

# Introduction to Regression Analysis

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# Topics Covered

## Empirical research approach

- Scientific method

## Data analysis and modeling

- Overview of regression models and concepts

## Large language models (e.g., ChatGPT)

- Use of artificial intelligence in data analysis

## Review of statistical concepts within the context of R/RStudio

# Hypothesis, Model, and Data

The empirical research approach in the social sciences consists of multiple steps:

① Statement of theory or hypothesis

- Example: *"People increase their consumption when their income increases by less than the income increase."*

② Specification of the mathematical model

$$\Delta consumption = \beta_0 + \beta_1 \cdot \Delta income$$

③ Obtaining the data

- Real personal consumption expenditures per capita
- Real disposable personal income per capita

④ Estimation of the parameters of the econometric model

# Estimation Results

##	
##	=====
##	Dependent variable:
##	-----
##	diff(consumption)
##	-----
##	diff(income) 0.549***
##	(0.109)
##	Constant 231.954**
##	(85.745)
##	-----
##	Observations 39
##	R2 0.409
##	Adjusted R2 0.393
##	Residual Std. Error 326.315 (df = 37)
##	F Statistic 25.567*** (df = 1; 37)
##	=====
##	Note: *p<0.1; **p<0.05; ***p<0.01

## Post-Estimation Procedures

- ⑥ Hypothesis testing on whether results are aligned with the theory
- ⑦ Forecasting or prediction
  - Example: Effect of income increase due to economic growth on consumption
- ⑧ Model use for policy purposes
  - Example: Effects of stimulus spending on the economy

Above approach at the core of social science research such as public administration, criminal justice, economics, sociology:

- Influence of trust and attitudes on the organic food purchases
- Relationship between automatic bill payment and electricity consumption

Caveat: Ideological bias in the production of research findings

# Bivariate and Multivariate Regression

Bivariate regression model:

- One dependent (e.g., home value) and one independent variable (e.g., square footage)

$$homevalue_i = \beta_0 + \beta_1 \cdot sqft_i + \epsilon_i$$

- Useful to explain the mechanics of ordinary least square (OLS) models

Multivariate regression model

- One dependent (e.g., home value) and multiple independent variables (e.g., square footage, bedrooms)

$$homevalue_i = \beta_0 + \beta_1 \cdot sqft_i + \beta_2 \cdot bedrooms_i + \epsilon_i$$

Assumptions required for consistent coefficient estimates.

# Advanced Multivariate Regression

## Concepts associated with the independent variables

- Dummy variables to describe a qualitative characteristic
- Use of natural logarithm to transform the dependent and/or independent variables
- Functional forms including squared terms
- Interaction effects if the marginal effect of one variable depends on the level of another variable

## Model misspecification

- Effects of inclusion of irrelevant or exclusion of relevant variables

## Regression diagnostics and tests

# Relaxing assumptions

## Heteroscedasticity vs. homoscedasticity

- Non-constant variance of the error term
- Tests to detect heteroscedasticity (i.e., Goldfeld-Quandt test, Breusch-Pagan-Godfrey test)

## Multicollinearity

- Variance Inflation Factor

## Autocorrelation of error terms



# Qualitative Choice Models

Binary choice (i.e., probit and logit) models

- Dependent variable: 1 or 0 (“yes” or “no”)
- Example: Recidivism (i.e., committing a crime after release from prison)

Ordered logit

- More than two categories for the dependent variable but ordered
- Example: Level of support for a particular policy (e.g., opposed, neutral, supportive)

Multinomial logit

- More than two categories of the dependent variable but no order
- Example: Commute to campus by bike, bus, car, or on foot

# Limited Dependent Variables

## Restrictions placed on the dependent variable

- Censoring (also known as a Tobit model): Observations from a restricted sample of the population
- Truncation: Reporting of the dependent variable above or below a certain value at that value
- Count regression: Positive, integer values (in addition to zero) of the dependent variable

## Extension of count regression models

- Hurdle and zero-inflated models given excessive number of zeros in count data

Duration (also known as hazard or survival) models to determine exogenous variables leading to a particular event occurring

## Panel data regression models

- Observation of the same individual or unit over multiple years
- Fixed effects versus random effects models

## Examples

- Household income and consumption patterns
- County-level data on crop yields and area allocation (outcome variables) as a function of output and input prices as well as weather data (e.g., growing degree days)
- State-level spending on higher education and education outcomes

Unit of analysis is the household, county, and state in the previous three examples

## Time series basics

- Trend and seasonality
- Finite-distributed lag models (e.g., adjustment of consumption after an increase income)

## Simple forecasting models

- Moving average and exponential smoothing methods

## Time series analysis

- Autoregressive and distributed-lag models

# Review of Statistical Concepts: Overview

Introduction  
to Regression  
Analysis

Jerome  
Dumortier

Empirical  
Research  
Approach

Data Analysis  
and Modeling

Linear Regression

Qualitative Choice  
and Limited  
Dependent Variables

Panel Data

Dynamic Models and  
Time Series

Review of  
Statistical  
Concepts

Basic  
Statistical  
Concepts

Confidence Intervals

Hypothesis Testing

## Basic statistical concepts

- Population versus sample, measures of dispersion, sampling variance

## Confidence interval (CI)

- CI for a mean

## Hypothesis testing

- One-group and two-group samples

# Population versus Sample

## Population versus sample

- The population is characterized by parameters that will always remain unknown.
- Given a sample taken from the population allows us to learn something about the population parameters.
- The sample needs to be drawn at random.

The sample mean is the arithmetic average of the values in a random sample. It is usually denoted

$$\bar{x} = \frac{x_1 + x_2 + \cdots + x_n}{n} = \frac{1}{n} \sum_{i=1}^n x_i$$

# Measures of Dispersion

Population variance

$$\sigma^2 = \frac{\sum_{i=1}^N (x_i - \mu)^2}{N}$$

Sample variance

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

Standard deviation is the square root of the variance, i.e.,  $\sigma = \sqrt{\sigma^2}$  or  $s = \sqrt{s^2}$ .

# Sampling Variance

The sampling variance is expressed as:

$$\text{Var}(\bar{X}_n) = \frac{\sigma^2}{n}$$

This is different from the sample variance! The sampling variance represents the variation of a particular statistic, e.g., mean. The larger  $n$ , the smaller the variance in the mean of the various drawings.



Definition

- A 95% confidence interval for a parameter is an interval obtained from a sample that has a 95% probability of producing a interval containing the true value of the parameter.

Computation:

$$\bar{x} \pm t_{df,\alpha} \cdot \frac{s}{\sqrt{n}}$$

Example data of starting salary (in 1,000) after college graduation:

Student	1	2	3	4	5	6	7	8	9	10
Salary	87	43	59	64	59	71	73	49	68	65

# Calculation of a Confidence Interval

Given the data salary, we have  $\bar{x} = 63.8$ ,  $s = 12.44$ , and  $t_{9,0.025} = 2.262$ . Using the equation:

$$\bar{x} \pm t_{df,\alpha} \cdot \frac{s}{\sqrt{n}}$$

and plugging in the data:

$$63.8 \pm 2.262 \cdot \frac{12.44}{\sqrt{10}} = 63.8 \pm 8.90$$

## Confidence Interval with R

```
salary = c(87,43,59,64,59,71,73,49,68,65)
t.test(salary)
```

```
##
##  One Sample t-test
##
## data:  salary
## t = 16.225, df = 9, p-value = 5.695e-08
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  54.90474 72.69526
## sample estimates:
## mean of x
##      63.8
```

# Introduction

A hypothesis is a statement about a parameter taking on a specific value. A hypothesis test is a procedure to verify the statement and the steps are:

- ① Formulating the null hypothesis  $H_0$  stating that the parameter takes a specific value:
  - One-sided test:  $H_0: \mu \geq \mu_0$  or  $\mu \leq \mu_0$
  - Two-sided test:  $H_0: \mu = \mu_0$
- ② Setting the significance level  $\alpha$ , e.g., 1%, 5%, or 10%.
- ③ Test statistic: Value based on the sample used to **reject** or **fail to reject** the null hypothesis.
- ④ Critical value and  $p$ -value:
  - Critical value represents the threshold between rejecting and failing to reject  $H_0$ .
  - $p$ -Value: Probability of observing the parameter given the null hypothesis. Small  $p$ -values represent evidence against  $H_0$ .

Note that equality is always part of  $H_0$ , i.e.,  $=$ ,  $\leq$ , or  $\geq$ .

# Decisions and Errors in Hypothesis Testing

Null Hypothesis	Fail to reject $H_0$	Reject $H_0$
$H_0$ is true	Correct	Type I Error
$H_0$ is false	Type II Error	Correct

## Type I Error:

- Probability of rejecting  $H_0$  when it is true.
- Also known as the significance level of a test denoted with  $\alpha$ .

## Type II Error:

- Probability of failing to reject  $H_0$  when it is false.

# Interpretation of the $p$ -Value

Each statistical software provides a  $p$ -value:

- Lowest level of significance at which the null hypothesis can be rejected.
- Represents the probability of observing the sample given that the hypothesis is true. The lower the  $p$ -value the more unlikely is the hypothesis.
- The null hypothesis  $H_0$  is rejected if the  $p$ -value is smaller than the significance level.

The smaller the  $p$ -value, the stronger the evidence against  $H_0$  being true. This is true for any type of hypothesis test.

# Two-sided and One-sided Hypothesis Tests

## Two-sided test

- $H_0: \mu = \mu_0$  and  $H_a: \mu \neq \mu_0$
- Reject  $H_0$  if  $|t| > t_{\alpha/2, n-1}$

## One-sided test (left-sided)

- $H_0: \mu \leq \mu_0$  and  $H_a: \mu > \mu_0$
- Reject  $H_0$  if  $|t| > t_{\alpha, n-1}$

## One-sided test (right-sided)

- $H_0: \mu \geq \mu_0$  and  $H_a: \mu < \mu_0$
- Reject  $H_0$  if  $|t| > t_{\alpha, n-1}$

In both cases,  $|t|$  refers to the absolute value of the test statistic. Two-sided tests are of importance in regression analysis.

# Hypothesis Testing: One-sample vs. Two-sample

## One-sample (or one-group) tests

- Population proportion
- Population mean with unknown variance

## Two-sample (or two-group) tests

- Population proportions
- Population means (differentiation between equal and unequal variance)
- Paired difference test

Note: Textbooks often include “population mean with *known* variance.” This is a highly unlikely case and thus, it is skipped.



# One-Group Proportion

Test statistic:

$$z = \frac{\bar{p} - p_0}{\sqrt{p_0 \cdot (1 - p_0)/n}}$$

where  $p_0$  is the hypothesized population proportion.

# One-Group Proportion in R

```
##  
## One Sample t-test  
##  
## data: gss$owngun  
## t = 24.073, df = 45862, p-value < 2.2e-16  
## alternative hypothesis: true mean is not equal to 0.3333333  
## 95 percent confidence interval:  
## 0.3836523 0.3925726  
## sample estimates:  
## mean of x  
## 0.3881124
```

# One-Group Mean

Unknown variance requires the use of the  $t$ -distribution given the following test statistic:

$$t = \frac{\bar{x} - \mu}{s/\sqrt{n}}$$

where  $\bar{x}$  is the sample mean,  $\mu$  is the hypothesized mean,  $s$  is the sample standard deviation, and  $n$  is the sample size.

# One-Group Mean in R

```
##  
## One Sample t-test  
##  
## data: eggweights$weight  
## t = 1.8378, df = 60, p-value = 0.07104  
## alternative hypothesis: true mean is not equal to 60  
## 95 percent confidence interval:  
## 59.90723 62.19113  
## sample estimates:  
## mean of x  
## 61.04918
```

# Two-Group Proportions

Hypothesis test for difference between two population proportions

$$H_0 : p_1 - p_2 = 0$$

```
t.test(gss$owngun~gss$female)
```

```
##
```

```
##  Welch Two Sample t-test
```

```
##
```

```
## data:  gss$owngun by gss$female
```

```
## t = 28.58, df = 42297, p-value < 2.2e-16
```

```
## alternative hypothesis: true difference in means between group 0 and group 1 is not equal to 0
```

```
## 95 percent confidence interval:
```

```
##  0.1217988 0.1397350
```

```
## sample estimates:
```

```
## mean in group 0 mean in group 1
```

```
##      0.4611440      0.3303771
```

# Two-Group Means

Difference between two mean:

$$H_0 : \bar{x}_1 - \bar{x}_2 = 0$$

Means of two dependent populations

- Assumption of equal variance, i.e.,  $\sigma_1^2 = \sigma_2^2$
- Example: Pre- and post-test
- Pooled-Variance t-test: One estimate of unknown  $\sigma^2$ , i.e.,  $s_p$ .

Means of two independent populations

- Assumption of unequal variance, i.e.,  $\sigma_1^2 \neq \sigma_2^2$
- Samples from two different populations
- Separate-Variance t-test: Two estimates for unknown  $\sigma_1^2$  and  $\sigma_2^2$ .

## Two-Group Means: Equal Variance

```
t.test(indyhomes$price~indyhomes$zip,var.equal=TRUE)
```

```
##  
##  Two Sample t-test  
##  
## data:  indyhomes$price by indyhomes$zip  
## t = 2.0005, df = 100, p-value = 0.04816  
## alternative hypothesis: true difference in means between group 46228 and group 46268  
## 95 percent confidence interval:  
##      1510.38 363678.01  
## sample estimates:  
## mean in group 46228 mean in group 46268  
##           381600.2           199006.0
```

## Two-Group Means: Unequal Variance

```
t.test(indyhomes$price~indyhomes$zip,var.equal=FALSE)
```

```
##  
##  Welch Two Sample t-test  
##  
## data:  indyhomes$price by indyhomes$zip  
## t = 2.0403, df = 51.323, p-value = 0.04648  
## alternative hypothesis: true difference in means between group 46228 and group 46268  
## 95 percent confidence interval:  
##      2953.984 362234.402  
## sample estimates:  
## mean in group 46228 mean in group 46268  
##      381600.2      199006.0
```



# Paired Difference Test I

Difference between paired (!) values:

$$D_i = x_{1,i} - x_{2,i}$$

Elimination of variation among subjects. Point estimate for paired difference

$$\bar{D} = \frac{1}{n} \sum_{i=1}^n D_i$$

Sample standard deviation

$$S_d = \sqrt{\frac{\sum_{i=1}^n (D_i - \bar{D})^2}{n - 1}}$$

# Paired Difference Test II

Test statistic

$$t_p = \frac{\bar{D} - \mu_D}{S_d / \sqrt{n}}$$

Confidence interval

$$\bar{D} \pm t_{\alpha/2} \frac{S_D}{\sqrt{n}}$$

$t_p$  has  $n-1$  degrees of freedom

## Textbook Example

Book	Online	Bookstore	Difference
History 1	10.20	11.40	-1.20
History 2	18.95	19.00	-0.05
Economics 1	184.53	200.75	-16.22
Business 1	236.75	247.20	-10.45
Business 2	67.41	71.25	-3.48

Note that  $\sum D_i = -31.76$ ,  $\bar{D} = -6.352$ , and  $s_D = 6.833$ .

# Textbook Example in R

```
online      = c(10.20,18.95,184.53,236.75,67.41)
bookstore   = c(11.40,19.00,200.75,247.20,71.25)
t.test(online,bookstore,paired=TRUE)
```

```
##
## Paired t-test
##
## data:  online and bookstore
## t = -2.0788, df = 4, p-value = 0.1062
## alternative hypothesis: true mean difference is not equal to 0
## 95 percent confidence interval:
##  -14.835834   2.131834
## sample estimates:
## mean difference
##          -6.352
```