Chapter 8: Empirical Strategies and Quantitative Macroeconomics

Graduate Macroeconomics Slides

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Outline

Quantitative Questions in Macroeconomics

- Quantitative macro requires empirical answers to theoretical or policy questions.
- Core question: How can we estimate causal effects (e.g., policy → output)?
- Main empirical strategies:
  1. Natural experiments
  2. Structural VARs
  3. Structural estimation
  4. Calibration
- Challenge: Data come from equilibrium outcomes; many variables co-move and are endogenous.

The Identification Problem

- Goal: Estimate causal effect of G_t (gov't spending) on y_t (output) — the fiscal multiplier.
- Causal $\neq$ Correlational: G_t must be **exogenous** with respect to output shocks.
- Problem: Productivity shocks can lead to increases in both G_t and y_t.
- Solution: Find an exogenous shift in G_t to trace its causal impact on y_t.

Definition (Fiscal Multiplier)

Change in output from a one-unit increase in government spending:

$$\text{Multiplier} = \frac{dy_t}{dG_t}$$

Only valid if G_t is exogenous.

- Many macro questions hinge on estimating **causal effects**.
- We need to identify how changing one variable (e.g., government spending) impacts another (e.g., GDP).
- A major obstacle: **no direct experiments** on the entire economy.
- Observed data are equilibrium outcomes: multiple variables endogenously determined, responding to myriad shocks.
- This chapter outlines **four empirical strategies** to tackle these challenges.

Modeling the Policy Shock

Representative agent utility:

$$U_t = \log c_t - \frac{\ell_t^{1+\psi}}{1+\psi} + \gamma \eta_t \log G_t$$

Subject to:

$$y_t = A_t \ell_t, \quad c_t + G_t = y_t$$

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Subject to:

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FOCs yield:

$$\frac{A_t}{c_t} = \ell_t^{\psi}, \quad G_t = \gamma\eta_t c_t$$

Use resource constraint $c_t = y_t - G_t$ to eliminate c_t, and derive:

$$y_t = A_t \left(1 - \frac{G_t}{y_t}\right)^{-\frac{1}{1+\psi}}, \tag{8.2}$$

$$G_t = \frac{\gamma\eta_t}{1+\gamma\eta_t} y_t. \tag{8.3}$$

Equilibrium of Supply and Fiscal Rule

- Equation (8.2) = Supply curve: relates y_t and G_t via preferences and productivity
- Equation (8.3) = Fiscal rule: determines G_t given exogenous η_t
- An exogenous increase in η_t shifts the fiscal rule

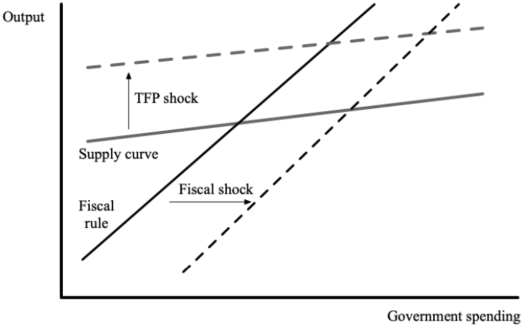

Figure: Figure 8.1: Supply and fiscal rule equilibrium

What Does the Fiscal Multiplier Measure?

- Graphically: slope of the supply curve in (G, y) space.
- From equations (8.2) and (8.3), total derivative with respect to η_t:

$$\text{Multiplier} = \frac{dy_t/d\eta_t}{dG_t/d\eta_t}$$

- Need η_t to shift only the fiscal rule, not the supply curve (A_t constant).
- In data, both G_t and y_t may respond to unobservables (e.g., A_t shocks), making identification hard.

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Identification Strategy

Exploit variation in η_t that shifts fiscal rule but not A_t (supply side).

Fiscal Multipliers in a Dynamic Setting

- In dynamic models, one-time increases in G_t have effects on y_t across many periods.
- Two approaches:
  1. **Peak multiplier:** $\max_t \frac{y_t}{G_t}$ (Blanchard and Perotti, 2002)
  2. **Cumulative multiplier:** $\frac{\sum_t \Delta y_t}{\sum_t \Delta G_t}$ (Mountford and Uhlig, 2009)
- Output path depends on persistence of G_t and economic conditions (state dependence).

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Impulse Response Function

Let ΔG_t be a one-time shock. Then the multiplier is computed using:

$$\mathcal{M} = \frac{\sum_{h=0}^{H} \mathrm{IRF}_y(h)}{\sum_{h=0}^{H} \mathrm{IRF}_G(h)}$$

Natural Experiments and Exogenous Variation

- We aim to identify the causal effect of government spending (G_t) on output (y_t).
- Key requirement: find exogenous variation in G_t unrelated to economic conditions.
- Wars provide such exogenous shifts → military spending spikes are not caused by A_t or y_t.
- Define z_t: an instrument correlated with G_t but uncorrelated with A_t.

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Identification Strategy

If z_t affects G_t and is orthogonal to productivity shocks, we can identify the effect of G_t on y_t from:

$$G_t = \gamma \eta_t c_t, \quad y_t = A_t \left(1 - \frac{G_t}{y_t}\right)^{-1/(1+\psi)}$$

Timing: Anticipation Effects and Policy Shocks

- If agents anticipate fiscal expansions, effects may occur before G_t rises.
- (Ramey, 2011): constructs series of anticipated military spending using news articles.
- Defines z_t as expected present value of defense spending → news shock.
- This approach controls for timing of fiscal policy transmission.

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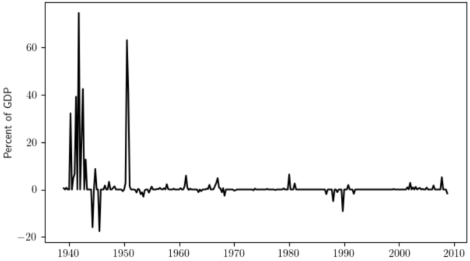

Figure: Figure: Change in the expected present value of military spending computed by (Ramey, 2011)

From News to Impulse Responses: Local Projection

- Suppose z_t is an exogenous news shock (e.g., Ramey's military news variable).
- Estimate impulse response function (IRF) via (Jordà, 2005) local projection:

$$y_{t+h} = \alpha_h + \beta_h z_t + \varepsilon_{t+h}$$

- Vary $h = 0, 1, \ldots, H$ to trace the dynamic output response to the news shock.
- IRFs can be used to compute dynamic fiscal multipliers:

$$\mathcal{M}_{cum} = \frac{\sum_{h=0}^{H} \text{IRF}_y(h)}{\sum_{h=0}^{H} \text{IRF}_G(h)}$$

Alternative Natural Experiments: Regional Variation

- (Nakamura and Steinsson, 2014): study regional variation in military contracts across U.S. states.
- Treatment: states receiving higher defense contracts.
- Control: states receiving little or no spending.
- Identification: assume cross-sectional variation in G_{it} is uncorrelated with unobserved shocks to y_{it}.
- Estimated multiplier: ≈ 1.5

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Note: Not Equivalent to National Multiplier

General equilibrium effects (e.g., tax changes) apply nationally but not across regions, so:

$$\text{Regional multiplier} \neq \text{National multiplier}$$

Caveats and Considerations

- Natural experiments require exogeneity, but:
  - Military spending $\neq$ general government spending
  - Effects may differ in other sectors or policy types
- Narrative methods (e.g.(Ramey, 2011), (Romer, 1986)) require historical judgment.
- External validity: Can results generalize beyond historical or regional context?
- Policy inference must consider full macroeconomic environment.

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Takeaway

Natural experiments offer valuable identification, but interpretation must be cautious and context-aware.

Motivation: Identifying Fiscal Policy Shocks

- Surprise changes in government spending may reflect endogenous responses.
- Structural Vector Autoregressions (SVARs) aim to uncover causal relationships.
- Goal: Identify shocks in fiscal policy from aggregate time-series data.

Structural VAR Formulation

$$B_0 Y_t = B_1 Y_{t-1} + B_2 Y_{t-2} + \cdots + B_J Y_{t-J} + \varepsilon_t \tag{8.4}$$

- $Y_t \in \mathbb{R}^n$: Vector of observed macro variables.
- B_j: $n \times n$ coefficient matrices.
- ε_t: Vector of i.i.d. structural shocks.
- SVARs allow causal interpretation of equations and shocks.

Log-linearized System and Interpretation

$$\hat{y}_t = \frac{\chi}{1+\chi}\hat{G}_t + \frac{1}{1+\chi}\hat{A}_t \tag{8.5}$$

$$\hat{G}_t = \hat{y}_t + \frac{1}{1+\gamma}\hat{\eta}_t \tag{8.6}$$

- $\hat{A}_t$: Supply shock; $\hat{\eta}_t$: Fiscal shock.
- $\chi = \frac{1}{1+\psi} \cdot \frac{\bar{G}/\bar{y}}{1-\bar{G}/\bar{y}}$
- Identification challenge: $\hat{G}_t$ depends on both $\hat{A}_t$ and $\hat{\eta}_t$.

Reduced-Form VAR and Identification Problem

$$Y_t = \underbrace{B_0^{-1} B_1}_{A_1} Y_{t-1} + \cdots + \underbrace{B_0^{-1} B_J}_{A_J} Y_{t-J} + \underbrace{B_0^{-1} \varepsilon_t}_{u_t} \tag{8.7}$$

- We estimate u_t via OLS, but not ε_t directly.
- $u_t = B_0^{-1} \varepsilon_t \Rightarrow$ need to recover B_0.
- Use $\text{Var}(u_t) = B_0^{-1} B_0^{-\top} \Rightarrow$ symmetric matrix.
- Only $\frac{n(n+1)}{2}$ equations: underidentified $\Rightarrow$ impose restrictions.

Recursive Identification Strategy

$$\hat{y}_t = \chi \hat{g}_t + \hat{A}_t \quad (8.8)$$

$$\hat{g}_t = \frac{1}{1+\gamma} \hat{\eta}_t \quad (8.9)$$

- $g_t = G_t - \hat{y}_t$ is exogenous $\Rightarrow$ recursive identification.
- No endogeneity in (8.9), and fiscal shocks identified cleanly.
- Recursive identification $\Rightarrow$ lower triangular B_0^{-1} via Cholesky.

Identification via Restrictions

- Recursive identification: order variables so some do not depend on contemporaneous others.
- Timing restrictions: set selected elements of B_0 to zero.
- Example: (Blanchard and Perotti, 2002) assume policy cannot respond within a quarter.
- Restrictions reduce model flexibility, but help identify shocks.

Alternative Identification Strategies

- Natural experiments as instruments for structural shocks.
- Sign restrictions: impose theoretical signs on responses (Uhlig, 2005).
- Long-run restrictions: demand shocks are temporary; supply shocks are permanent (Blanchard and Quah, 1989).
- Each approach imposes different identifying assumptions.

Invertibility and Structural VAR Limitations

- Invertibility assumption: reduced-form shocks are linear combinations of structural shocks.
- Often implausible: ignores omitted variables.
- Including more variables $\Rightarrow$ overfitting risk.
- Tradeoff: parsimony vs. capturing all relevant information.
- Still useful: SVARs impose fewer assumptions than fully specified models.

Motivation: Model of Fiscal Policy

- Models help extrapolate from observed data to answer policy questions.
- Useful when relevant experiments have never occurred.
- Must strike a balance between assumption-based conclusions and factual grounding.
- The fiscal multiplier depends on how the economy adjusts to government spending.

Setup of the Model

- Households maximize lifetime utility:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t U_t$$

- Production function:

$$y_t = A_t k_t^{\alpha} \ell_t^{1-\alpha}$$

- Capital accumulation:

$$k_{t+1} = (1-\delta)k_t + I_t$$

- Resource constraint:

$$y_t = c_t + k_{t+1} - (1-\delta)k_t + G_t$$

Household and Government

- Budget constraint:

$$c_t + k_{t+1} = (1 + r_t - \delta)K_t + w_t \ell_t - T_t$$

- Government uses lump-sum taxes: $T_t = G_t$
- Shocks:

$$A_t = (1 - \rho_a) + \rho_a A_{t-1} + \varepsilon_{A,t}, \quad \eta_t = (1 - \rho_\eta) + \rho_\eta \eta_{t-1} + \varepsilon_{\eta,t}$$

Optimality Conditions

- Consumption Euler equation:

$$\frac{1}{c_t} = \beta \mathbb{E}_t \left[(1 + r_{t+1} - \delta) \frac{1}{c_{t+1}} \right]$$

- Labor-leisure trade-off:

$$\frac{w_t}{c_t} = \ell_t^{\psi}$$

- Firm's FOC:

$$r_t = \alpha \frac{y_t}{k_t}, \quad w_t = (1 - \alpha) \frac{y_t}{\ell_t}$$

Government Optimization

- Government equates marginal benefit to cost:

$$\frac{\gamma \eta_t}{G_t} = \frac{1}{c_t}$$

- Equilibrium: a set of stochastic processes satisfying (8.10)–(8.18).
- Solution via functional forms, calibration, and log-linearization.

Fiscal Multiplier: Intuition

- No investment response $\Rightarrow$ only consumption or labor adjust.
- More work $\Rightarrow$ multiplier = 1, less consumption $\Rightarrow$ multiplier = 0.
- Realistic case: somewhere between 0 and 1.

Fiscal Multiplier: With Investment

- Less investment frees resources for government.
- But reduces future capital $\Rightarrow$ lower output later.
- If shock is persistent, effect is more pronounced.
- Hence, multiplier is increasing in the persistence of G_t shock.

What is Structural Estimation?

- Structural estimation treats an economic model as a statistical model for observed data.
- Idea: different parameter configurations imply different likelihoods for the observed data.
- Use likelihood-based methods (Maximum Likelihood or Bayesian Estimation) to estimate structural parameters.
- Focus: start with the simplified static model (Section 8.2), then generalize to richer models (e.g., Section 8.5).

Estimating Shocks Using Observables

- Assume: (A_t, η_t) i.i.d. with densities p_A, p_η
- Given time series of output y_t and government spending G_t, we back out implied shocks:

$$A_t = y_t\left(1 - \frac{G_t}{y_t}\right)^{1/(1+\psi)}, \quad \eta_t = \frac{G_t/y_t}{\gamma(1 - G_t/y_t)}$$

- Likelihood:

$$\mathbb{P}(G_t, Y_t|\psi, \gamma) = p_A(A_t) \cdot p_\eta(\eta_t)$$

- Full sample:

$$\mathbb{P}(\{G_t, Y_t\}_{t=1}^{T}|\psi, \gamma) = \prod_{t=1}^{T} p_A(A_t) p_\eta(\eta_t)$$

Likelihood Construction and Filtering

- For dynamic models with capital: need to solve policy rules (e.g. $k_{t+1} = f(k_t, A_t, \eta_t)$)
- State space:

$$X_t = (k_t, A_t, \eta_t), \quad X_{t+1} = F(X_t, \varepsilon_{t+1})$$

- Observation:

$$Y_t = H(X_t)$$

- Linearized form (around steady state):

$$\hat{X}_{t+1} = \mathcal{A}(\theta)\hat{X}_t + \mathcal{B}(\theta)\varepsilon_{t+1}, \quad Y_t = \mathcal{C}(\theta)\hat{X}_t$$

Kalman Filter and Maximum Likelihood

- Assume: $\varepsilon \sim \mathcal{N}(0, I)$
- Use Kalman filter to estimate unobserved states and construct the likelihood:

$$Y_t \sim \mathcal{N}(\mathcal{C}(\theta)\hat{X}_{t|t-1}, \mathcal{C}(\theta)P_{t|t-1}\mathcal{C}(\theta)^\top)$$

- Full sample likelihood:

$$\mathbb{P}(\{Y_t\}_{t=1}^T|\theta) = \prod_{t=1}^T \mathcal{N}(Y_t \mid \mathcal{C}X_{t|t-1}, \mathcal{C}P_{t|t-1}\mathcal{C}^\top)$$

- Use this for MLE or Bayesian estimation.

Limited-Information Estimation

- Uses only selected moments (vs full-information likelihood methods).
- E.g. estimate one structural equation using GMM.
- Requires identification but relaxes full model structure.
- **Impulse Response Matching:** match IRFs from structural VAR or natural experiments to model IRFs.
- Serves as a bridge between natural experiments and full structural estimation.

Introduction: Estimating IRFs

- **Goal:** Estimate Impulse Response Functions (IRFs) to summarize dynamic responses to innovations.
- Two dominant methodologies in empirical macroeconomics:
  1. **Local Projections (LP):** Estimate horizon-by-horizon.
  2. **Vector Autoregressions (VAR):** Estimate a system and iterate forward.
- **Key Question:** How do these methods compare in terms of structure, identification, and the *bias-variance tradeoff*?

1. Local Projections (LP)

- **Methodology:** Construct the IRF one horizon (h) at a time via direct linear regression.
- **Specification:** For a horizon $h \geq 0$:

$$y_{i,t+h} = \beta_{i,h} y_{1,t} + \sum_{j=1}^{J} A_{i,j} y_{t-j} + \varepsilon_{i,h}$$

- **Estimation:**
  - Run a separate regression for each horizon $h = 0, 1, \ldots, H$.
  - The IRF is simply the sequence of coefficients $\{\beta_{i,h}\}_{h=0}^{H}$.
- **Intuition:** This is a "direct" forecast. It imposes minimal structure on how the system evolves between t and $t + h$.

2. Vector Autoregressions (VAR)

- **Methodology:** Specify a dynamic system for one step ahead, then iterate.
- **Reduced-Form Specification:**

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_J y_{t-J} + u_t$$

- **Calculation:**
  - Estimate A matrices via OLS equation-by-equation.
  - *Simple Case* ($J = 1$)*:* The IRF at horizon h is given by A_1^h.
  - *General Case* ($J > 1$)*:* Requires the **Companion Form** to express as a first-order system.

VAR: The Companion Form

To compute dynamic IRFs for $J > 1$, we stack the variables. For $J = 2$:

$$\mathcal{A} = \begin{pmatrix} A_1 & A_2 \\ I & 0 \end{pmatrix}$$

The system evolves as:

$$\begin{pmatrix} y_t \\ y_{t-1} \end{pmatrix} = \mathcal{A} \begin{pmatrix} y_{t-1} \\ y_{t-2} \end{pmatrix} + \begin{pmatrix} u_t \\ 0 \end{pmatrix}$$

- The IRFs at horizon h are found in the upper-left $n \times n$ block of $\mathcal{A}^h$.
- **Implication:** The VAR *extrapolates* long-run dynamics entirely from short-run (one-step-ahead) estimates.

Equivalence and Interpretation

- **Plagborg-Møller and Wolf (2021):** Show that IRFs from reduced-form VARs can be combined to theoretically match LP IRFs.
- **What are they estimating?**
  - *Local Projections:* Estimate a conditional expectation:

$$\mathbb{E}[y_{i,t+h}|y_{1,t} = 1, \dots] - \mathbb{E}[y_{i,t+h}|y_{1,t} = 0, \dots]$$

  - *VAR:* Assumes the statistical model is correct and iterates.
- While they can target the same population parameter, their finite-sample properties differ significantly.

The Bias-Variance Tradeoff: Variance

Local Projections (High Variance)

Regresses y_{t+h} on $y_{1,t}$. As h grows, many intervening shocks occur, lowering the signal-to-noise ratio.

- Result: **Wide standard errors** at long horizons.

VAR (Low Variance)

Regresses y_{t+1} on y_t. Uncertainty accumulates as we power up the matrix $\mathcal{A}^h$, but usually slower than in LPs.

- Result: **Tighter confidence bands** (more efficient).

The Bias-Variance Tradeoff: Bias

VAR

Relies on the assumption that the data is well-approximated by a VAR(J).

- If the auto-covariance structure is misspecified, the iteration $\mathcal{A}^h$ compounds the error.
- Result: **Potentially large bias**.

Local Projections

Does not impose dynamic structure between t and $t + h$.

- More robust to misspecification of the dynamic model.

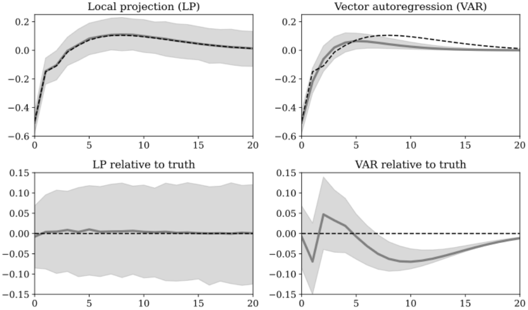


Figure 8.3: Bias-variance tradeoff in simulated data

Notes: We simulated 1,000 draws of length $T = 200$ from a VAR(2) in two variables. For each simulation draw, we estimate the impulse responses using local projection and a VAR but with only one lag. The solid lines are the median impulse responses at each horizon across the 1,000 draws. The shaded areas show the 5th and 95th percentiles at each horizon. The dashed lines show the true impulse responses. The lower panels show the differences between the estimated impulse responses and the true values.

Simulation Evidence and Practical Choice

Figure 8.3: simulates a VAR(2) process but estimating with only 1 lag.

- **LP:** Captures the shape (low bias) but with high sampling variation (MSE = 0.0047).
- **VAR:** Smoother curve (low variance) but systematically wrong level (high bias) (MSE = 0.0027).

How to choose? (Li, Plagborg-Møller, and Wolf, 2024)

- **For Point Estimates (MSE):** VAR is often preferred. The reduction in variance usually outweighs the bias cost.
- **For Inference:** VAR bias distorts coverage probabilities. Standard CIs may not cover the true IRF.
- *Tradeoff*: VAR for precision, LP (or bias-corrected VAR) for robust inference.

What is Calibration?

- Calibration involves selecting parameter values so that the model captures key features of real-world data.
- Parameters can be set using:
  - Empirical moments (e.g., volatility of GDP)
  - Prior literature or micro data
- Distinct from estimation: we do **not** optimize the model to match data exactly.
- Goal: Assess how well the model mechanisms explain observed economic dynamics.

Calibration Strategy and Fiscal Multiplier

- Focus: Government spending shock and its effect on output.
- The fiscal multiplier is affected by:
  - Elasticity of labor supply ψ
  - Ability of households to reduce/increase consumption
- Chapter 3 calibration used:

$$\alpha = \text{Capital share} \approx \frac{1}{3}$$

$$\delta = \text{Depreciation rate} = 0.019$$

$$\text{Investment-to-capital ratio} = 0.076 \Rightarrow \text{Quarterly depreciation} = 0.019$$

Calibrating β and ψ

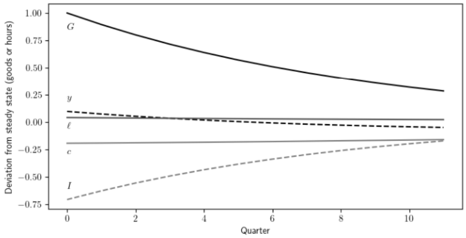
- Steady-state Euler equation:

$$\beta = \left(1 + \alpha \bar{y}/\bar{k} - \delta\right)^{-1} \Rightarrow \beta = 0.994$$

- Frisch elasticity of labor supply: $\frac{1}{\psi}$
  - Empirical estimates $\Rightarrow \psi \approx 2$
  - Calibration using tax changes and lottery income
- Lottery evidence (Golosov et al. 2021): \$100 gain $\Rightarrow$ \$2.30 drop in annual earnings

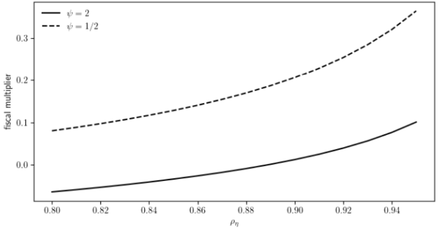
$$\text{Change in earnings} = -\frac{4w\ell}{\psi \cdot c} \cdot \frac{r}{1+r} \cdot \$100 \Rightarrow \psi \approx 2.1$$

Impulse Response to Fiscal Shock



- Positive government spending shock ($\rho_\eta = 0.9$)
- Initial increase in output and labor supply
- Decline in investment over time → falling capital stock
- Fiscal multiplier calculated as integrated output over 12 quarters

Cumulative Fiscal Multiplier



- ψ affects labor supply elasticity:
  - Lower $\psi \Rightarrow$ more elastic labor supply $\Rightarrow$ larger multiplier
- Persistent shocks ($\rho_\eta \uparrow$) $\Rightarrow$ greater cumulative effect

Model Validation

- Even after calibration, we ask:
  - Does the model reproduce other observed facts?
- Validation links the model to evidence beyond calibration targets.
- Aims to build confidence in the model as a credible approximation of reality.

Principles for Calibration

(i) Understand the economics:

- Match key mechanisms to real-world forces.

(ii) Discipline the mechanisms:

- Use microeconomic evidence to calibrate key behavioral margins.

(iii) Robustness:

- Analyze sensitivity of model outcomes to parameter changes.
- Be aware that some mechanisms (e.g. wealth effects) may be understated.

Overview of Methods

- **Natural Experiments**:
  - High identification clarity, but specific events may not be generalizable.
- **Structural VARs**:
  - Fewer *a priori* restrictions than fully-structural models, yet need identification assumptions.
- **Structural Models**:
  - Provide deeper insight into mechanisms and welfare, but risk of mis-specification.
- **Calibration** vs. **Estimation**:
  - Calibration: highlight and "discipline" specific channels.
  - Estimation: treat the entire model as data-generating, match likelihood or posterior.

Practical Takeaways

- Combining methods:
  - Use natural experiments to *validate* or *calibrate* parts of a structural model.
  - Perform structural estimation or VAR analysis for out-of-sample questions (e.g., policy design).
- No single method is a silver bullet; **triangulation** with multiple approaches often yields more robust insights.
- The **fiscal multiplier** example:
  - Empirical estimates $\approx 0.7 - 1.5$ (depending on approach).
  - Neoclassical calibration often yields *lower* multipliers, especially when investment crowd-out is strong.
  - Including additional features (e.g. sticky prices) can raise multipliers.

Next Steps

- Explore **tax distortions** (Chapter 14) and **Keynesian channels** (Chapter 17) for further implications of fiscal policy.
- Deeper understanding of **micro-level** heterogeneity (labor supply, consumption constraints, borrowing constraints).
- Larger **DSGE frameworks** for policy evaluation with structural estimation.

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Thank you!

Questions or comments?

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