

Applied Econometrics: An Introduction

應用計量經濟學：課程介紹

Prof. Tzu-Ting Yang
楊子霆

Institute of Economics, Academia Sinica
AGEC/STAT, NTU

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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-AGEC, NTU-ECON, and NCCU-IMES
 - Office at NTU: 農業綜合館 218-B5 / 社科院 724
- Research Fields: Public/Labor Economics and Applied Econometrics
- Website: <https://sites.google.com/view/cpelab/>
- Email: ttyang@g.ntu.edu.tw

Teaching Assistants

- 黎宏濬 (農經碩二)
 - Email: r11627065@ntu.edu.tw
- 吳子欣 (農經碩二)
 - Email: r12627007@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 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

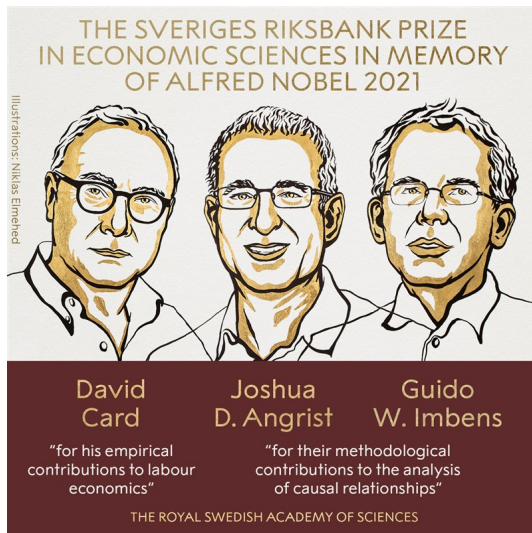
Economics and Causal Inference

Economics and Causal Inference

- 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

2021 Nobel Laureates

Causal Inference in Economics



Economics and Causal Inference

- 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

Economics and Causal Inference

- 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 economics

Causal Inference

Causal Inference

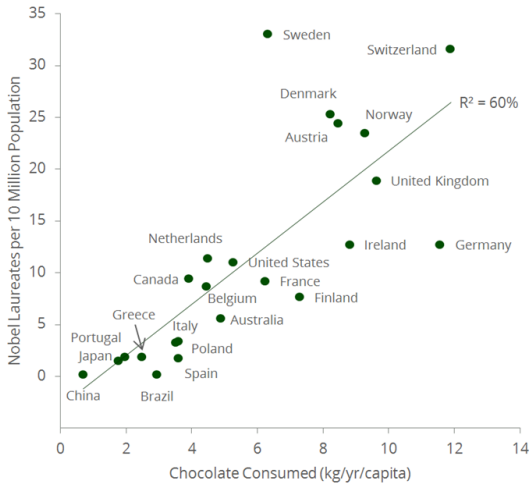
- Social science (Economics) theories are almost always causal in their nature
 - X causes Y
 - An increase in price of oil causes consumer's demand for oil to decrease
 - An increase in schooling years can raise people's productivity (wage)
 - Implementation of a carbon pricing incentivizes firms to adopt more environmentally friendly practices

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

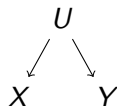
Chocolate Consumption and Nobel Laureates



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 causal questions!
- The effect of **changes in interest rates** on **house prices**
 - Does increasing interest rates cause house prices to decrease?
 - Ideally, we should get causal effect by comparing the house prices of **the same economy** with and without the interest rate change
 - Again, we have an unobserved outcome problem

Causal Inference

Example 2

- The effect of **changes in interest rates** on **house prices**
 - Countries with low interest rates v.s. Countries with high interest rates:
 - Two groups are not directly comparable
 - Why do central banks change interest rates?
 - They might lower rates during economic downturns \Rightarrow may underestimate the positive effect of low interest rates on house prices
 - Or, they might raise rates when the economy is overheating \Rightarrow may underestimate the negative effect of high interest rates on house prices

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 climate change on crop yields
 - Do renewable energy subsidies lead to increased adoption of clean technologies?
 - Does eliminating estate tax increase wealth inequality?
 - Do immigrant workers depress the wages of native workers?
 - Can democracy increase economic growth?

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

Randomized Experiment

- In this course, we will introduce at least 7 methods of causal inference:

1 Randomized Experiment

- 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

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

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

4 Differences-in-Differences (DID)

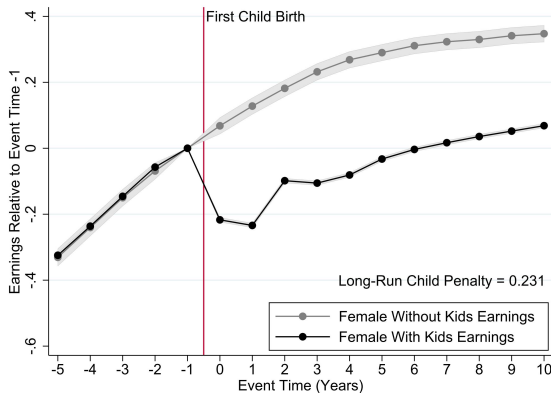
- If treatment and comparison group's outcomes move in parallel in the absence of treatment
- Then, we can use trend in outcome of a comparison group to represent counterfactual trend for the treatment group

Differences-in-Differences

- Example: The effect of **having children** on **female earnings**
 - Despite considerable gender convergence over time, substantial gender inequality persists in all countries
 - Henrik Kleven et. al (2019) uses Danish administrative data from 1980-2013 and an DID approach
 - They show that most of the remaining gender inequality in earnings is due to children
 - The arrival of children creates a gender gap in earnings of around 20% in the long run

Differences-in-Differences

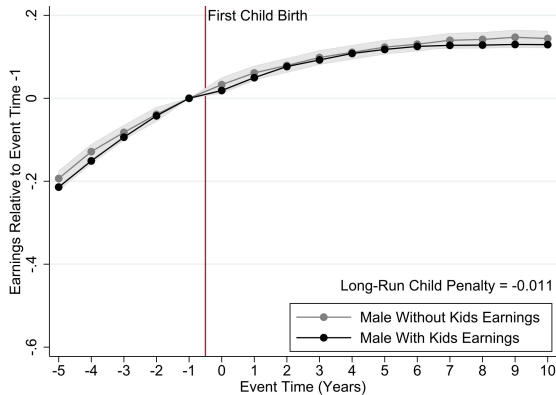
A: Women Who Have Children vs Women Who Don't Earnings Impact



Source: Henrik Kleven et. al (2018)

Differences-in-Differences

B: Men Who Have Children vs Men Who Don't Earnings Impact

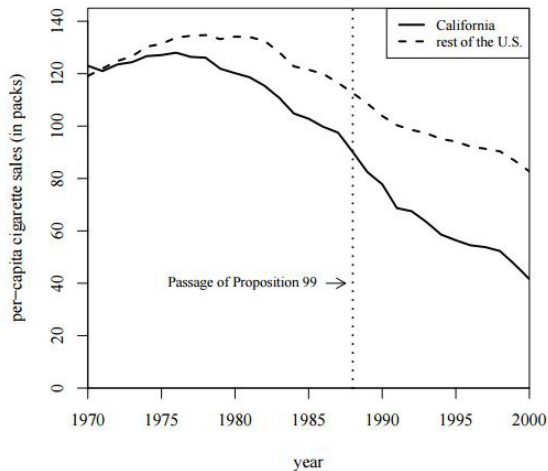


Source: Henrik Kleven et. al (2018)

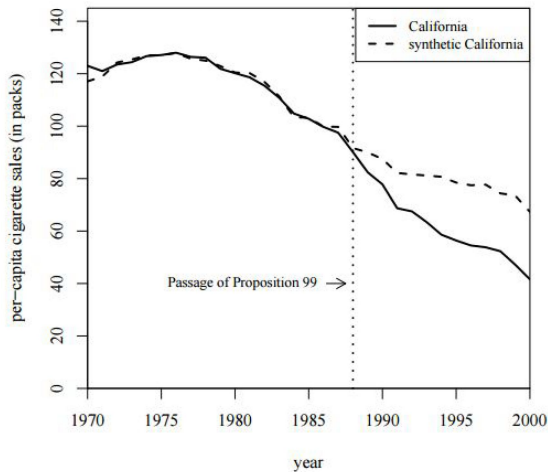
5 Synthetic Control Method (SCM)

- 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

Synthetic Control Method



Synthetic Control Method



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

Regression Discontinuity Design

- Example: The effect of college major on early-career wages
 - Forty-year-old US workers with undergraduate degrees in economics earned median wages of \$90,000 in 2018
 - By comparison, college graduates with any major other than economics earned \$66,000
 - However, average wage differences between majors do not necessarily reflect the causal effect of choosing one major over another
 - Most students self-select their college major, and many universities use grade requirements to restrict entry into certain majors
 - Observational wage differences across majors may reflect other confounding factors

Regression Discontinuity Design

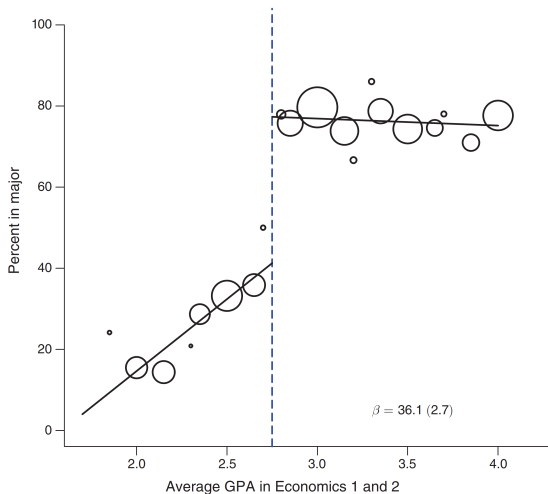


FIGURE 1. THE EFFECT OF THE UCSC ECONOMICS GPA THRESHOLD ON MAJORING IN ECONOMICS

Source: Bleemer, Zachary, and Aashish Mehta (2022)

Regression Discontinuity Design

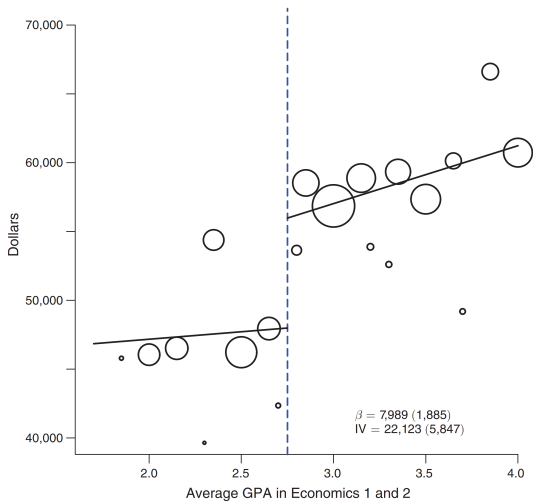


FIGURE 2. THE EFFECT OF THE UCSC ECONOMICS GPA THRESHOLD ON ANNUAL WAGES

Source: Bleemer, Zachary, and Aashish Mehta (2022)

Regression Discontinuity Design

- Because students with GPAs just below 2.8 are generally similar to students with GPAs just above 2.8, on average
 - The only difference could be their major
 - Those just above 2.8 GPA threshold have much higher wage
 - This suggests that the economic major causes this effect
- Students who just met the 2.8 GPA threshold to major in economics earned \$22,000 (46%) higher early-career wages than they would have in their second-choice majors

7 Instrumental variables

- 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

1 Shift-Share IV Design

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

2 Staggered DID Design

- Treatment adoption that occurs at different times across units

3 Synthetic DID Design

- Combine synthetic control method and DID Design

4 Spatial RD Design

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

5 Causal Forest

- A machine learning technique used to estimate heterogeneous treatment effects

Course Content: Data Analysis

Data Analysis

- A good causal inference requires a well-established DATA
- Create an “analysis-ready” dataset is a challenging task, especially for large-scale data or unstructured data
- A lot of data analysis time is spent data cleaning and preparing data, up to 80% of the time.
- In this course, you will learn how to clean data, create your own dataset and visualize your data
 - You might also learn how to collect your own data

Data Analysis

- Economists had a long tradition of utilizing the evidence from data to verify their theories
- In the past, the major data sources were the government surveys
- The data revolution of the past decade have a further and profound effect on economic research

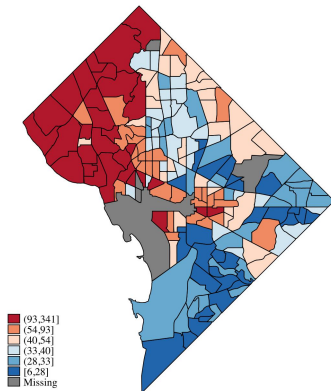
Data Analysis

- Increasingly, economists make use of newly available large-scale administrative data with near-universal population coverage
 - Health insurance claims data:
 - Record every Taiwanese's healthcare utilization whenever they visit doctors
 - Tax return data:
 - Record income and wealth of each taxpayer
 - Housing transactions Data:
 - Record all housing and land transactions in Taiwan

- Due to the growth of the internet, economists also begin to use new data formats (unstructured data)
 - Online document
 - Social media
 - Geolocations
- In this course, I will also teach you how to handle with these new types of datasets
 - Geographic data

Geographic data

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



Source: Maurizio Pisati (2012)

Course Structure

- 1 Focus on how to implement various empirical methods of drawing causal inference
- 2 Discuss the applications in economics
- 3 Let you know how to use statistical softwares to conduct data analysis

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

Course Goals, Grading Policy, and 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 (20%)
- Reading group presentation (20%)
- Term paper presentation (20%)
- Term paper (40%): milestones throughout the semester
- You will get extra 5 points in your grade for term paper (equivalent to 2 points in final grade) if you upload your codes and related files to *GitHub* for replication.

Course Requirements

- You should use **Latex** to type your term paper in Chinese or English
 - **Latex** is a tool for typesetting professional-looking documents
- In addition, you are encouraged to upload your code to **GitHub** for replication (Bonus!)
 - **GitHub** is an online repository that store and share your source code projects
- You can use "homework" to practice the above "requirements"

Important Dates

- Compulsory Office Hour: 10/9 week and 11/20 week
- Homework 1: 10/20
- Homework 2: 11/24
- Reading group presentation: 11/20, 11/27 and 12/4
- Term paper presentation: 12/4, 12/11 and 12/18
- Term paper deadline: 12/30

Two Compulsory Office Hour

10/9 week and 11/20 week

- We will have two compulsory office hour
 - Help you find a research topic: brainstorming
- Before each office hour, please send me an **research questions slide** (1-5 pages)
- Describe 1-2 research ideas
- For each idea, you should briefly describe causal relationship you are interested in and possible dataset you can use
- If possible, you should try to point out possible empirical methods
- 5 minutes presentation

Reading group presentation

11/20, 11/27 and 12/4

- 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

12/4, 12/11 and 12/18

- 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

12/30

- Feel free to discuss your term paper with me before the deadline
- Send your term paper to me through email
- Email: ttyang@g.ntu.edu.tw

Guideline for Writing a Term Paper

Guideline for Writing a Term Paper

- You should start early, the paper is due on 12/30
- Letter style: roughly 5-10 pages including tables, figures, footnotes, appendices, and references
- Word count: less than 3,000 words
 - See **Economics letters**
 - See **AER: Insight**
- Typed, double-spaced, and using one-inch margins and 12 point type

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