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?

$\Rightarrow$ Attack problem from many different angles.

This Class

- Research advice & econometrics review, & identification in macro (1 class)
- Cross-sectional identification and aggregation (4 classes)
- Macro models with micro heterogeneity (4 classes)
- Student presentations (1 class)

Course Requirements

1. Required reading and participation (35%).
   - Read * papers on syllabus before class.
   - We will often pause for discussion.
   - Insufficient participation $\Rightarrow$ Midterm / Final
2. Paper draft (65%)
   - Paper should connect micro data with macro model.
   - Does not have 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 replicate the paper figures and tables with one click or command, we will ask you to resubmit.
  - Submit by giving us read access to your GitHub repository.

Paper draft deadlines

1. 5/1/2022: Submit New micro data fact / causal effect.
   - Submission = giving us read access to your GitHub repository.
2. Week 6: meeting for feedback.
3. 6/1/2022: Presentation in class.
4. 6/8/2022: Paper draft due.

Outline

Outline

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!
  - 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 my classmates today.

How To Come Up With Ideas

- Most difficult part of research.
- DON'T just sit there waiting for an idea.
  - Work on something. You will bump into things.
- Talk to others! Often papers come out of conversations.
- Read a lot, and read critically.
  - Look for connections between topics.
  - Look for holes in literature, reasons to doubt papers.
- Play with data, look for facts.
- Go through *lots* of ideas. Discard aggressively.
  - Market rewards the max of all your ideas.
  - When you do come up with something, ask: "What is the best case scenario for this paper if everything works out?"
  - If not good enough, move on.
  - Try to get a sense within 1-2 weeks if it is worth continuing.
  - Can always return later if you see a way to get a more promising outcome.
- Work on what you love.

Outline

Organizing Research

- In my view, the following tools are indispensable for organizing research:

    1. Git
    2. Make
    3. Tasks

- Invest in these now and you will reap benefits for years.
- For more details and step-by-step instructions, see https://github.com/johanneswieland/Research-Manual/

Git

- Git solves three problems:

  1. Easily work on code with collaborators and share journals.
  2. Back-up of your code and writing.
  3. Back-up of previous *versions* of your code and writing.

- Do you find yourself carrying multiple versions of a file?
  "chapter1.tex,"
  "chapter1J_final.tex,"
  "chapter1final_comments.tex,"
  "chapter1_comments_conflict_final.tex"
  (Which is final?)

- With Git you only see one version (the newest!) of your code. But you can always revert to previous versions of your code.

Why Git and not Dropbox?

- While you work on your code, the code that collaborators have is undisturbed. You can try out major changes without disrupting their work.
- Git stores a snapshot of all your work. If you want to revert to a previous working version of your code all it takes is one command.
  - Great for tracking why results changed.
  - "Why is that coefficient now 0.8?"
- It has a learning curve (command line based), but you will earn back the time invested in 3 months max.
- Knowing Git is a requirement in technology jobs.

Make

- Make is one answer to the replication crisis.
- It is a versatile tool which can run commands to read files, process these files in some way (such as compiling and linking them), and write out the processed files.
- I now set up my projects so that one command—*make*—processes all the data, generates all the empirical results based on the generated, solves the model targeting the empirical moments, and compiles the latex paper and presentation.
- Anyone can take my code, type *make* and replicate the paper exactly.
- Make can be very cryptic to start with, but you will earn back the time invested in 3 months max. And you will sleep better.

Make Basics

- You should think of a *makefile* as a cooking recipe.

  1. You want an output, "table1.tex".
  2. "table1.tex" is built using data from "maindataset.csv" and the script "createtable.py."
  3. In *make* you type:

     ```
     table1.tex: createtable.py maindataset.csv
             python createtable.py
     ```

- The general syntax is:

  ```
  output: dependencies
          steps to generate output from dependencies
  ```

- It is straightforward to chain makefiles together to perform tasks in sequence.

Why Make?

- *Make* will only execute the code if it sees that the current output ("table1.tex") is older than the dependencies (the python file or the csv file have changed).
- Chaining makefiles removes errors from manual execution order.
- Makefiles are documentation. The makefile tells you how "table1.tex" is generated. It is much more reliable documentation than keeping script headers updated.
    - Helpful for both you (if you have not worked on the project for a few weeks) and your co-authors.
- Can easily handle multiple programs (python, matlab, stata, R) and shell commands.

Tasks

- A typical organization of empirical work is by type of document. In a project folder you will see folders such as “Data”, “Stata”, “Matlab”, etc.
- I now believe this organization is unhelpful as the relationship between the different files is not clear.
- Instead, I now organize my work by Task. The folders in my directory are called “downloaddata”, “createhousepriceindex”, “aggregateACSdata”.
- In each folder performs a dedicated task, which should be fairly evident from the title of the folder.
- Each task folder has at three subfolders: “input”, “code”, “output”.
- Can you guess how the subfolders are related?

Why Tasks?

- Automatic documentation: the code transforms the input into output. You do not need to write a pdf explaining how the files are related.
- Straightforward to feed in output from one tasks as input in another by using symbolic links in makefiles.
- Easy to audit, as only need to check that a specific task is performed correctly.
- Simple to port tasks to another project.
- I find it much easier to return to a task based project after a few months.

Outline

Key Concepts[1]

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

[1] This 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 $P_\theta(\boldsymbol{y})$ of observing any possible vector valued realization of the data $\boldsymbol{Y}$.

- Example: A DGP for (Y_i, X_i) is

$$\begin{gathered} Y_i = X_i + \varepsilon_i \\ (X_i, \varepsilon_i) \sim N(0, I_2) \end{gathered}$$

- 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 $\mathscr{F}$.
- A set of restrictions indexing a particular DGP in $\mathscr{F}$ is called a *structure* $\mathscr{S}$.
- A *model* $\mathscr{M}$ is a family of possible structures.
- Example of a *model*:

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

- 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 $\boldsymbol{\theta}'$ and $\boldsymbol{\theta}''$ are *observationally equivalent* if $P_{\boldsymbol{\theta}'}(\boldsymbol{y}) = P_{\boldsymbol{\theta}''}(\boldsymbol{y})$.
- The structure $\boldsymbol{\theta}'$ is *globally point identified* if there is no other $\boldsymbol{\theta}$ 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 $\boldsymbol{\theta}$ (think parameters) in the model $\mathscr{M}$ or you cannot.
- "Identifying assumptions" are restrictions on the model $\mathscr{M}$ (family of DGPs) such that $\boldsymbol{\theta}$ is identified.
- Don't run a regression if you can't describe the model $\mathscr{M}$ 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

$$
\begin{aligned}
Y_i^0 &= \beta_0 + \varepsilon_i \\
Y_i^1 &= \beta_0 + \beta_{i1} + \varepsilon_i
\end{aligned}
$$

- 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.

SUTVA

- Potential outcomes are not commonly used in macroeconomics.
- I believe this is because the *stable unit treatment value assumption* (SUTVA) is less plausible.
- SUTVA:
    1. The potential outcome is unaffected by the mechanism by which treatment is assigned.
    2. The potential outcome is unaffected by the treatment exposure of all other individuals.
- In macro we often worry about "spillovers" through general equilibrium price changes, migration, etc, which would violate (2).
- If SUTVA is invalid then the (conditional) difference in means no longer identifies the ATE.
- This is closely related to the aggregation problem from micro to macro.

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.

Outline

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- Why no progress? Idenitifcation problem, plus high dimensionality of effects (external validity)

- Means structure is important

- Identified moment $=$ causal effect

- Write down models that match causal effects. What do we learn from them? How do they restrict the model space?