

TOPICS IN MACROECONOMICS

Juan Herreño Johannes Wieland

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ABOUT US



THE MODERN MACROECONOMIST

- A jack of all trades:
 - ▶ Simple theoretical models.
 - ▶ Quantitative models.
 - ▶ Cross-sectional identification.
 - ▶ Time-series identification.
 - Why? Identification problems massive:
 - ▶ Fed lowers interest rates in 2008. What do we learn about effects of monetary policy?
- ⇒ Attack problem from many different angles.

THIS CLASS

- Identification in macro & research advice (1 class)
- Cross-sectional identification (4 classes)
- Macro models with micro heterogeneity (4 classes)
- Student presentations (1 class)

COURSE REQUIREMENTS

① Required reading and participation (30%).

- ▶ Read * papers on syllabus before class.
- ▶ We will often pause for discussion.
- ▶ Insufficient participation \Rightarrow Midterm / Final

② Paper draft (70%)

- ▶ Paper should connect micro data with macro model.
- ▶ Does not have to be a completed paper.
- ▶ Needs to be original.

PAPER DRAFT

- The paper should contain two parts:
 - 1 A new micro data fact or causal effect.
 - ★ Ok to build on (but not copy!) other work.
 - 2 A (simple) macro model that connects the micro data fact to macroeconomic outcomes.
 - ★ Should have computational component (unless waived).
- At the end of class you need to submit the paper and code.
 - ▶ If we cannot easily replicate the paper figures and tables, we will ask you to resubmit.

PAPER DRAFT DEADLINES

- ① Week 5: Submit New micro data fact / causal effect.
- ② Week 6: meeting for feedback.
- ③ Week 10: Presentation
- ④ Week 11: Paper draft

OUTLINE

- 1 INTRODUCTION
- 2 RESEARCH ADVICE
- 3 ECONOMETRICS REVIEW
- 4 IDENTIFICATION IN MACRO
- 5 ORGANIZING APPLIED WORK

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SEMINARS, LUNCHES, ETC

- Attending seminar and lunch is an important part of your PhD.
 - ▶ Allows you to see cutting edge research, help improve peer's research, become part of research community.
 - ▶ See how the sausage is made.
 - ▶ In grad school I learned a lot from others' questions.
 - ▶ Even if the topic is outside your immediate research area there are large spillovers from learning about techniques, data, and presentational skills.
- Great line-up of external speakers this quarter:
 - ▶ Atif Mian, Sanjay Singh, Janice Eberly, John Mondragon, Diego Perez, Ricardo Reis, Kim Ruhl, Cecile Gaubert, Amy Handlan, Nick Bloom.
- If macro is a secondary field, fine to only attend seminar and lunch for your primary field. But should attend something!

RESEARCH ADVICE

- Becoming a researcher is hard.
 - ▶ Requires learning by doing. Only so much one can explain.
- *Persistence* is key.
 - ▶ *Every* paper hits a roadblock that initially appears fatal.
 - ▶ *Every* idea is related to something else and has a moment where someone says "that sounds like [insert citation here]."
 - ▶ *Every* researcher has days (or weeks or months) where they work extremely hard and have nothing to show for it.
- The key is being able to wake up and work just as hard and be just as dogged on the 10th day (or 30th or 100th) as you were on the first.
 - ▶ Work on something you love that motivates you.
 - ▶ Every paper has boring parts or frustrating parts. Learn to love the challenge.
 - ▶ Use habit formation to your advantage.

WORKING TOGETHER

- I personally love to work with others.
 - ▶ More fun.
 - ▶ Fewer dead ends, less of an echo chamber.
 - ▶ Motivate each other, give each other deadlines.
- Talk to each other. Co-author if you come up with an interesting idea.
- You will learn as much from your peers as from the faculty
 - ▶ Get to know each other! It's hard because of COVID, but it's crucial!
 - ▶ Help each other with research. Workshop ideas. Talk economics. Have fun together.
 - ▶ My PhD classmates are some of my best friends.
 - ▶ I continue to learn from them long after I was done with the PhD.

HOW TO COME UP WITH IDEAS

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KEY CONCEPTS¹

- Data Generating Process
- Identification
- Causal Effect / Treatment Effect
- Moment

¹This material draws on Pat Kline's Econ 244 notes.

DATA GENERATING PROCESS

- A *data generating process* (DGP) is a complete specification of the stochastic process generating the observed data.
- Equivalently, a specification of the probability $P_{\theta}(\mathbf{y})$ of observing any possible vector valued realization of the data \mathbf{Y} .
- Example: A DGP for (Y_i, X_i) is

$$Y_i = X_i + \varepsilon_i$$
$$(X_i, \varepsilon_i) \sim N(0, I_2)$$

- In general a DGP is something you should be able to program in your computer and draw a sample from.

DATA GENERATING PROCESS

- The DGP is assumed to belong to some family \mathcal{F} .
- A set of restrictions indexing a particular DGP in \mathcal{F} is called a *structure* \mathcal{S} .
- A *model* \mathcal{M} is a family of possible structures.
- Example of a *model*:

$$\begin{aligned} Y_i &= \beta_0 + \beta_1 X_i + \varepsilon_i \\ (X_i, \varepsilon_i) &\sim N \begin{pmatrix} \mu_1 & \sigma_1^2 & \sigma_{12}^2 \\ \mu_2 & \sigma_2^2 & \sigma_{12}^2 \end{pmatrix} \\ \boldsymbol{\theta} &= (\beta_0, \beta_1, \mu_1, \mu_2, \sigma_1^2, \sigma_2^2, \sigma_{12}^2) \end{aligned}$$

- Example of a *structure*: $\boldsymbol{\theta} = (0, 0, 0, 0, 1, 1, 0)$

IDENTIFICATION

- What is it?

IDENTIFICATION

- The problem of determining the structure from the joint distribution of the data in the population.
- Population \Rightarrow What is knowable in infinite datasets.
- Tells us whether it is worth constructing estimators for use in real datasets.
- Two structures θ' and θ'' are *observationally equivalent* if $P_{\theta'}(\mathbf{y}) = P_{\theta''}(\mathbf{y})$.
- The structure θ' is *globally point identified* if there is no other θ in the model space with which it is observationally equivalent.

EXAMPLES

$$Y_i \sim N(\mu, \sigma^2)$$

$$\boldsymbol{\theta} = (\mu, \sigma^2)$$

- Is $\boldsymbol{\theta}$ identified? How?

$$Y_i = \beta_1 X_i + \varepsilon_i$$

$$(X_i, \varepsilon_i) \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_1^2 & 0 \\ 0 & \sigma_2^2 \end{pmatrix}\right)$$

$$\boldsymbol{\theta} = (\beta_1, \sigma_1^2, \sigma_2^2)$$

- Is $\boldsymbol{\theta}$ identified? How?
- Neoclassical growth model. Identified? How?

LANGUAGE

- In econometrics you can either identify the structure θ (think parameters) in the model \mathcal{M} or you cannot.
- “Identifying assumptions” are restrictions on the model \mathcal{M} (family of DGPs) such that θ is identified.
- Don’t run a regression if you can’t describe the model \mathcal{M} under which the parameter(s) of interest are identified.

CAUSALITY

- Identification by itself has nothing to do with causality.
- Structural models postulate functional relationships for how endogenous variables are generated from exogenous variables. E.g.:

$$Y_i = f(S_i, X_i, U_i)$$
$$(s, x, u) \in \Omega_s \times \Omega_x \times \Omega_u$$

with (Y, S, X) observed and U unobserved.

- If S can be varied independently of X and U , then the model implies a set of *counterfactual* values that the outcome $y = f(s, x, u)$ would take under various values of the treatment s .
- The *causal effect* or *treatment effect* of changing s from s' to s'' is

$$\Delta_i = f(s'', x_i, u_i) - f(s', x_i, u_i)$$

POTENTIAL OUTCOMES

- Microeconomists will often use potential outcome notation for specifying causal questions.
- An advantage of this framework is that it forces the researcher to be very explicit about the counterfactual.
- $D_i \in [0, 1]$ is the treatment indicator.
- Y_i is the observed data, Y_i^0 the outcome under treatment $D_i = 0$, and Y_i^1 the outcome under treatment $D_i = 1$,

$$Y_i = D_i Y_i^1 + (1 - D_i) Y_i^0$$

- The causal / treatment effect is

$$\Delta_i = Y_i^1 - Y_i^0$$

AVERAGE TREATMENT EFFECT

- We are often interested in the *average treatment effect* (ATE), $E(\Delta_i)$.
- If treatment is independent of potential outcomes,

$$D_i \perp (Y_i^1, Y_i^0)$$

then a simple difference in means uncovers the ATE:

$$\begin{aligned} E(Y_i^1 | D_i = 1) - E(Y_i^0 | D_i = 0) &= E(Y_i^1) - E(Y_i^0) \\ &= E(Y_i^1 - Y_i^0) \\ &= E(\Delta_i) \end{aligned}$$

- Independence is an identifying assumption. This condition is sometimes called “unconfoundedness.”

CONDITIONAL INDEPENDENCE

- It is rare in (macro-)economics that the independence assumption is reasonable.
- Most of empirical we will see in this class will assume

$$D_i \perp (Y_i^1, Y_i^0 | X_i)$$

- X could be a set of controls, in which case this will be termed “conditional independence assumption” or “selection on observables”.
- X could also be an instrument that is correlated with the treatment.

POTENTIAL OUTCOMES AND STRUCTURAL MODELS

- Any model of potential outcomes can be written as a degenerate structural model and any structural model implies a set of potential outcomes.
- Example: $Y_i = \beta_0 + \beta_{i1}D_i + \varepsilon_i$, $E(\beta_{i1}) = \mu$ implies potential outcomes

$$Y_i^0 = \beta_0 + \varepsilon_i$$

$$Y_i^1 = \beta_0 + \beta_{i1} + \varepsilon_i$$

- Independence implies $E(\varepsilon_i|D_i) = 0$. This is a restriction on the model. The parameter (structure) we are identifying is μ .
- Key result: Under (conditional) independence, a difference in (conditional) means will identify the ATE regardless of the underlying DGP.

MOMENTS

- Identification and causality are population-level concepts.
- A *moment* is a statistic of the data, either in population or in a finite sample.
- Examples:
 - ▶ $E(Y_i^1|D_i = 1) - E(Y_i^0|D_i = 0)$.
 - ▶ Every estimator is a moment.
- Causal effects or parameters are equal to population moments under suitable identifying assumption.
- But not vice versa.

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