Advanced Macroeconomics

Calibration and the use of Data in Macroeconomics

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Introduction

- A discussion on the use of data in macro models and empirical strategies in macro.
- Most of the discussion here is my own thoughts on the topic (that changes constantly over time) and mostly applied to het. agents models.
  - Some material came from the notes of Matthias Kredler.

References

- Nakamura and Steinsson (2018, JEP): Modern review of the "Identification in Macro".
- Canova (2007, Book), Fernández-Villaverde et al (2009): Great references for estimation in Macro. Chapter 7 of Canova has a very nice discussion on "calibration".
- Chodorow-Reich (2020, JEDC), Guren et al. (2021, NBER Macro). Good references for the cross-regional empirical methods. Check Chodorow-Reich class notes as well.

Model

- **What is a model?**
  - **Sargent**: define a model as a probability distribution over a sequence of outcomes, possibly indexed by a parameter vector;
  - **Wikipedia:** a theoretical construct representing economic processes by a set of variables and a set of logical and/or quantitative relationships between them.
  - **Statistics:** a data generating process.

- **Why use models?**

- We are usually interested in *counterfactuals*: i.e. what happens to Y when we change X?
  - **Applied Micro:** counterfactual comes from natural experiments + statistical assumptions.
  - **Quantitative Macro:** counterfactual comes from a set of structural assumptions using economic theory and the parameters chosen for the models.

- Must choose a set of parameters θ to make counterfactuals.

Choosing parameters

- How we identify parameter values often matters a great deal for results in quantitative work.
- A method that is (or tries to be) fully transparent and has a cookbook recipe: maximum-likelihood.
- Another approach is to use some type of moment-based estimation, i.e. GMM, minimum distance.
- Often authors refer to choosing parameters as **calibration**. What is the difference?

Likelihood based

- Systematically uses all moments (full information).
- Used for DSGE models $\Rightarrow$ few data points!
- Use Bayesian estimation to make feasible.
- But: Have to choose which data series to match $\Rightarrow$ Similar issue arises as for moment-matching – what to choose?

Calibration

- What calibration might mean (from Canova's book):
  - "...one wants to calibrate a model (in the sense of selecting reasonable parameters values) because there is no data to estimate its parameters."
  - "..one may prefer to calibrate (as opposed to estimated it) if the misspecification is so large that statistical estimation of its parameters will produce inconsistent and/or unreasonable estimates and formal statistical testing will lead to outright rejection."
  - "...some users interpret calibration as an econometric technique where the parameters are estimated using "economic", as opposed to "statistical", criteria."
- "the term calibration is used to indicate a particular collection of procedures designed to provide an answer to economic questions using "false" models."

Calibration

The essence of calibration by Kydland and Prescott (1991, 1996):

(i) Choose an economic question to be addressed.

(ii) Select a model design which bears some relevance to the question asked.

(iii) Choose functional forms for the primitives of the model and find a solution for the endogenous variables in terms of the exogenous ones and of the parameters.

(iv) Select parameters and convenient specifications for the exogenous processes and simulate paths for the endogenous variables.

(v) Evaluate the quality of the model by comparing its outcomes to a set of "stylized facts" of the actual data.

(vi) Propose an answer to the question, characterize the uncertainty surrounding the answer and do policy analyses if required.

Calibration

- Still many questions:
  - What are the set of "stylized facts"?
  - What is the measure of distance used to compare the model with actual data?
- A lot of discretionary choices by the research.
- Here it lies important philosophical aspect of the methodology:
  - In a strict sense, all models are approximations to the DGP and, as such, false and unrealistic;
  - Once this point of view is accepted, it makes no sense to examine the validity of a model using standard statistical tools which assume it to be true, at least under the null.
  - This is what is implicitly assumed with GMM and ML.

Calibration

- The modern definition of calibration can be summarized by this set of tweets from Jon Steinsson.
- **Jon Steinsson**: "Calibration is just moment matching without standard errors."
- Std. errors are important, but parameter uncertainty is minor relative to model misspecification.
  - Sometimes is too computationally cost to calculate standard errors (especially in heterogeneous-agents economies).
  - Not everybody agrees with this point.
- Model evaluation by calibration gives rise to "portable statistics", i.e., statistics that are used over and over again to evaluate different models.

Calibration

- The moments are generated after a full solution of the model (as opposed to only one FOC or eq. equation).
    - In some sense, this type of moment matching is similar to ML since requires solving the full model.
    - Calibration gives the freedom to choose which moments to match, in ML the freedom is selecting the set of observables to use for estimation.
- Nowadays, we are moving from moments that are just averages/correlations/variances, to matching causal estimates:
    - e.g., marginal propensity to consume out of a transitory fiscal rebate;

Models as over-identifying Restrictions

- A good theory imposes restrictions on the data.
- These restrictions/predictions can be tested and falsified.
- **Example**: Have normal distributions of body height for n countries: $\{\hat{\mu}, \hat{\sigma}\}_{i=1}^{n}$
- The model $x_i \sim N(\mu_i, \sigma_i)$ with $2n$ parameters is not particularly interesting: no degrees of freedom!
- Better: Posit that μ_i is a function of some covariate at country level: $\mu_i = \alpha x_i$, removes $n-1$ parameters.
- **Perfect theory**: Few parameters, but can match all moments.

The name of the game (usually)

- Calibrate m free model parameters to m targets.

- Then show k additional (non-targeted) moments in model and data:“model validation”.

- Fit should be decent to have a good model.

- **Example:** Target levels of an economy in 2000, then see how model does for period 2000-2020.

- Alternative (not done much): Could choose m moments to minimize distance to $m + k$ moments.
  - Perfect model: Cannot reject over-identifying restrictions statistically $\Rightarrow$ almost impossible in practice in economics!
  - OK model: We feel the quantitative economic fit of the moments is satisfactory to use the model to do policy evaluation etc.

Calibration in Practice

(i) Calibrate parameters before solving the model ("outside the model"):
- Estimate some parameters using data without having to solve the model: Earnings/productivity process, progressive taxation/transfers.
- Take (uncontroversial) parameters from other studies.

(ii) Calibrate the remaining parameters to match moments (exactly or over-identified method of moments).
- In HA models, we usually target micro moments in the steady state of model: wealth distribution, marginal propensities to consume, firm size distribution.
- If your model have transitions/cycles you can target some macro moments (time-series) after you calibrated the steady state.

(iii) Validate your model using non-target moments.

Step 1: Parameters directly identified outside model

Examples:

- Processes the model takes as exogenous and that we can estimate from data:
  - Income process in heterogeneous-agents model.
  - TFP in business cycles models.
  - Exogenous process for exit in firm dynamics models.
- Variables that can be taken from institutional environment/prices:
  - tax rates, tax schedules, tariffs.
  - relative prices for goods pin down technology in simple settings: $y = An$.

Step 2: Take parameters from other studies

- Kydland and Prescott (1991): choosing parameters using information obtained from other studies imposes coherence among various branches of the profession.
- Prime example: CES-utility curvature parameter ($\gamma = 2$).
- But careful: Does the same Greek letter really mean the same in my model and the other? Often not!
- **Example**: Risk aversion
  - measured in lab experiment with small sums;
  - risk aversion coefficient of representative agent in RBC model.
- A good compromise is to test the robustness of your results in an interval of these parameters consistent with empirical estimates.
  - e.g.: $\gamma \in [0.5, 1, 2, 3]$.

Step 3: Moment-matching

- What is often done: Minimize percentage differences.

$$\min_{\theta} \sum_{i=1}^{n} W_i [\ln \mu_i(\theta; \psi) - \ln \hat{\mu}]^2$$

  where ψ is a vector of "deep parameters" chosen in the previous step and W_i some arbitrary weight.
  - resembles usual moment-based estimators like SMM;
  - in fact, if we use some statistical criteria to minimize the loss function (i.e., minimize MSE, choose W_i efficiently, etc), the two methods are exactly the same;
  - the difference is in the discretionary choice of the calibrator;
  - **Canova**: "...a calibrator may look like an econometrician who uses different loss functions in different parts of the model"
  - "...a calibrator may also look like as an inefficient GMM econometrician."
- **Important**: the parameters θ are *conditional* on ψ.

Detour: Indirect Inference

- Another approach similar to SMM is **indirect inference**.
  - Simulate model data;
  - Estimate an auxiliary model (e.g., a linear regression) in both the simulated and actual data;
  - Minimize the distance between the coefficients of the **auxiliary model**.

- Useful when the structural relationships are difficult to express as simple unconditional moments.

- **Examples:**
  - Guvenen and Smith (E2014, ECTA): Consumption-savings with uncertainty about income-process.
  - Search-friction models with wage dispersion (e.g., Lise (2013, ReStud)).

- How to choose the auxiliary model?

Step 3: Moment-matching

Practical Issues:

- Hard task computationally
  - If moments smooth in θ: Use gradient-based method.
  - Otherwise: Use more robust methods (simplex, genetic algorithms, etc).
  - If too slow/impossible: try around to understand how parameters change the moments generate by the model.
- **Key challenge**: Which moments to pick?
  - informative moments: Which statistics are especially affected by a certain parameter?
  - Often hardest, but most important: elasticity-type (curvature) parameters. (labor-supply elasticity, risk aversion,...)

Informative moments

- Before estimating: Draw comparative-statics graphs with your model.
- Which parameter affects which moment most? Use this to moment to pin down parameter.
- Can also choose by economic reasoning on model properties.
- Good papers have discussion on identification (usually no proof since no direct one-to-one match).

Elasticity/curvature moments

- Determines how much agents change behavior when prices/incentives change.
- Can use cross-sectional distribution to pin this down.
- Ríos-Rull: "Don't identify elasticity/slope moment by a level moment".
- **Causal Effects as Identified Moments**
  - Target a "causally" estimated by the applied micro literature;
  - Target an impulse response function.
  - The advantage of identified moments is that they can provide evidence on specific causal mechanisms of a model and may be relatively invariant to other model features.

Other useful tricks

- Re-parameterize your model to have an unconstrained optimization problem. Examples:
- $\sigma = \exp(\hat{\sigma})$ for $\sigma > 0$ or $\beta = logist(\hat{\beta})$ for $\beta \in (0,1) \Rightarrow \hat{\sigma}$ and $\hat{\beta}$ live on entire real line
- Include equilibrium conditions in the loss function.
  - Example: Net demand of assets must be zero in equilibrium.
  - Penalize (net demand)^2; put harsher penalties than on other moments.
  - Useful when equilibrium-finding loop is computationally costly.
- Smooth discrete choices by adding preference shocks
  - Choice probabilities instead of 0-1.
  - Makes moments smoother in parameters.

Step 4: Model validation

- There are no free parameters and no uncertainty is allowed, so how to validate the model?
- Typical approach: use non-target moments
- **Examples**:
  - Kaplan-Moll-Violante (HANK): calibrate share of hand-to-mouth, validate using moments of wealth distribution;
  - Midrigan-Xu: calibrate productivity process, validate using autocorrelations of investment and employment.
- Bonus (hard) approach: replicate empirical studies!
  - Berger-Herkenhoff-Mongey (2022, AER): GE model of firms' labor market power.
  - Replicate "natural experiments" from empirical papers.

Step 4: Model validation

- It is useful to assess whether the moments are able to identify the parameters.

- A simple test is to "perturb" a parameter and compute how "sensible" is the loss function to changes in parameters.
  - Perturb each parameter (one at a time) by 1% (or any small value);
  - Compute the % change of the loss function relative to the value evaluated at the "estimated parameters"

- if the model is well identified, the loss function should not be flat in the region around the vector of estimated parameters.

- You can even go further and compute the % change for the contribution of **each moment** to the total loss.

Estimating useful parameters of HA models: stochastic processes, distributions, and more.

Stochastic Process

- The first, and perhaps one of the most important parameters in HA models are the parameters of the earnings/productivity process.
- In the simplest version, the stochastic process is given by:

$$y_{it} = \rho y_{it-1} + \varepsilon_{it}, \qquad \varepsilon_t \sim N(0, \sigma^2) \tag{1}$$

- To estimate this process you need panel data of income/productivity of at least 2-periods so you have enough information on the persistence (ρ) and inequality (σ^2).
- As it will become clear later, this is a simple process, more involved processes will require more information - either higher moments or longer time series.

Intuition Stochastic Process

- Note that there are two settings of moments informative about the process, the variance of earnings/productivity in levels, $V(y_{it})$, $V(y_{it-1})$ and in growth $V(\Delta y_{it})$, where $\Delta y_{it} = y_{it} - y_{it-1}$
- Taking the variance in equation (1)

$$V(y_{it}) = \rho^2 V(y_{it-1}) + \sigma^2$$

- Subtracting y_{t-1} in both sides and taking the variance in equation (1):

$$y_{it} - y_{t-1} = (\rho - 1) y_{it-1} + \varepsilon_{it},$$
$$V(\Delta y_{it}) = (\rho - 1)^2 V(y_{it-1}) + \sigma^2$$

Basic Stochastic Process

- You have 2 equations, 2 unknowns (ρ, σ^2), and three moments $V(y_{it}),\ V(y_{it-1}),\ V(\Delta y_{it})$ $\Rightarrow$ overidentified system:

$$V(y_{it}) = \rho^2 V(y_{it-1}) + \sigma^2$$
$$V(\Delta y_{it}) = (\rho - 1)^2 V(y_{it-1}) + \sigma^2$$

- If you assume the system is stationary you can use either $V(y_{it-1})$ or $V(y_{it})$ (in infinite horizon).

- In life-cycle models, you could the extra moment to identify in initial heterogeneity.

- Note that you can substitute $V(\Delta y_{it})$ by the autocovariance $C(y_{it}, y_{it-1})$.

Transitory-persistent Process

- A popular alternative is to model the earnings/productivity process as the sum of transitory and a persistent component:

$$
\begin{aligned}
y_{it} &= z_{it} + \varepsilon_{it} \\
z_{it} &= \rho z_{it-1} + \eta_{it}
\end{aligned}
$$

  where $\varepsilon_{it} \sim N(0, \sigma_\varepsilon^2)$ is the shock of the transitory component,and $\eta_{it} \sim N(0, \sigma_\eta^2)$ the shock of the persistent component.

  - **Transitory:** Bonus, health shocks, short unemployment spells
  - **Persistent:** Promotions, unemployment spells with scarring effects.

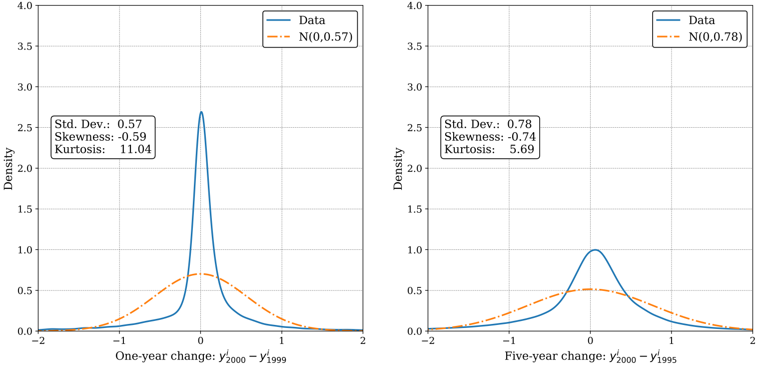
- Persistent shocks matter more for welfare and savings behavior. In firms dynamic models, persistence productivity interacts with adjustment costs or financial frictions.

Transitory-persistent Process

- The transitory-persistent provides better fit and captures the income dynamics of longer horizon.
- Requires **at least four periods** of panel data.
- It can still be discretized using the usual methods, but the state space increases fast.
- Identification requires the autocovariance matrix of of earnings (in growth rate or in levels). Estimation usually done using minimum distance/GMM.
- More information on the econometric identification: Guvenen (RED, 2009) identification in levels; Blundell, Pistaferri and Preston (AER, 2008) identification in growth.

Higher moments of earnings growth

- Guvenen et al (ECTA, 2021) emphasizes the role of higher-moments, non-linearities and age-dependence of earnings growth.



- This is also true in Brazil.

Stochastic process with higher moments

- Higher moments give additional incentives for precautionary savings. We can specify the earnings processes with higher-moments:

$$
\begin{aligned}
y_{it} &= z_{it} + \varepsilon_{it}, \\
z_{it} &= z_{it-1} + \eta_{it}, \\
\eta_{it} &\sim \begin{cases} N(\mu_{\eta,1}, \sigma^2_{\eta,1}) & \text{with prob. } p_\eta \\ N(\mu_{\eta,2}, \sigma^2_{\eta,2}) & \text{with prob. } 1 - p_\eta \end{cases} \\
\varepsilon_{it} &\sim \begin{cases} N(\mu_{\varepsilon,1}, \sigma^2_{\varepsilon,1}) & \text{with prob. } p_\varepsilon, \\ N(\mu_{\varepsilon,2}, \sigma^2_{\varepsilon,2}) & \text{with prob. } 1 - p_\varepsilon. \end{cases}
\end{aligned}
$$

where the shocks are drawn from a mixture of normals. Other distributions are also possible.

Stochastic process with higher moments

- Still requires long panel data and specially you must feed **higher moments** of the distribution in the estimation of the extra parameters $(p_\eta, p_\varepsilon, ...)$.
- Luckily, the moments of the earnings growth distribution (for Brazil) are available in the GRID project: https://www.grid-database.org/.
- You must be careful and think whether your moments identify the higher moments.
- Estimation is usually done through simulated methods of moments (SMM). It is slow, but it is done outside of the model.
- Discretization is not trivial, but can be done relatively fast using simulation methods. The reference is: DiNardi et al (JEEA, 2020).

Other approaches and Extra Issues

- You can combine other shocks in the stochastic process to capture different dimensions not captured by income:
  - **Unemployment:** with some exogenous probability the agent becomes unemployed.
  - **Superstar shock/entrepreneurs:** with some exogenous probability the agent becomes an entrepreneur (Castañeda et al, 2003; Bayer and Luetticke many papers).

- What other features could be incorporated?

- Business cycles: There is a large literature on the cyclicality of risk, including higher moments.
  - HA literature knows that this matter for precautionary savings and consumption (McKay, JME, 2017) but still relatively unexplored in HANK (exception is Bayer et al. ECTA, 2019).

Productivity Process

- Earnings are observable, but usually productivity are not. To estimate the productivity process one must first estimate productivity or infer from either employment or sales data.

- The usual method to retrieve firm-level TFP requires production function estimation:

$$Y_{jst} = \exp(z_{jst}) K_{jst}^{\alpha_s} L_{jst}^{\beta_s}$$

  where j is firm, s is sector and t time. Y_{jst} can be either sales or physical output.
  - Take the logs, add an error term ε and you have an equation to estimate the parameters.
  - The IO people worked really hard on the identification of this equation: Olley and Pakes (1996), Levinsohn and Petrin (2003), Ackerberg et al. (2015), De Loecker and Syverson (2021).
  - Under some assumptions about the inputs, you can also retrieve the markups (De Loecker and Warzynski, 2012; De Loecker and Eeckhout, 2020) and even markdowns (Yeh et al, 2022).
  - Usually requires firm-level panel data, but with very strong assumptions you are able to identify using a cross-section (i.e., cost share approach).

Productivity Process

- If you cannot estimate the production function, you can try recover the productivity process using employment or sales data.

- Recall that in the basic Hopenhayn model, there is a one-to-one map between productivity and labor demand:
$$n = \left(\frac{\alpha z}{w}\right)^{\frac{1}{1-\alpha}},$$
so movements in $\ln z$ correlates with movements in $\ln n$.

- You have to be careful about things that break this correlation: labor (and capital) adjustment cost, changes in firm-specific wedges, etc.

- See Sterk, Sedláček and Pugsley (2021).

Firm Size Distribution

- The firm size distribution in het. firms model is closely related to the productivity distribution.
- Calibration typically involves a combination of: dispersion of shock, distribution of entrants, fixed costs, entry costs.
- Additional moments from firm dynamics should also be targeted, including: Entry and exit rates, labor reallocation, etc.
  - If you have adjustment costs, you can use moments such as the fraction of inaction as targets.
- Typically, relative moments (e.g., size of entrants relative to average size) are targeted, but sometimes you want the actual firm size in number of workers.
  - Use aggregate parameters such as a labor supply shifter or aggregate productivity to align average firm size (the level) with data.

Progressive Taxation

- Idiosyncratic shocks imply earnings inequality. Progressive taxation matters, since it redistribute from the top to the bottom: changes wealth distribution, MPCs, etc.

- Suppose the tax function has the following form:

$$y_i^n = F(y_i),$$

  where y_i^n is net income and y_i is gross income.

- What function should we use? Two approaches:
  - Log-linear form;
  - Brackets;

Log-linear Form

- A functional form that captures progressivity (See Benabou (2002), Heathcote et al. (2017)):

$$T(y) = y - \tau_1 y^{1-\tau_2} \qquad \text{where } y \text{ is the individual gross labor income.}$$

  - τ_2 gives the degree of progressivity, i.e. it measures the elasticity of posttax to pretax income.
  - Given τ_2, τ_1 shifts the tax function and determines the average level of taxation in the economy.

- This implies that map from gross income to net income is:

$$y_i^n = F(y_i) = y_i - T(y_i) = \tau_1 y_i^{1-\tau_2}$$

- Parameters can be easily estimated in regressing $\log y_i^n$ on $\log y_i$.

Log-linear Form

- The tax is progressive if the ratio of marginal to average tax rates is larger than 1 for every level of income.
  - $\tau_2 = 1$: full redistribution $\Rightarrow T(y) = y - \tau_1$.
  - $0 < \tau_2 < 1$: progressivity $\Rightarrow T'(y) > \frac{T(y)}{y}$.
  - $\tau_2 = 0$: no redistribution $\Rightarrow T'(y) = \frac{T(y)}{y} = 1 - \tau_1$.
  - $\tau_2 < 0$: regressivity $\Rightarrow T'(y) < \frac{T(y)}{y}$.
- Break-even income: $y_{be} = \tau_1^{\frac{1}{\tau_2}}$.
  - If $y_i > y_{be}$, i is a taxpayer.
  - If $y_i < y_{be}$, i receives a transfer.

Progressive Taxation

- **Log-linear**:
  - **Good**: Flexible; Easy to estimate if you have the data.
  - **Bad**: Cannot account for specific marginal rates; Cannot be estimated if you do not have gross and net income for the same i (in the US they input using TAXSIM).

- Alternative: replicate the actual tax system in the function F.

- Include brackets of all marginal rates, but also possible transfers. **Brackets**:
  - **Good**: Account for top marginal rates. Very flexible.
  - **Bad**: How to model the **entire** transfer system? What to include and what to leave out?

Wealth Distribution

- Getting a "correct" wealth distribution was at the core of the early literature of heterogeneous agents.

- Early papers $\rightarrow$ getting the top right

- Various approaches (see DiNardi and Fella, RED, 2017):
  - Correct income process;
  - Preference heterogeneity;
  - Life-cycle motives: bequest, human capital, health shocks;
  - Entrepreneurship.
  - Heterogeneity (and shocks) in r_t.

- HANK papers $\rightarrow$ getting the bottom right $\rightarrow$ getting the right MPC (core mechanism of transmission of aggregate shocks).

Wealth Distribution

- Which moments to target?
- **Example:** Kaplan, Moll and Violante:

TABLE 5

	Data	Model
Mean illiquid assets	2.92	2.92
Mean liquid assets	0.26	0.23
Frac. with $b = 0$ and $a = 0$	0.10	0.10
Frac. with $b = 0$ and $a > 0$	0.20	0.19
Frac. with $b < 0$	0.15	0.15

	Liquid wealth		Illiquid wealth	
Moment	Data	Model	Data	Model
Top 0.1 percent share	17	2.3	12	7
Top 1 percent share	47	18	33	40
Top 10 percent share	86	75	70	88
Bottom 50 percent share	−4	−3	3	0.1
Bottom 25 percent share	−5	−3	0	0
Gini coefficient	0.98	0.86	0.81	0.82

Notes: Left panel: moments targeted in calibration and reproduced by the model. Means are expressed as ratios to annual output. Right panel: statistics for the top and bottom of the wealth distribution not targeted in the calibration.

Source: SCF 2004

Calibrating the Wealth Distribution

- Early approach: permanent heterogeneity in β (Krussel-Smith, 1998).
- For instance, suppose: $\beta \in [\overline{\beta} - \epsilon, \overline{\beta} + \epsilon]$.
- Discretize the space of β with uniform probability (Krueger, Mitman and Perri, 2016).
- You can also calibrate the beta of each group g individually: β targeting specific moments of the percentiles of the wealth distribution.
- Then $\overline{\beta}$ to match wealth-to-income ratio / avg. interest rate / avg. level of liquid asset.

Calibrating the Wealth Distribution

- Use the portfolio adjustment cost function (Kaplan and Violante ECTA 2014, Kaplan, Moll, Violante).
- Recall in KMV: $\chi(d, a) = \chi_0|d| + \chi_1|d/a|^{\chi_2}$
- Choose $(\rho, \kappa, \chi_1, \chi_2, \chi_3)$ to match fraction of individuals at the borrowing constraint, with negative wealth and mean liquid/illiquid assets.
- **Bayer, Born and Luetticke**: use wedge of interest rate between deposits and debt, and probability of portfolio rebalance to match ratio of liquid-illiquid, share of borrowers.

MPCs

- **Even better** $\Rightarrow$ we can also target the aggregate MPC.
- Auclert, Rognlie, Straub (2023): target the MPC over the wealth distribution.
- **Problem**: In Brazil there are little data on wealth, MPC is even worse.
- What data there is in the BCB to calibrate these models?
  - Share borrowers?
  - Avg. value of liquid assets?
  - Fluctuation in credit card?

Cross-Sectional Identification in Macro

Building Empirical Evidence

- Having theoretically sounding models in macro are nice but we still need empirical evidence to back-up our results.

- Macroeconomists have traditionally used time-series to identify fiscal and monetary shocks (among other). Often relies on some type of identified VAR:
  - Structural restrictions, i.e., restrictions of response of variables to shocks;
  - Sign-restrictions;
  - Narrative approach, e.g.., wars, oil shocks, identified tax changes;

- **Last 20 years**: tons of development in the applied micro literature $\Rightarrow$ macro researchers should embrace the causal-revolution!

Data and Methods in Macro

Table 10: Econometric Methods and Data Types Over Time

	Methods		Data				
Year Year	Time series	Applied micro	Micro data	Time series	Cross section	Panel	Proprietary
1980	75	25	22	89	8	3	13
1990	62	38	28	70	14	16	32
2000	58	42	28	54	8	38	30
2006–10	46	54	41	42	13	45	41
2016–18	35	65	56	34	10	56	52

Note: The figures are the shares, expressed as percentages, of econometrics-based articles articles in the *JME* and *JMCB*, plus the E-designated articles in the five general-interest journals. The method and data attributes are defined in section 3.2. The 2006–10 figures use data from 2006, 2008 and 2010; and the 2016–18 figures use data from 2016, 2017 and 2018.

Cross-Sectional (Regional) Identification

- A particular useful approach is to explore the cross-sectional/regional exposure to an identified aggregate shock.

- **Example**:
  - Industry-specific international shock (aggregate time-series shock) affects disproportionally places with high-shares of the industry;
  - Monetary policy might affect low-wealth region differently than high-wealth.

- **Issues**:
  - Still need identification (narrative/instrument/diff-diff): is the monetary policy/international shock exogenous?
  - The region-individual must be exposed **before** the shock happen.
  - How to go from cross-sectional estimates to aggregate?

Example: Mian & Sufi (2014, ECTA)

- Impact of "housing net worth" on non-tradable employment at the county-level.
  - weaker household balance sheet $\Rightarrow$ demand shocks $\Rightarrow$ decline in real activity;

$$\Delta \log E_i^{NT} = \alpha + \eta \Delta \mathsf{HNW}_i + \varepsilon_i$$

where $\Delta \mathsf{HNW}_i = (\Delta p_{06-09}^{H,i} \times H_{2006}^i)/NW_{2006}^i$.

- **Aggregate Shock**: 2007-2009 housing prices' collapse;
- **Cross-sectional Heterogeneity**: county i housing as a share of net-worth.

Example: Autor, Dorn and Hansen (2013, AER)

- Effect of rising Chinese import competition on US employment.

$$\Delta L_i^M = \alpha + \beta \Delta \mathsf{IPW}_i + \gamma X_i + \varepsilon_i$$

where i denote region and j denote industry:

$$\Delta \mathsf{IPW}_i = \sum_j \frac{L_{ij,1990}}{L_{j,1990}} \frac{\Delta M_j}{L_{i,1990}}.$$

  - **Aggregate Shock**: 1990-2007 change in imports from China by industry (ΔM_j);
  - **Cross-sectional Heterogeneity**: initial differences in regional industry specialization.
  - **Instrumental variables**: Chinese imports by other high-income countries.

Cross-Sectional Identification

- This type of regional identification is known as **Bartik** instrument or **shift-share**. Good references on the econometrics behind:
  - Goldsmith-Pinkham, Sorkin, and Swift (2020, AER), Borusyak, Hull, and Jaravel (2022, ReStud);
- **Main Problem**: in macro sometimes we want to know the aggregate impact of treatment, but the regression only tells you what happens in some regions relative to others;
  - The true aggregate relationship is different than the cross-sectional because of GE effects, spillovers, etc.
  - This is known as **the missing intercept problem**.
  - Example: it could be that trading with China increased aggregate employment, but it did *relatively less* in exposed regions $\Rightarrow$ the regression will say $\uparrow \Delta IPW \rightarrow \downarrow L^M$.

The Aggregation Issue

- **Problem**: (micro-) spillovers?
- **Example**:
  - Bad shock (treatment) in a region induces employment migration to a region that did not receive the shock;
  - Regression identifies differences in employment response from shock between regions $\Rightarrow$ migration increases the difference $\Rightarrow$ estimated β is larger;
  - But aggregate employment did not change as much, it just reallocated from one region to the other.
- **Stable Unit Treatment Value (SUTVA) Assumption**: treatment of one unit does not affect outcomes of non-treated units.
- If this assumption does not hold our regression estimates will be biased.

The Aggregation Issue

- **Problem**: General equilibrium effects (macro spillovers)?
- **Example**:
  - Good shock (treatment) in a region induces more consumption of tradable goods;
  - Price of the tradable good increases;
  - Control regions reduce consumption;
  - **Regression:** good shock increases consumption! but aggregate consumption did not really increase...
- Good theory tells you what the price transmission should look like.

The Aggregation Issue

- **Problem**: Endogenous responses?
- **Example**:
  - Bad output shock (treatment) in a region should not (alone) induce response by the monetary policy;
  - If we are interested in the total impact of the shock in the aggregate, we may want to consider the reaction of the monetary authority...
  - Feature or bug? Maybe we want to know effect of policy or shock separate from effect of policy response.
- Be aware of locally identified tax changes, federal government rebalacing budget, and any interactions between local and federal government.

The Aggregation Issue

- Does that mean we should not use this evidence? NO!
  - The micro evidence can help us to build better models...
  - if the empirical evidence rejects your model go back to the drawing board.
  - Look for the empirical evidence regarding the key elasticities of your model!
- The solutions to the aggregation issues are really problem dependent.
  - Estimate spillovers;
  - Use theory to guide general equilibrium/partial equilibrium effects;
  - Match causal moment in structural model (this is a type of indirect inference);