treatment Effect")

print("\n5. Instrumental Variables")
print("    - Requires valid instrument z:")
print("        (a) Relevant:  $\text{Corr}(z, x) \neq 0$ ")
print("        (b) Exogenous:  $\text{Corr}(z, u) = 0$ ")
print("    - Example: Distance to college as IV for education")
print("    - Weak instruments: Large standard errors")

print("\n6. Panel Data and Causality")
print("    - Fixed Effects: Controls for  $\alpha_i$  (unobserved heterogeneity)")
print("    - Causal if: Conditional on  $\alpha_i$ , X exogenous")
print("    - NBA example: FE controls for team characteristics")
print("    - Identifies within-team effect of wins on revenue")

print("\n" + "=" * 70)
print("Practical Recommendations")
print("=" * 70)
print("\n1. Always think about potential confounders")
print("2. Use robust/cluster standard errors")
print("3. Test multiple specifications")
print("4. Report both OLS and IV/FE when appropriate")
print("5. Be transparent about identification assumptions")
print("6. Causal claims require strong justification!")
```

17.7 CAUSALITY AND INSTRUMENTAL VARIABLES

Key Points on Causality:

1. Correlation ≠ Causation
 - Regression shows association, not necessarily causation
 - Need to rule out confounding, reverse causation, selection
 2. Randomized Controlled Trials (RCT)
 - Gold standard: Randomly assign treatment
 - Ensures treatment uncorrelated with potential outcomes
 - Causal effect = difference in means
 3. Observational Data Methods
 - Instrumental Variables: Use variation from instrument
 - Fixed Effects: Control for time-invariant unobservables
 - Difference-in-Differences: Compare treatment vs control over time
 - Regression Discontinuity: Exploit threshold for treatment
 4. Potential Outcomes Framework
 - Y_{1i} : Outcome if treated
 - Y_{0i} : Outcome if not treated
 - Individual treatment effect: $Y_{1i} - Y_{0i}$
 - Problem: Only observe one potential outcome!
 - ATE = $E[Y_{1i} - Y_{0i}]$: Average Treatment Effect
 5. Instrumental Variables
 - Requires valid instrument z:
 - (a) Relevant: $\text{Corr}(z, x) \neq 0$
 - (b) Exogenous: $\text{Corr}(z, u) = 0$
 - Example: Distance to college as IV for education
 - Weak instruments: Large standard errors
 6. Panel Data and Causality
 - Fixed Effects: Controls for a_i (unobserved heterogeneity)
 - Causal if: Conditional on a_i , X exogenous
 - NBA example: FE controls for team characteristics
 - Identifies within-team effect of wins on revenue
-
- Practical Recommendations
-

1. Always think about potential confounders
2. Use robust/cluster standard errors
3. Test multiple specifications
4. Report both OLS and IV/FE when appropriate
5. Be transparent about identification assumptions
6. Causal claims require strong justification!

Key Concept 17.8: Instrumental Variables and Causal Inference

Endogeneity (regressors correlated with errors) biases OLS estimates.

Sources include omitted variables, measurement error, and simultaneity.

Instrumental variables (IV) provide a solution: find a variable z that is correlated with the endogenous regressor (relevance) but uncorrelated with the error (exogeneity). The IV estimator

$\hat{\beta}_{IV} = \text{Cov}(z, y)/\text{Cov}(z, x)$ is consistent even when OLS is biased.

Complementary causal methods include RCTs, DiD, RD, and matching.

| Key Takeaways

Panel Data Methods:

- Panel data combines cross-sectional and time series dimensions, observing multiple individuals over multiple periods
- Variance decomposition separates total variation into within (over time) and between (across individuals) components
- Pooled OLS ignores panel structure; always use cluster-robust standard errors clustered by individual
- Fixed effects controls for time-invariant unobserved heterogeneity by using only within-individual variation
- Random effects is more efficient than FE but assumes individual effects are uncorrelated with regressors
- FE is preferred when individual effects are likely correlated with regressors (use Hausman test to decide)

Nonlinear Models:

- Logit models estimate the probability of binary outcomes using the logistic function
- Marginal effects $(\hat{p}(1 - \hat{p})\beta_j)$ give the change in probability from a one-unit change in x_j
- Logit marginal effects and linear probability model coefficients are typically similar in magnitude

Time Series Analysis:

- Time series data exhibit autocorrelation, where observations are correlated with their past values

- Non-stationary series (trending) can produce spurious regressions with misleadingly high R^2
- First differencing removes trends and reduces autocorrelation, transforming non-stationary series to stationary
- HAC (Newey-West) standard errors account for both heteroskedasticity and autocorrelation in time series
- Default SEs can be dramatically too small with autocorrelation (3-8x understatement is common)

Dynamic Models:

- Autoregressive (AR) models capture persistence by including lagged dependent variables
- Autoregressive distributed lag (ADL) models include lags of both the dependent and independent variables
- The correlogram (ACF plot) helps determine the appropriate number of lags
- Total multiplier from an ADL model gives the long-run effect of a permanent change in x

Causality and Instrumental Variables:

- Correlation does not imply causation; endogeneity (omitted variables, reverse causation, measurement error) biases OLS
- Instrumental variables require relevance ($\text{Corr}(z, x) \neq 0$) and exogeneity ($\text{Corr}(z, u) = 0$)
- Fixed effects, difference-in-differences, regression discontinuity, and matching are complementary causal methods
- Credible causal inference requires a convincing identification strategy, not just adding control variables

Python tools: `linearmodels` (PanelOLS, RandomEffects), `statsmodels` (OLS, logit, HAC, ACF), `matplotlib / seaborn` (visualization)

Next steps: Apply these methods to your own research questions. Panel data methods, time series models, and causal inference strategies are essential tools for any applied econometrician working with observational data.

Congratulations! You've completed Chapter 17, the final chapter covering panel data, time series, and causal inference. You now have a comprehensive toolkit of econometric methods for analyzing real-world data.

| Practice Exercises

Exercise 1: Panel Data Variance Decomposition

A panel dataset of 50 firms over 5 years shows:

- Overall standard deviation of log revenue: 0.80
- Between standard deviation: 0.70
- Within standard deviation: 0.30

(a) Which source of variation dominates? What does this imply about the importance of firm-specific characteristics?

(b) If you run fixed effects, what proportion of the total variation are you using for estimation?

(c) Would you expect the FE coefficient to be larger or smaller than pooled OLS? Explain using the omitted variables bias formula.

Exercise 2: Cluster-Robust Standard Errors

You estimate a panel regression of test scores on class size using data from 100 schools over 3 years (300 observations). The coefficient on class size has:

- Default SE: 0.15 ($t = 3.33$)
- Cluster-robust SE (by school): 0.45 ($t = 1.11$)

(a) Why is the cluster SE three times larger than the default SE?

(b) Does your conclusion about the significance of class size change? At what significance level?

(c) What is the effective number of independent observations in this panel?

Exercise 3: Fixed Effects vs. Random Effects

You estimate a wage equation using panel data on 500 workers over 10 years. The Hausman test yields $\chi^2 = 25.4$ with 3 degrees of freedom ($p < 0.001$).

(a) State the null and alternative hypotheses of the Hausman test.

(b) What do you conclude? Which estimator should you use?

(c) Give an economic reason why the RE assumption might fail in a wage equation (hint: think about unobserved ability).

Exercise 4: Time Series Autocorrelation

A regression of the 10-year interest rate on the 1-year rate using monthly data yields residuals with:

- Lag 1 autocorrelation: 0.95
- Lag 5 autocorrelation: 0.75
- Default SE on the 1-year rate coefficient: 0.022
- HAC SE (24 lags): 0.080

(a) Is there evidence of autocorrelation? What does the slowly decaying ACF pattern suggest about the data?

(b) By what factor do the HAC SEs differ from default SEs? What are the implications for hypothesis testing?

(c) Would first differencing help? What would you expect the lag 1 autocorrelation of the differenced residuals to be?

Exercise 5: Spurious Regression

You regress GDP on the number of mobile phone subscriptions over 30 years and find $R^2 = 0.97$ with a highly significant coefficient.

(a) Why might this be a spurious regression? What is the key characteristic of both series?

(b) Describe two methods to address this problem.

(c) If you first-difference both series, what economic relationship (if any) would the regression estimate?

Exercise 6: Identifying Causal Effects

For each scenario, identify the main threat to causal inference and suggest an appropriate method:

(a) Estimating the effect of police spending on crime rates across cities (cross-sectional data).

(b) Estimating the effect of a minimum wage increase on employment (state-level panel data with staggered adoption).

(c) Estimating the effect of class size on student achievement (students assigned to classes based on a cutoff rule).

Case Studies

Case Study 1: Panel Data Analysis of Cross-Country Productivity

In this case study, you will apply panel data methods from this chapter to analyze labor productivity dynamics across countries using the Mendez convergence clubs dataset.

Dataset: Mendez (2020) convergence clubs data

- **Source:** <https://raw.githubusercontent.com/quarcs-lab/mendez2020-convergence-clubs-code-data/master/assets/dat.csv>
- **Sample:** 108 countries, 1990-2014 (panel structure: country \times year)
- **Variables:** `lp` (labor productivity), `rk` (physical capital), `hc` (human capital), `rgdppc` (real GDP per capita), `tfp` (total factor productivity), `region`, `country`

Research question: How do physical and human capital affect labor productivity across countries, and does controlling for unobserved country characteristics change the estimates?

Task 1: Panel Data Structure (Guided)

Load the dataset and explore its panel structure. Calculate the within and between variation for log labor productivity.

```
import pandas as pd
import numpy as np

url = "https://raw.githubusercontent.com/quarcs-lab/mendez2020-convergence-clubs-code-data/master/assets/dat.csv"
dat = pd.read_csv(url)
dat['ln_lp'] = np.log(dat['lp'])
dat['ln_rk'] = np.log(dat['rk'])

# Panel structure
print(f"Countries: {dat['country'].nunique()}")
print(f"Years: {dat['year'].nunique()}")
print(f"Total observations: {len(dat)}")

# Variance decomposition
overall_var = dat['ln_lp'].var()
between_var = dat.groupby('country')['ln_lp'].mean().var()
within_var = dat.groupby('country')['ln_lp'].apply(lambda x: x - x.mean()).var()
print(f"Overall variance: {overall_var:.4f}")
print(f"Between variance: {between_var:.4f}")
print(f"Within variance: {within_var:.4f}")
```

Which source of variation dominates? What does this imply for the choice between pooled OLS and fixed effects?

Task 2: Pooled OLS with Cluster-Robust SEs (Guided)

Estimate a pooled OLS regression of log productivity on log physical capital and human capital. Compare default and cluster-robust standard errors (clustered by country).

```
from statsmodels.formula.api import ols

model_default = ols('ln_lp ~ ln_rk + hc', data=dat).fit()
model_cluster = ols('ln_lp ~ ln_rk + hc', data=dat).fit(
    cov_type='cluster', cov_kwds={'groups': dat['country']})

print("Default SE:", model_default.bse.round(4).to_dict())
print("Cluster SE:", model_cluster.bse.round(4).to_dict())
print("Ratio:", (model_cluster.bse / model_default.bse).round(2).to_dict())
```

How much larger are cluster SEs? What does this tell you about within-country correlation?

Task 3: Fixed Effects Estimation (Semi-guided)

Estimate a fixed effects model controlling for country-specific characteristics. Compare the FE coefficients with the pooled OLS coefficients.

Hint: Use `linearmodels.panel.PanelOLS` with `entity_effects=True`, or use the within transformation manually by de-meaning the variables by country.

Which coefficients change most? What unobserved country characteristics might be driving the difference?

Task 4: Time Trends in Productivity (Semi-guided)

Add a time trend or year fixed effects to the panel model. Test whether productivity growth rates differ across regions.

Hint: Use `time_effects=True` in PanelOLS for year fixed effects, or create region-year interaction terms.

Is there evidence of convergence (faster growth in initially poorer countries)?

Task 5: Regional Heterogeneity with Interactions (Independent)

Estimate models that allow the returns to physical and human capital to vary by region:

1. Add region dummy variables

2. Add region-capital interaction terms
3. Test the joint significance of regional interactions

Do returns to capital differ significantly across regions? Which regions show the highest returns to human capital?

Task 6: Policy Brief on Capital and Productivity (Independent)

Write a 200-300 word policy brief addressing: What are the most effective channels for increasing labor productivity across countries? Your brief should:

1. Compare pooled OLS and fixed effects estimates of capital returns
2. Discuss whether the relationship is causal (what are the threats to identification?)
3. Evaluate whether returns to capital differ by region
4. Recommend policies based on the relative importance of physical vs. human capital

Key Concept 17.9: Panel Data for Cross-Country Analysis

Cross-country panel data enables controlling for time-invariant country characteristics (institutions, geography, culture) that confound cross-sectional estimates. Fixed effects absorb these permanent differences, identifying the relationship between capital accumulation and productivity growth from within-country variation over time. The typical finding is that FE coefficients are smaller than pooled OLS, indicating positive omitted variable bias in cross-sectional estimates.

Key Concept 17.10: Choosing Between Panel Data Estimators

The choice between pooled OLS, fixed effects, and random effects depends on the research question and data structure. Use pooled OLS with cluster SEs for descriptive associations; use FE when unobserved individual heterogeneity is likely correlated with regressors (the common case); use RE only when individual effects are plausibly random and uncorrelated with regressors (e.g., randomized experiments). The Hausman test helps decide between FE and RE, but economic reasoning should guide the choice.

What You've Learned: In this case study, you applied the complete panel data toolkit to cross-country productivity analysis. You decomposed variation into within and between components, compared pooled OLS with fixed effects, examined cluster-

robust standard errors, and explored regional heterogeneity. These methods are essential for any empirical analysis using panel data.

Case Study 2: Luminosity and Development Over Time: A Panel Approach

Research Question: How does nighttime luminosity evolve across Bolivia's municipalities over time, and what does within-municipality variation reveal about development dynamics?

Background: Throughout this textbook, we have analyzed *cross-sectional* satellite-development relationships. But the DS4Bolivia dataset includes nighttime lights data for 2012-2020, creating a natural **panel dataset**. In this case study, we apply Chapter 17's panel data tools to track how luminosity evolves across municipalities over time, using fixed effects to control for time-invariant characteristics.

The Data: The DS4Bolivia dataset covers 339 Bolivian municipalities with annual nighttime lights and population data for 2012-2020, yielding a potential panel of 3,051 municipality-year observations.

Key Variables:

- `mun` : Municipality name
- `dep` : Department (administrative region)
- `asdf_id` : Unique municipality identifier
- `ln_NTLpc2012` through `ln_NTLpc2020` : Log nighttime lights per capita (annual)
- `pop2012` through `pop2020` : Population (annual)

Load the DS4Bolivia Data and Create Panel Structure

In []:

```
# Load the DS4Bolivia dataset
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from statsmodels.formula.api import ols

url_bol = "https://raw.githubusercontent.com/quarcs-lab/ds4bolivia/master/ds4bolivia_v20250523.csv"
bol = pd.read_csv(url_bol)

# Display available NTL and population variables
ntl_vars = [c for c in bol.columns if c.startswith('ln_NTLpc')]
pop_vars = [c for c in bol.columns if c.startswith('pop') and c[3:].isdigit()]

print("=" * 70)
print("DS4BOLIVIA: PANEL DATA CASE STUDY")
print("=" * 70)
print(f"Cross-sectional units: {len(bol)} municipalities")
print(f"\nNTL variables available: {ntl_vars}")
print(f"Population variables available: {pop_vars}")
```

Task 1: Create Panel Dataset (Guided)

Objective: Reshape the wide-format DS4Bolivia data into a long panel dataset.

Instructions:

1. Select municipality identifiers (`mun`, `dep`, `asdf_id`) and annual NTL/population variables
2. Reshape from wide to long format using `pd.melt()` or manual reshaping
3. Create columns: `municipality`, `year`, `ln_NTLpc`, `pop`, `ln_pop`
4. Verify the panel structure: 339 municipalities x 9 years = 3,051 observations
5. Show `head()` and `describe()` for the panel dataset

In []:

```
# Your code here: Reshape to panel format
#
# Example structure:
# # Reshape NTL variables
# ntl_cols = {f'ln_NTLpc{y}': y for y in range(2012, 2021)}
# pop_cols = {f'pop{y}': y for y in range(2012, 2021)}
#
# # Melt NTL
# ntl_long = bol[['mun', 'dep', 'asdf_id']] + list(ntl_cols.keys()).melt(
#     id_vars=['mun', 'dep', 'asdf_id'],
#     var_name='ntl_var', value_name='ln_NTLpc'
# )
# ntl_long['year'] = ntl_long['ntl_var'].str.extract(r'(\d{4})').astype(int)
#
# # Melt Population
# pop_long = bol[['asdf_id']] + list(pop_cols.keys()).melt(
#     id_vars=['asdf_id'],
#     var_name='pop_var', value_name='pop'
# )
# pop_long['year'] = pop_long['pop_var'].str.extract(r'(\d{4})').astype(int)
#
# # Merge
# panel = ntl_long.merge(pop_long[['asdf_id', 'year', 'pop']],
#                         on=['asdf_id', 'year'], how='left')
# panel['ln_pop'] = np.log(panel['pop'])
# panel = panel.sort_values(['asdf_id', 'year']).reset_index(drop=True)
#
# print(f"Panel shape: {panel.shape}")
# print(f"Municipalities: {panel['asdf_id'].nunique()}")
# print(f"Years: {sorted(panel['year'].unique())}")
# print(panel.head(18)) # Show 2 municipalities
# print(panel[['ln_NTLpc', 'ln_pop', 'pop']].describe().round(3))
```

Key Concept 17.10: Satellite Panel Data

Annual nighttime lights observations create **panel datasets** even where traditional economic surveys are unavailable or infrequent. For Bolivia's 339 municipalities over 2012-2020, the NTL panel provides 3,051 municipality-year observations. This temporal dimension allows us to move beyond cross-sectional associations and study changes within municipalities over time—a crucial step toward understanding development dynamics rather than just static patterns.

Task 2: Pooled OLS with Cluster-Robust SEs (Guided)

Objective: Estimate a pooled OLS regression of NTL on population with cluster-robust standard errors.

Instructions:

1. Estimate $\ln_NTLpc \sim \ln_pop + year$ using all panel observations
2. Use cluster-robust standard errors clustered by municipality
3. Compare default and cluster-robust SEs

4. Interpret: How does population relate to NTL? Is there a significant time trend?

In []:

```
# Your code here: Pooled OLS with cluster-robust SEs
#
# Example structure:
# panel_reg = panel[['ln_NTLpc', 'ln_pop', 'year', 'mun', 'asdf_id']].dropna()
#
# model_pooled = ols('ln_NTLpc ~ ln_pop + year', data=panel_reg).fit(
#     cov_type='cluster', cov_kwds={'groups': panel_reg['asdf_id']})
#
# print("POOLED OLS WITH CLUSTER-ROBUST SEs")
# print(model_pooled.summary())
```

Task 3: Fixed Effects (Semi-guided)

Objective: Estimate a fixed effects model controlling for time-invariant municipality characteristics.

Instructions:

1. Add municipality fixed effects using `C(asdf_id)` or entity demeaning
2. Compare FE coefficients with pooled OLS coefficients
3. How does controlling for time-invariant municipality characteristics change the population-NTL relationship?
4. Discuss: What unobserved factors do municipality fixed effects absorb (altitude, remoteness, climate)?

Hint: You can use `C(asdf_id)` in the formula, or manually demean variables by subtracting municipality means. For large datasets, demeaning is more computationally efficient.

In []:

```
# Your code here: Fixed effects estimation
#
# Example structure (demeaning approach):
# # Demean variables within each municipality
# for col in ['ln_NTLpc', 'ln_pop']:
#     panel_reg[f'{col}_dm'] = panel_reg.groupby('asdf_id')[col].transform(
#         lambda x: x - x.mean())
#
# panel_reg['year_dm'] = panel_reg['year'] - panel_reg.groupby('asdf_id')[
#     'year'].transform('mean')
#
# model_fe = ols('ln_NTLpc_dm ~ ln_pop_dm + year_dm - 1', data=panel_reg).fit(
#     cov_type='cluster', cov_kwds={'groups': panel_reg['asdf_id']})
#
# print("FIXED EFFECTS (WITHIN ESTIMATOR)")
# print(model_fe.summary())
#
# print("\nCOMPARISON:")
# print(f" Pooled OLS ln_pop coef: {model_pooled.params['ln_pop']:.4f}")
# print(f" Fixed Effects ln_pop coef: {model_fe.params['ln_pop_dm']:.4f}")
```

Key Concept 17.11: Fixed Effects for Spatial Heterogeneity

Municipality fixed effects absorb all time-invariant characteristics: altitude, remoteness, climate, historical infrastructure, cultural factors. After removing these fixed differences, the remaining variation identifies how changes in population (or other time-varying factors) relate to changes in NTL within the same municipality. This within-municipality analysis is more credible for causal interpretation than cross-sectional regressions, because it eliminates bias from unobserved time-invariant confounders.

Task 4: Time Trends (Semi-guided)

Objective: Examine how nighttime lights evolve over time using year fixed effects.

Instructions:

1. Replace the linear time trend with year dummy variables: C(year)
2. Test whether the year effects are jointly significant
3. Plot the estimated year coefficients to visualize the NTL trajectory
4. Discuss: Did NTL grow steadily, or were there jumps or declines?

Hint: Use one year as the reference category. The year coefficients show NTL changes relative to the base year.

In []:

```
# Your code here: Year fixed effects
#
# Example structure:
# # Estimate with year dummies (demeaned for municipality FE)
# panel_reg['year_cat'] = panel_reg['year'].astype(str)
#
# # Simple approach: use year means of demeaned NTL
# year_means = panel_reg.groupby('year')[['ln_NTLpc']].mean()
# year_means_dm = year_means - year_means.iloc[0] # relative to base year
#
# fig, ax = plt.subplots(figsize=(10, 6))
# ax.plot(year_means.index, year_means.values, 'o-', color='navy', linewidth=2)
# ax.set_xlabel('Year')
# ax.set_ylabel('Mean Log NTL per Capita')
# ax.set_title('Average Municipal NTL Over Time (2012-2020)')
# ax.grid(True, alpha=0.3)
# plt.tight_layout()
# plt.show()
```

Task 5: First Differences (Independent)

Objective: Estimate the relationship using first differences as an alternative to fixed effects.

Instructions:

1. Compute first differences: $\Delta \ln_NTLpc = \ln_NTLpc_t - \ln_NTLpc_{t-1}$ and $\Delta \ln_pop = \ln_pop_t - \ln_pop_{t-1}$
2. Estimate $\Delta \ln_NTLpc \sim \Delta \ln_pop$
3. Compare the first-difference coefficient with the fixed effects estimate
4. Discuss: When do FE and FD give different results? What assumptions does each require?

In []:

```
# Your code here: First differences estimation
#
# Example structure:
# panel_reg = panel_reg.sort_values(['asdf_id', 'year'])
# panel_reg['d_ln_NTLpc'] = panel_reg.groupby('asdf_id')[['ln_NTLpc']].diff()
# panel_reg['d_ln_pop'] = panel_reg.groupby('asdf_id')[['ln_pop']].diff()
#
# # Drop first year (no difference available)
# fd_data = panel_reg.dropna(subset=['d_ln_NTLpc', 'd_ln_pop'])
#
# model_fd = ols('d_ln_NTLpc ~ d_ln_pop', data=fd_data).fit(
#     cov_type='cluster', cov_kwds={'groups': fd_data['asdf_id']})
#
# print("FIRST DIFFERENCES ESTIMATION")
# print(model_fd.summary())
#
# print(f"\nFD coefficient on ln_pop: {model_fd.params['d_ln_pop']:.4f}")
```

Task 6: Panel Brief (Independent)

Objective: Write a 200-300 word brief summarizing your panel data analysis.

Your brief should address:

1. What do within-municipality changes in NTL reveal about development dynamics?
2. How does the FE population coefficient differ from the cross-sectional (pooled OLS) one?
3. What time trends in NTL are visible across 2012-2020?
4. How do FE and FD estimates compare? Which assumptions matter most?
5. What are the advantages and limitations of satellite panel data for tracking municipal development over time?
6. What additional time-varying variables would improve the analysis?

```
In [ ]:
```

```
# Your code here: Additional analysis for the panel brief
#
# You might want to:
# 1. Decompose variance into between and within components
# 2. Plot NTL trajectories for selected municipalities
# 3. Compare growth rates across departments
# 4. Create a summary table of all estimation results
#
# Example: Variance decomposition
# overall_var = panel_reg['ln_NTLpc'].var()
# between_var = panel_reg.groupby('asdf_id')['ln_NTLpc'].mean().var()
# within_var = panel_reg.groupby('asdf_id')['ln_NTLpc'].apply(lambda x: x - x.mean()).var()
# print(f"Overall variance: {overall_var:.4f}")
# print(f"Between variance: {between_var:.4f}")
# print(f"Within variance: {within_var:.4f}")
# print(f"Between share: {between_var/overall_var:.1%}")
```

What You've Learned from This Case Study

This is the final DS4Bolivia case study in the textbook. Across 12 chapters, you have applied the complete econometric toolkit—from simple descriptive statistics (Chapter 1) through panel data methods (Chapter 17)—to study how satellite data can predict and monitor local economic development. The DS4Bolivia project demonstrates that modern data science and econometrics, combined with freely available satellite imagery, can contribute to SDG monitoring even in data-scarce contexts.

In this panel data analysis, you've applied Chapter 17's complete toolkit:

- **Panel construction:** Reshaped cross-sectional data into a municipality-year panel
- **Pooled OLS:** Estimated baseline relationships with cluster-robust standard errors
- **Fixed effects:** Controlled for time-invariant municipality characteristics
- **Time trends:** Examined the trajectory of nighttime lights across 2012–2020
- **First differences:** Used an alternative estimation strategy and compared with FE
- **Critical thinking:** Assessed what within-municipality variation reveals about development dynamics

Congratulations! You have now completed the full DS4Bolivia case study arc across the textbook.
