

# Topics in Labor Economics: Empirical Methods and Applications

Prof. Tzu-Ting Yang  
楊子霆

Institute of Economics, Academia Sinica  
中央研究院經濟研究所

March 26, 2026

# About Me

- Name: Yang, Tzu-Ting (楊子霆)
- Affiliation:
  - Institute of Economics, Academia Sinica
  - Office at Academia Sinica: 中央研究院經濟研究所 B308
- Other Appointments:
  - NTU-ECON, NTU-AGEC and NCCU-IMES
  - Office at NTU: 社科院 724 / 農業綜合館 218-B5
- Research Fields: Public/Labor Economics and Applied Econometrics
- Website: <https://sites.google.com/view/cpelab/>
- Email: [ttyang@g.ntu.edu.tw](mailto:ttyang@g.ntu.edu.tw)

# This Course

- The goal of this course is equip students with a comprehensive set of statistical tools that are useful in conducting high-quality empirical research in (labor) economics
- Specifically, the course places a strong emphasis on **causal inference** and understanding their applications
- We will especially focus on the practical implementation of these empirical methods by writing a term paper
  - How to conduct an empirical research
  - Provide a good start for your thesis or writing sample

# Labor Economics and Empirical Methods

# Labor Economics and Empirical Methods

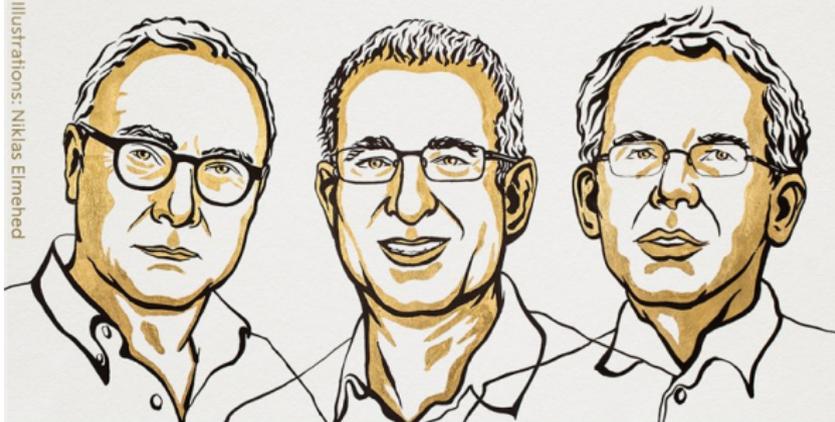
- Empirical research is experiencing two methodological “revolutions” over the past few decades
- On the one hand, there is the “credibility revolution”
  - A movement that emphasizes the goal of empirical research is to understand causality
  - Labor economists play an crucial role in this movement

# 2021 Nobel Laureates

## Labor Economics and Causal Inference

THE SVERIGES RIKSBANK PRIZE  
IN ECONOMIC SCIENCES IN MEMORY  
OF ALFRED NOBEL 2021

Illustrations: Niklas Elmehed



David  
Card

"for his empirical  
contributions to labour  
economics"

Joshua  
D. Angrist

"for their methodological  
contributions to the analysis  
of causal relationships"

Guido  
W. Imbens

# Labor Economics and Empirical Methods

- On the other hand, there is the “big data revolution”
  - A movement that emphasizes how our increasing ability to collect and analyze vast amounts of data can transform our understanding of the human behaviors
- Recent trend in empirical research
  - Use large scale dataset to identify causal relationship
  - Emerging role of generative AI in automating data processing, coding, and workflow design
  - AI-assisted tools reduce technical barriers, but do not replace identification strategy or economic reasoning

# Labor Economics and Empirical Methods

- Economic theory plays an important role in the causal analysis of large data sets with complex structure
  - It can be difficult to study this type of data or even to decide which variables to construct
  - Economic models can provide conceptual frameworks to point out what are key variables or what kind of relationship we should care about
- Better data and more credible empirical methods can help researchers test economic theories that had previously been difficult to assess

# This course

- This course will go through several useful techniques based on recent methodological developments in empirical methods
  - Focus on **causal inference** and its applications in labor economics

# Causal Inference

# Causal Inference

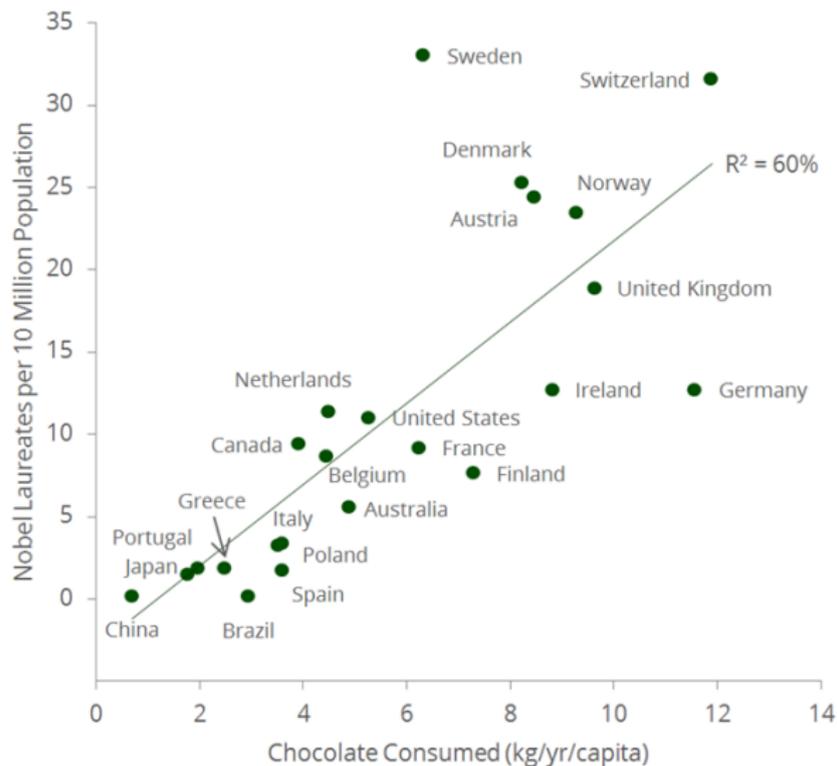
- Social science (Economics) theories are almost always causal in their nature
  - X causes Y
  - An increase in price of oil causes consumer's demand for oil to decrease
  - An increase in schooling years can raise people's productivity (wage)
  - Raising minimum wage would reduce employment opportunity of low-skilled workers

# Causal Inference

- Two key features of causality:
  - 1 Causes are asymmetrical
    - In general, if X causes Y, Y does not cause X
  - 2 Causes are effective
    - A cause must be distinguished from an accidental correlation

# Correlation is not Causality

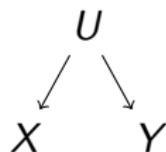
## Chocolate Consumption and Nobel Laureates



# Correlation is not Causality

- In order to increase number of Nobel Laureates (proxy for human capital)
- Should government enforce everyone to eat chocolate everyday?

## Correlation is not Causality



- $X$  (Chocolate Consumption) is associated (correlated) with  $Y$  (Number of Nobel Laureates)
- Even if  $X$  has no causal effect on  $Y$
- Since confounding factor  $U$  (GDP) can result in the co-movement between  $X$  and  $Y$

# Causal Inference

- Understanding a causal relationship is useful for making predictions about the consequences of changing circumstances or policies
- Causal inference is a type of statistical methods that help us verify the causal relationship
- In general, a typical causal question is:
  - The effect of a **treatment** on an **outcome**
  - **Outcome:** A variable that we are interested in
  - **Treatment:** A variable that has the (causal) effect on our outcome of interest

# Causal Inference

## Example 1

- The effect of **getting a master's degree** on **earnings**
  - Ideally, we should get causal effect by comparing the earnings of **the same individuals** with and without receiving a master's degree
  - For each particular individual, we can observe **only one outcome with specific treatment at the same time**:
    - Getting a master's degree
    - Not getting a master's degree
  - The **unobserved outcome** is called the “**counterfactual**” outcome

# Causal Inference

## Example 1

- The effect of getting a master's degree on earnings
  - What if we compare observed outcomes:
    - Earnings of those getting a master's degree
    - Earnings of those choosing not to get it
  - Simply comparing those who are and are not treated may provide a misleading estimate of a causal effect
  - There must be a reason why some people choose to have and some choose to not have a master's degree
    - For example, those who get a master's degree may be from rich families or have high ability
    - Two groups of people might not be comparable
  - We need to isolate casual effect from the effect of other confounding factors

# Causal Inference

## Example 2

- Macro economists also ask casual questions !
- The effect of **fiscal stimulus spending** on **economic growth**
  - Does government stimulus increase GDP growth?
  - Ideally, we want to compare the **same country** with and without stimulus
  - But we cannot observe both outcomes

# Causal Inference

## Example 2

- Compare countries with stimulus vs. without stimulus?
  - Governments often implement stimulus during recessions
  - Countries with weak growth are more likely to adopt stimulus
  - $\Rightarrow$  Simple comparison may underestimate the true effect

# Causal Inference

## More Examples

- More examples include:
  - The effect of advertisement on product sales
  - The effect of military service on earnings and employment
  - The effect of unemployment insurance on job search behavior
  - The effect of credit regulation on housing prices
  - Do immigrant workers depress the wages of native workers?
  - Does eliminating estate tax increase wealth inequality?
  - Can democracy increase economic growth?
  - What is the effect of **AI adoption** on firm productivity?
  - Does the introduction of **generative AI tools** change worker wages or employment?
  - What is the long-term impact of COVID-19 on the global economy?

# Causal Inference

- The fundamental problem of inferring the causal effect is that:
  - For every unit (e.g. individual, household, state, or country), we fail to observe the outcome if the chosen level of the treatment had been different
- Basically, causal inference is the study of **unobservable counterfactuals**:
  - It tells us what happened in alternative (or “counterfactual”) world
  - What would have happened if we were to change this aspect of the world ?

# Causal Inference

## Unobservable Counterfactuals



# Causal Inference

- Since it is impossible to observe the **unobserved** counterfactual outcome
- Causal inferences help us infer the values of these **unobserved counterfactual outcomes** from **observed data** by imposing specific assumptions
- Under specific assumptions, we are able to construct a comparison group that can represent counterfactual outcomes
- Then, we can obtain the causal effect of treatment

## Course Content: Causal Inference

# Gold Standard

## Randomized Experiment

### 0 Randomized Experiment (RCT)

- Randomly assign treatment ensures that every observation has the same probability of being assigned to the treatment group
- The characteristics of treatment and comparison groups are similar since receiving treatment is unrelated to any other confounding factors
- Then, we can obtain causal effect of treatment by simply comparing outcomes between treatment and comparison groups

# Gold Standard

## Randomized Experiment

- RCT is the gold standard of causal inference
- However, it has some limitations
  - Often costly, unethical, or infeasible
  - Many important economic questions cannot be randomized
- In this course:
  - We briefly introduce RCT logic
  - Main focus: the methods when we can not implement RCT

# Control-based Methods

## Matching Methods

### 2 Matching Methods

- Assume key differences between treatment and comparison groups are **observable**
- Construct a comparison group that have similar **observable** characteristics as treatment group

# Control-based Methods

## Regression and Causal Machine Learning

### 3 Regression and Causal Machine Learning

- Use regression to control for observable confounding factors
- Use machine learning method to decide which observable characteristics is important so that we should include in regression
  - Post-Double selection method

# Design-based Methods

## Differences-in-Differences Design

### 4 Differences-in-Differences Design (DID)

- If treatment and comparison group's outcomes move in parallel in the absence of treatment
- then we can use the trend in the outcome of the comparison group to represent the counterfactual trend for the treatment group

# Design-based Methods

## Synthetic Control Method

### 5 Synthetic Control Method (SCM)

- In some situations, treatment and comparison group's outcomes do not move parallelly before a treatment happens
- Use **data-driven procedure** and a **small number of non-treated units** to build a suitable counterfactual outcome

# Design-based Methods

## Regression Discontinuity Design

### 6 Regression Discontinuity Design (RDD)

- When a treatment is applied depending on some thresholds
  - Assume the choices of thresholds are arbitrary
- We can estimate causal effects by comparing outcomes for those just above threshold and those just below threshold
  - Two groups should be similar since they are around threshold

# Design-based Methods

## Instrumental Variables Design

### 7 Instrumental Variables Design

- The instrumental variable (IV) is:
  - An exogenous source of variation that drives the treatment
  - But it is unrelated to other confounding factors that affect outcome
- Intuitively, IV breaks variation of the treatment into two parts
  - 1 A part that might be correlated with other confounding factors
  - 2 A part that is not (driven by IV)
- We can use the variation in treatment that is driven by IV to estimate causal effect of the treatment

# Advanced Topics

## 8 Shift-Share IV Design

- Utilizes an instrument based on national trends in the treatment exposure that are unrelated to local confounders

## 9 Spatial RD Design

- Estimate treatment effects by comparing observations just above and below a geographic boundaries for treatment assignment

## 10 Causal Forest

- A machine learning technique used to estimate heterogeneous treatment effects

## Course Content: Data Analysis

# Data Analysis and Research Workflow

- Credible causal inference requires a well-constructed dataset
- Creating an “analysis-ready” dataset is often the most time-consuming step
  - Data cleaning, merging, reshaping, and validation
  - Often accounts for 70–80% of research time
- In this course, you will do:
  - Data cleaning and transformation
  - Collecting/Constructing your own dataset
  - Visualization and exploratory analysis

# Data Sources

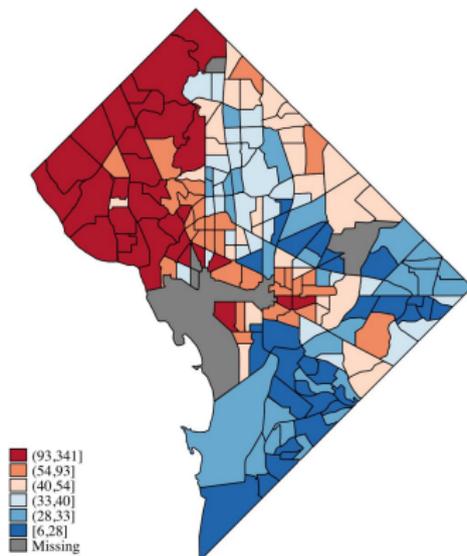
- Traditional sources
  - Government surveys
  - Official statistics
- Data revolution in the past decade
  - Large-scale administrative data
    - Near-universal population coverage
  - Examples in Taiwan
    - Health insurance claims
    - Tax return data
    - Housing transaction records

# Unstructured and High-Dimensional Data

- Increasing use of non-traditional data formats
  - Text documents
  - Social media
  - Geolocation data
  - Satellite and image data

# Geographic data

Mean family income (in thousands of US dollars)  
Washington D.C. (2000)



Source: Maurizio Pisati (2012)

# Generative AI in Data Processing

- Generative AI as a coding assistant
  - Writing and debugging code on demand
  - Translating data tasks described in plain language into working scripts
  - Accelerating iteration when exploring data or testing specifications
- AI agents for semi-autonomous data workflows
  - Executing multi-step, repetitive operations across files or datasets
  - Parsing and restructuring unstructured or irregularly formatted raw data

# Course Structure

- 1 Focus on how to implement various empirical methods of drawing causal inference
- 2 Discuss the applications in labor economics
- 3 Learn how to use statistical software and generative AI tools to conduct data analysis/empirical research

# Applications in Labor Economics

- AI Impact on Labor Market
- Human Capital and Earnings
- Corporate tax and Labor Demand
- Minimum Wage and Labor Demand
- Unemployment Insurance and Job Search
- Pension and Labor Supply
- Fertility and Female Labor Supply

# Reading Materials

- Lecture slides: posted on my website
- Suggested Readings:
  - **The Effect: An Introduction to Research Design and Causality** by Huntington-Klein
  - **Causal Inference: The Mixtape** by Scott Cunningham
    - New textbook and cover more methods
    - Provide STATA and R examples
  - **Econometric Methods for Program Evaluation** by Alberto Abadie and Matias D. Cattaneo
    - This is an academic paper not a textbook
    - It can help you understand causal inference methods in a short time

# Reading Materials

- Suggested Readings:
  - **Mastering Metrics: The Path from Cause to Effect** by Angrist and Pischke
    - Chatty, opinionated, but intuitive approach to causal inference
  - **Mostly Harmless Econometrics** by Angrist and Pischke
    - More advanced
  - **An Introduction to Statistical Learning with Applications in R** by Gareth James, Daniela Witten, Trevor Hastie and Robert Tibshirani
    - An introductory book for machine learning
  - **Labor Economics** by Pierre Cahuc, Stephane Carcillo and Andre Zylberberg (graduate level)
  - **Labor Economics** by George Borjas (undergraduate level)

# Reading Materials

- Suggested Readings:
  - **Korinek (2023), Generative AI for Economic Research**
    - JEL article on how LLMs assist economists across research tasks
  - **Korinek (2025), AI Agents for Economic Research**
    - Update on AI agent frameworks and autonomous workflows

# Course Requirements

# Course Goals

- Get a solid understanding of the empirical methods to estimate causal effect and conduct data analysis
  - Be able to implement a good empirical research
  - Be able to critically evaluate empirical studies
- Be familiar with techniques and tricks of data management and visualization
  - Use STATA
  - Use R
- Have a good start of your thesis/writing sample

# Grading Policy

- Two empirical homework & Two Oral Exams (30%)
  - Each homework is followed by an individual oral exam
  - The oral exam will assess your understanding of your own code and empirical design
- Reading group presentation (15%)
- Term paper presentation (15%)
- Term paper (40%): milestones throughout the semester

# Course Requirements

- You should use **Latex** to type your term paper in Chinese or English
  - **Latex** is a tool for typesetting professional-looking documents
- You can use "homework" to practice the above "requirements"

# Important Dates

- Homework 1: 4/12
  - Oral Exam 1: 4/22
- Homework 2: 5/17
  - Oral Exam 2: 5/27 Week
- Reading group presentation: 5/28 and 6/4
- Term paper presentation: 6/11
- Term paper deadline: 6/18

# Oral Exams

4/22 week and 5/27 Week

- Each oral exam will last about 20–30 minutes
- You will be asked to explain:
  - The code you wrote in your homework
  - The empirical question you want to study
  - The regression equation you plan to estimate
  - Why your empirical specification makes sense
- The goal is to assess your understanding of:
  - Empirical methods you learn in this courses
  - Statistical programming languages: R/Stata

# Oral Exams

4/22 week and 5/27 Week

- After the oral exam, we will discuss your term paper progress
  - Discuss/Refine your research question
  - Clarify identification strategy
  - Discuss possible datasets and regression specifications
- You can prepare in advance
  - All questions are based on your own submitted work
  - If you understand your code and empirical design clearly, the oral exam will be straightforward
- This format reflects the rise of generative AI tools and emphasizes genuine understanding

# Reading group presentation

5/27 and 6/3

- Present one of the paper that applies causal inference from reading list
- Students in a group of **3-4** persons will give a presentation
  - 1 Introduction and Background
  - 2 Data and Empirical strategy
  - 3 Results and Conclusion
- Around 30-40 minimutes

# Term paper presentation

6/10

- Present the research progress of your term paper
- 10 minutes presentation
  - Introduce your research question
  - Discuss your empirical methods
  - Describe the data you use and summary statistics of estimated sample
  - Discuss your preliminary results

# Term paper deadline

6/17

- Feel free to discuss your term paper with me before the deadline

# Guideline for Writing a Term Paper

# Guideline for Writing a Term Paper

- You should start early; the paper is due on 6/17
- Short paper style: less than 3,000 words
  - See **Economics Letters**
  - See **AER: Insights**
- Typed, double-spaced, using one-inch margins and 12-point font

# Guideline for Writing a Term Paper

- For senior graduate students, you cannot just submit your thesis as a term paper
  - Let me know if you have any question about this issue

# Guideline for Writing a Term Paper

- Use credible causal inference methods to answer an empirical question
  - Test economics (social science) theory
  - Estimate policy effect
  - Any interesting questions regarding to human behavior/social phenomenon
- **Don't worry if you don't find anything significant as long as your methods are credible and you have interpreted the results well**

# How to Find Research Topics

# Approaches to Find Research Topics

- There are two main approaches to identifying research topics:
  - 1 Starting from your own interests and curiosities
  - 2 Doing an extensive literature review first
- These approaches are not mutually exclusive but iterative, with different starting points.

# Approaches to Find Research Topics

Starting from your own interests and curiosities

- I personally prefer the first approach
  - It allows you to arrive at topics you are really interested in
  - You can start by asking questions based on your personal experience
- Then, examine the current literature to see the state of knowledge and feasibility given accessible resources for answering the research question
- However, the risk is higher as the topic may be unimportant or boring for other people
- Requires personal judgment

# Approaches to Find Research Topics

## Doing an extensive literature review first

- This is more common approach
  - Review important literature in your broad area first
  - Focus on high quality papers (e.g. NBER working paper, top journals)
- Then, identify extensions or gaps in knowledge
- Examine feasibility given accessible resources for answering the research question