

# ECON 0150 | Economic Data Analysis

*The economist's data analysis pipeline.*

## *Part 2.5 | Merging Data*

# Final Project Preview

*Exploring real questions with real data*

Lets start working through a project together:

- **Question 1:** *Were there systematic patterns in vote share changes between 2020 and 2024?*
- **Question 2:** *Do income levels relate to these voting shifts?*
- **Data:** *MIT Election Lab (county-level returns) + Census (median income)*

> *this is the kind of analysis you'll do for your final project*

# The Data Challenge

*We have two separate datasets that need to be connected*

## **Dataset 1:** Presidential election results by county

- *County name*
- *State*
- *Vote counts for 2020*
- *Vote counts for 2024*

## **Dataset 2:** Median household income by county

- *County identifier*
- *Median income*

# Step 1: Explore Vote Shares

*Q. What do county-level vote shares look like?*

First understand what we're working with.

```
1 # Histogram of 2024 vote shares  
2 sns.histplot(elections, x='2020')
```

```
1 # Histogram of 2024 vote shares  
2 sns.histplot(elections, x='2024')
```

## Step 2: Compare Elections

*Q. How did county vote shares change between 2020 and 2024?*

Second, let's look at the relationship between Democratic Share in 2020 and 2024.

```
1 # Scatterplot comparing elections
2 sns.scatterplot(elections, x='2020', y='2024', alpha=0.5)
3
4 # Add 45-degree line
5 plt.plot([0,1], [0,1], 'r--', alpha=0.5)
```

> *points above the line shifted more Democratic*

> *points below the line shifted more Republican*

> *but what explains these shifts?*

# Step 3: Add Income Data

*Q. Does county income relate to voting shifts?*

To answer this, we need to:

- 1. Load the income data*
- 2. **Merge** it with our election data*
- 3. Calculate the vote share change*
- 4. Visualize the relationship*

*> but how do we connect two separate datasets?*

# Merging Data: The Concept

*Combining datasets based on common identifiers*

**The Key:** Find a common column that uniquely identifies observations

- *In our case: County FIPS codes (Federal Information Processing Standards)*
- *FIPS uniquely identify every US county*
- *Format: State code (2 digits) + County code (3 digits) = 5 digits total*

> *example: Allegheny County, PA = 42003*

# Types of Merges

*Different ways to combine datasets*

Merge Type	Description	Example
<b>1:1</b>	Each row in A matches exactly one row in B	County → County
<b>1:m</b>	One row in A matches multiple rows in B	State → Counties
<b>m:1</b>	Multiple rows in A match one row in B	Counties → State

*> our county merge is 1:1 - each county appears once in each dataset*



# Step 3: Perform the Merge

*Combining our datasets*

```
1 # Merge datasets on county FIPS
2 data = pd.merge(elections,
3                 income,
4                 left_on='county_fips',
5                 right_on='county_fips',
6                 how='inner')
```

## Merge options:

- *inner*: Keep only counties in both datasets
- *left*: Keep all counties from elections data
- *right*: Keep all counties from income data
- *outer*: Keep all counties from either dataset

> we use 'inner' to focus on counties with complete data

# Step 4: Calculate Vote Shifts

*Creating our analysis variable*

```
1 # Calculate the shift in Democratic vote share  
2 data['dem_shift'] = data['2024'] - data['2016']
```

```
1 # Summarize this new variable  
2 sns.histplot(elections, x='dem_shift')
```

*> now we can explore the relationship with income*

# Step 5: Analyze the Relationship

*Q. Does county income relate to voting shifts?*

```
1 # Scatterplot of income vs vote shift
2 sns.scatterplot(data,
3                 x='median_income',
4                 y='dem_shift',
5                 alpha=0.3)
6
7 # Add horizontal line at zero
8 plt.axhline(y=0, color='r', linestyle='--', alpha=0.5)
9
10 plt.xlabel('Median Household Income ($)')
11 plt.ylabel('Change in Democratic Vote Share (2024-2016)')
```

*> what patterns do you see?*

# Common Merge Issues

*Watch out for these problems*

- **Missing values:** *Some counties might not have income data*
- **Duplicate keys:** *Same county appearing multiple times*
- **Type mismatches:** *FIPS stored as numbers vs strings*
- **Different naming:** *“St. Louis” vs “Saint Louis”*

```
1 # Check for duplicates before merging
2 elections['county_fips'].duplicated().sum()
3 income['FIPS'].duplicated().sum()
```

# Summary

*Merging allows us to answer richer questions*

- *Identify common columns to join on (FIPS codes)*
- *Prepare data for merging (create consistent identifiers)*
- *Merge using appropriate join type (inner, left, right, outer)*
- *Transform to create analysis variables (vote shift)*
- *Analyze the combined dataset*

# ECON 0150 | Economic Data Analysis

*Part 2: Data Operations Practice*

*Practice Problems for MiniExam 2*

# Practice 1: Trace the Filter

*Which products remain after filtering?*

Product_ID	Category	Price	In_Stock
P001	Electronics	299	True
P002	Clothing	49	False
P003	Electronics	89	True
P004	Food	12	True
P005	Clothing	79	True

**Filter:** (Price < 100) AND (In\_Stock == True)

*Answer: P003, P004*

# Practice 2: Multi-Step Operations

*Track data through multiple transformations*

Sale_ID	Store	Amount
S001	North	120
S002	South	80
S003	North	150
S004	South	90
S005	North	100

## Operations:

- 1. Filter for Amount  $\geq 100$*
- 2. Group by Store*
- 3. Calculate mean Amount*

*Answer: North, 125*



# Practice 3: Data Cleaning Decisions

*What cleaning is needed for each entry?*

Response_ID	Duration
R001	“5 minutes”
R002	“180”
R003	“about 3 min”
R004	“N/A”

For each entry, select ALL that apply:

**R001:** [Extract number] [Remove text] [Convert type] [Handle missing] [Already clean]

**R002:** [Extract number] [Remove text] [Convert type] [Handle missing] [Already clean]

**R003:** [Extract number] [Remove text] [Convert type] [Handle missing] [Already clean]

# Practice 4: Build Complex Filters

*Construct the correct boolean logic*

**Goal:** Find all employees who:

- *Work in either Tech or Sales departments*
- *AND have been with company more than 2 years*
- *AND earn less than \$70,000*

Use these components to construct a filter:

1. *(Department == 'Tech')*
2. *(Years > 2)*
3. *(Department == 'Sales')*
4. *(Salary < 70000)*

*Answer: (1 OR 3) AND 2 AND 4*

# Practice 5: Choose the Right Transformation

*Why transform data?*

**Scenario:** Comparing test scores across different schools where class sizes vary dramatically (10-50 students)

You have:

- *Total\_Points\_Earned* (all students combined)
- *Number\_of\_Students*

Which transformation makes schools comparable?

- a. *Total\_Points\_Earned* + *Number\_of\_Students*
- b. *Total\_Points\_Earned* - *Number\_of\_Students*
- c. *Total\_Points\_Earned* / *Number\_of\_Students*
- d. *Total\_Points\_Earned* \* *Number\_of\_Students*

**Answer: c) Creates average score per student**

# Practice 6: Predict Grouping Output

*What will the grouped data look like?*

Order_ID	Customer	Amount	Region
O001	Alice	50	East
O002	Bob	30	West
O003	Alice	70	East
O004	Charlie	40	East
O005	Bob	60	West

We've **Grouped by Customer** then **Summed by Amount**.

How many rows in output? \_\_\_\_\_

What's the sum for Bob? \_\_\_\_\_

Which customer has highest total? \_\_\_\_\_

*Answers: 3 rows, 90, Alice (120)*

# Tips for MiniExam 2

*Key concepts to remember*

## **Filtering:**

- *AND: both conditions must be true*
- *OR: at least one condition must be true*

## **Grouping:**

- *Output has one row per group*
- *Choose the right aggregation (sum, mean, count, etc.)*

# Tips for MiniExam 2

*Key concepts to remember*

## **Transformations:**

- *Division normalizes for fair comparison*
- *Log transformation helps with different scales*

## **Data Cleaning:**

- *Text  $\rightarrow$  Number needs type conversion*
- *Missing values: drop or fill (not both!)*
- *Consistent format before analysis*