Evaluating Policy Counterfactuals

Theory and Measurement

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Fiscal and Monetary Policy Research Boot Camp

Evaluating policy counterfactuals

How does the **systematic design** of fiscal & monetary policy shape the economy?

E.g., what if the Fed had followed a simple Taylor rule post-2021?

- Traditional approaches:

  1. *Structural*: build complete general equilibrium model, then change policy rule

     Smets-Wouters (2007) is the classic, Bocola-Dovis-Jørgensen-Kirpalani (2025) more recently.

     - What moments should I be targeting in estimating my model?
     - What shocks drive the cycle? Are they "dubiously structural"? Is that a problem?

  2. *Empirical*: use evidence on policy shock transmission to change policy through shocks

     Sims-Zha (1995) is the classic reference. Uses as input estimates from VAR/LP literature.

     - Can we just do that? What's the link between policy shocks and policy rules?

- **Today**: **sufficient statistics**-type results for policy evaluation, to inform both 1. & 2.

Structure for today

1. **Identification results**
   - Warm-up: recap of Sims-Zha empirical **policy shock** strategy
   - Main **sufficient statistics** result: reduce policy evaluation to ...
     a) reduced-form **second moments** [variances, covariances, autocovariances, ...]
     b) **policy causal effects**
2. **Implementation**
   - *Empirics* alone are already enough to give **a)** and at least parts of **b)**
     Important methodological aside: how do we actually interpret regressions on policy shocks?
   - Residual role of *model structure* is extrapolation: supplement empirics to get rest of **b)**
3. **Application**
   Evaluation of fiscal-monetary interactions using sufficient statistics, from Angeletos-Lian-Wolf (2026).

Identification Results

Defining policy counterfactuals

How does the **systematic design** of fiscal & monetary policy shape the economy?

- We will study three particular versions of this question:

  Q1 **Shock propagation**: how is the propagation of a particular shock affected?
  E.g., how would oil shocks propagate in the absence of a central bank reaction?

  Q2 **Business-cycle statistics**: how different would the average business cycle look?
  E.g., how would strict adherence to a Taylor rule have shaped post-war cycles?

  Q3 **Alternative history**: how would a particular historical episode have unfolded?
  E.g., how would the post-COVID inflation have unfolded with earlier rate hikes?

- Next up: identification results for **Q1**, then extend to **Q2** - **Q3**
  Main references: McKay-Wolf (2023) and Caravello-McKay-Wolf (2026).

Identification Results

A Review of Sims-Zha

Sims-Zha

Illustration using **Q1**: **shock propagation** w/ counterfactual monetary policy

Concretely: how would shock $\boldsymbol{\varepsilon}_t$ have propagated if the rule had been $i_t = \tilde{\phi}_\pi \pi_t + \tilde{\phi}_y y_t$?

Sims-Zha

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- Sims-Zha is an empirical, model-free way to give an answer to **Q1**. Required **inputs**:
  1. IRFs to the shock ε_t under the baseline, prevailing policy rule

     $$\{\boldsymbol{i}^{\varepsilon}, \boldsymbol{\pi}^{\varepsilon}, \boldsymbol{y}^{\varepsilon}\}$$

     Each of these is a $T \times 1$ IRF vector. Can estimate using a single VAR/LP for the shock ε_t.
  2. IRFs to a monetary policy shock ν_t^m

     $$\{\boldsymbol{i}^{\nu}, \boldsymbol{\pi}^{\nu}, \boldsymbol{y}^{\nu}\}$$

     Each of these is a $T \times 1$ IRF vector. Can also estimate using a single VAR/LP for monetary shocks.

Sims-Zha

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- Note that these **inputs** can be recovered purely from data. How do they then get used?
    1. Choose a policy shock ν_0^m at date 0 to enforce the **counterfactual rule**:

$$i_0^\varepsilon + \nu_0^m \times i_0^\nu = \tilde{\phi}_\pi \times [\pi_0^\varepsilon + \nu_0^m \times \pi_0^\nu] + \tilde{\phi}_y \times [y_0^\varepsilon + \nu_0^m \times y_0^\nu]$$

This is one equation in one unknown.

Sims-Zha

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  2. Iteratively continue for all $t = 1, 2, \ldots$. For $t = 1$:

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3. Compute IRFs of everything to $\boldsymbol{\varepsilon}$ plus the *sequence* of policy shocks $\{\boldsymbol{\nu_0^m, \nu_1^m, \nu_2^m, \ldots}\}$.

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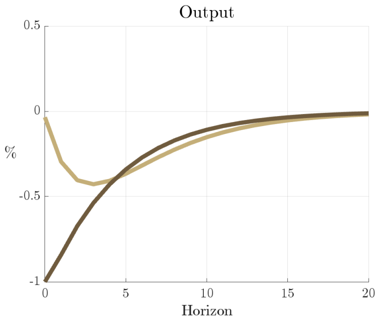
Next slide: illustration of what this method recovers when the true DGP is a standard macro model.

Interpreting the Sims-Zha estimand



Experiment: cost-push shock under **baseline rule** & **cnfct'l rule $i_t = \tilde{\phi}_\pi \pi_t + \tilde{\phi}_y y_t$**

These are the true IRFs in some linearized HANK model. For now the details don't matter.

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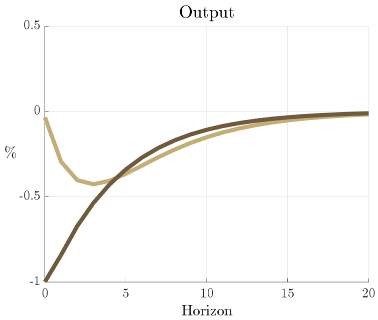
Q: What would an econometrician living in this model recover if she followed Sims-Zha?



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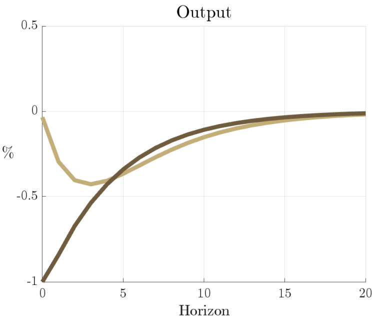

- Sims-Zha: use **ε IRFs under baseline policy rule** + **policy shock IRFs**

Strategy: enforce **counterfactual rule** using sequence of one-time **monetary shocks**

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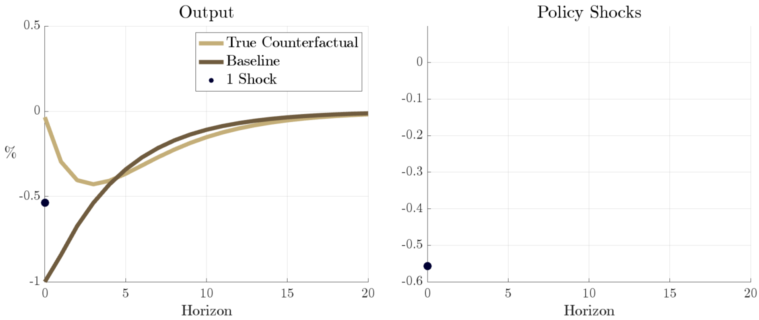

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- Set MP shocks to values $\{\nu_0^m, \nu_1^m, \nu_2^m, \ldots\}$ so that $\{i_t, \pi_t, y_t\}$ are related as

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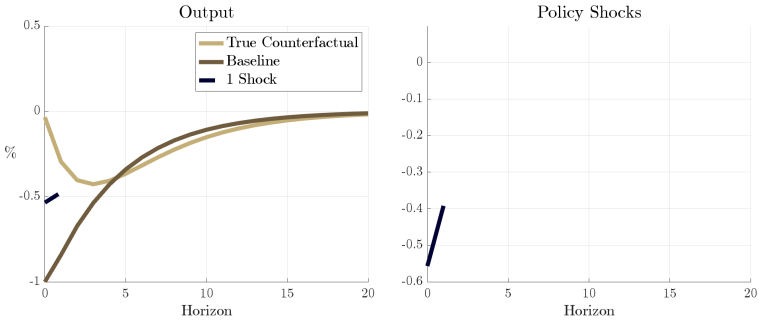

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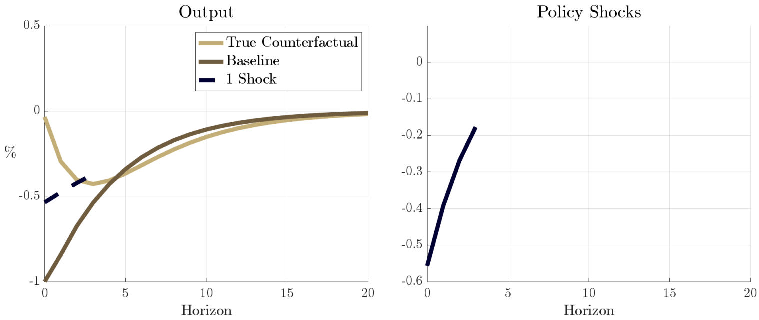

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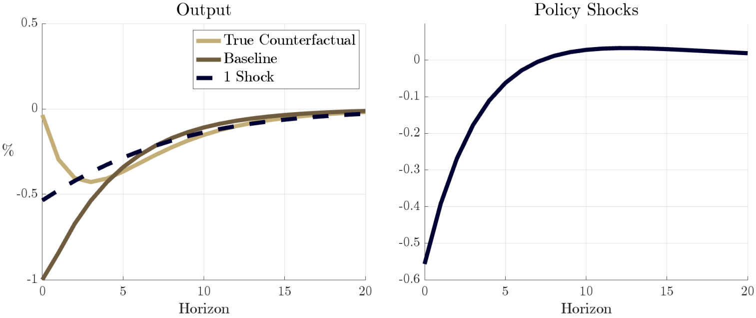

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Strategy: enforce **counterfactual rule** using sequence of one-time **monetary shocks**

Problem: at each t, private sector expects return to old rule from $t+1$ onwards, so $\neq$ true cnfct'l.

Identification Results

Generalizing Sims-Zha

Some preliminary intuition

Concern so far: implementation using one-off policy shocks misses **expectational effects**

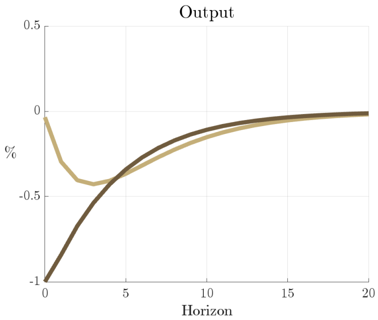
- Solution idea: use *multiple distinct* **policy shocks**
  - Concrete example: consider the monetary policy rule + shocks

$$i_t = f(\Omega_t) + \nu^m_{0,t} + \sum_{\ell=1}^{\infty} \nu^m_{\ell,t-\ell}$$

    where Ω_t is the date-t information set, $f(\bullet)$ is the systematic policy rule, and we suppose our econometrician is able to estimate the effects of the first n policy shocks
  - Now we have more degrees of freedom: we could enforce the counterfactual rule ex post in eq'm, but also in ex ante expectation for $n-1$ periods
- **Q**: does that get us closer to the truth? what happens as n gets large?

More graphical explorations

Q: What would the econometrician recover if she followed our generalization of Sims-Zha?



- Info: get IRFs to MP shocks

$$i_t = f(\Omega_t) + \nu^m_{0,t} + \nu^m_{1,t-1} + \dots$$

Insight: with **multiple monetary shocks** we can start to also match *expectations*

With n shocks we can enforce the rule today and in expectation for the next $n-1$ periods.

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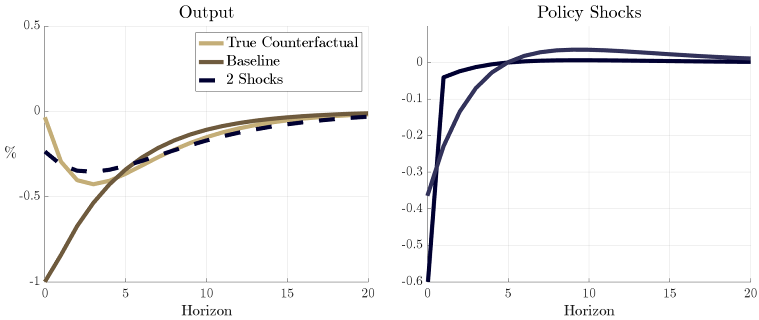

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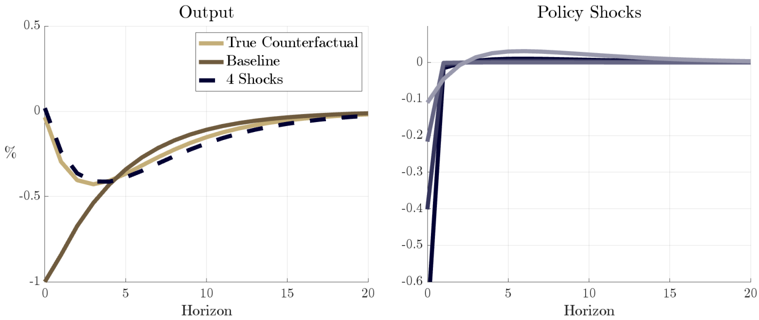

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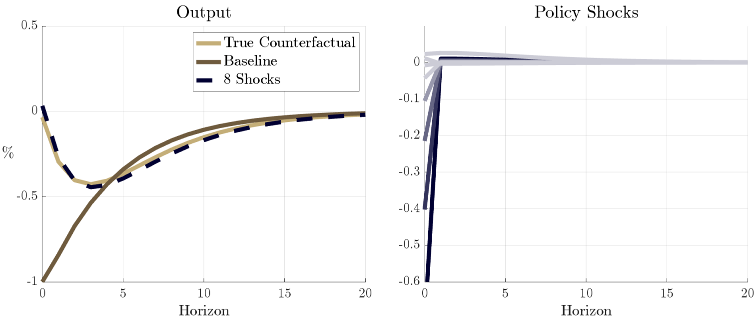

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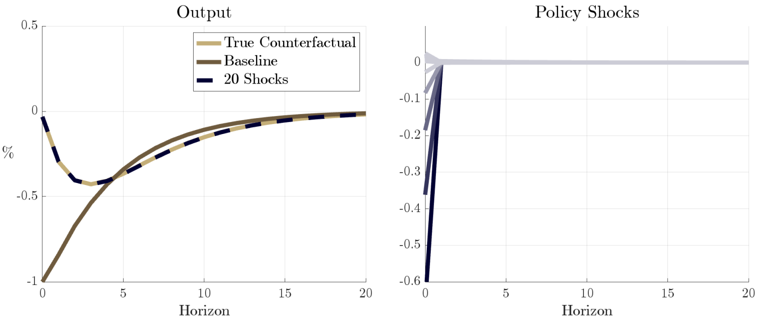

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Limit: with **many monetary shocks** we seem to recover the **true counterfactual**

Note: counterfactual rule is enforced *ex-post* and *ex-ante* using only date-0 shocks. No ex-post surprises.

Discussion and next steps

- **Expectation effects** were an obvious wedge between **truth** & **Sims-Zha estimand**
- Preceding figures: using more **policy shocks** to align expectations seemed to work
    - Specifically, we compared two experiments:
        1. Propagation of $\boldsymbol{\varepsilon}$ if new, counterfactual rule is followed
        2. Propagation of $\boldsymbol{\varepsilon}$ if old rule is followed, but it is subject to a vector of date-0 policy shocks so that new rule holds in expectation
    - They gave the same answer, so Lucas critique seemed to bite *only* via expectations.
      And so Sims-Zha $\neq$ true systematic policy counterfactual only because of ex-post surprises.
- Obvious **Q**: how general is that? what's the underlying economics?

Identification Results

Answering Q1

Towards a general identification result

- **Model** [perfect foresight = 1st-order perturbation w/ aggregate risk]

$$\mathcal{H}_x \boldsymbol{x} + \mathcal{H}_z \boldsymbol{z} + \mathcal{H}_\varepsilon \boldsymbol{\varepsilon} = \boldsymbol{0} \quad (1)$$

$$\mathcal{A}_x \boldsymbol{x} + \mathcal{A}_z \boldsymbol{z} + \boldsymbol{\nu} = \boldsymbol{0} \quad (2)$$

Boldface denotes time paths, e.g. $\boldsymbol{x} = (x_0, x_1, x_2, \ldots)'$. Solution of (1) - (2) = impulse responses.

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  - Illustrative example: three-equation NK model

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$$\begin{pmatrix} 1 & -1 & 0 & \dots \\ 0 & 1 & -1 & \dots \\ 0 & 0 & 1 & \dots \\ \vdots & \vdots & \vdots & \ddots \end{pmatrix} \boldsymbol{y} + \frac{1}{\gamma} \boldsymbol{i} - \frac{1}{\gamma} \begin{pmatrix} 0 & 1 & 0 & \dots \\ 0 & 0 & 1 & \dots \\ 0 & 0 & 0 & \dots \\ \vdots & \vdots & \vdots & \ddots \end{pmatrix} \boldsymbol{\pi} = \boldsymbol{0}$$

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$$-\boldsymbol{i} + \phi \boldsymbol{\pi} + \begin{pmatrix} \nu_0 & \nu_1 & \nu_2 & \dots \end{pmatrix}' = \boldsymbol{0}$$

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  - This environment has **two key features**:

    (i) Instrument sufficiency: private sector responds only to policy instrument, not rule *per se*
    Changing $\mathcal{A}_\bullet$'s does not affect $\mathcal{H}_\bullet$'s, only effect is *via* $\boldsymbol{z}$. Full Lucas critique discussion later.

    (ii) Linearity in aggregates: can restrict attention to expected values [not sign, size, state, ...]

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- **Equilibrium**: bounded $\{\boldsymbol{x}, \boldsymbol{z}\}$ that solves (1) - (2) given bounded $\{\boldsymbol{\varepsilon}, \boldsymbol{\nu}\}$
  - Assume that, under baseline rule, eq'm exists & is unique
  - Write IRFs to path $\boldsymbol{\varepsilon}$ under baseline rule – i.e., $\boldsymbol{\nu} = \boldsymbol{0}$ – as $\{\boldsymbol{x}(\boldsymbol{\varepsilon}), \boldsymbol{z}(\boldsymbol{\varepsilon})\}$

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- **Model** [perfect foresight = 1st-order perturbation w/ aggregate risk]

$$\mathcal{H}_x \boldsymbol{x} + \mathcal{H}_z \boldsymbol{z} + \mathcal{H}_\varepsilon \boldsymbol{\varepsilon} = \boldsymbol{0} \quad (1)$$

$$\mathcal{A}_x \boldsymbol{x} + \mathcal{A}_z \boldsymbol{z} + \boldsymbol{\nu} = \boldsymbol{0} \quad (2)$$

Boldface denotes time paths, e.g. $\boldsymbol{x} = (x_0, x_1, x_2, \dots)'$. Solution of (1) - (2) = impulse responses.

- **Equilibrium**: bounded $\{\boldsymbol{x}, \boldsymbol{z}\}$ that solves (1) - (2) given bounded $\{\boldsymbol{\varepsilon}, \boldsymbol{\nu}\}$
  - Assume that, under baseline rule, eq'm exists & is unique
  - Write IRFs to path $\boldsymbol{\varepsilon}$ under baseline rule – i.e., $\boldsymbol{\nu} = \boldsymbol{0}$ – as $\{\boldsymbol{x}(\boldsymbol{\varepsilon}), \boldsymbol{z}(\boldsymbol{\varepsilon})\}$
- **Object of interest**: IRFs $\{\tilde{\boldsymbol{x}}(\boldsymbol{\varepsilon}), \tilde{\boldsymbol{z}}(\boldsymbol{\varepsilon})\}$ if (2) is replaced by cnfct'l rule $\tilde{\mathcal{A}}_x \boldsymbol{x} + \tilde{\mathcal{A}}_z \boldsymbol{z} = \boldsymbol{0}$.

Dynamic causal effects

- Solving the system under the baseline rule gives

$$\begin{pmatrix} \boldsymbol{x} \\ \boldsymbol{z} \end{pmatrix} = \underbrace{- \begin{pmatrix} \mathcal{H}_x & \mathcal{H}_z \\ \mathcal{A}_x & \mathcal{A}_z \end{pmatrix}^{-1} \times \begin{pmatrix} \mathcal{H}_\varepsilon & 0 \\ 0 & I \end{pmatrix}}_{\equiv \boldsymbol{\Theta}} \times \begin{pmatrix} \boldsymbol{\varepsilon} \\ \boldsymbol{\nu} \end{pmatrix}, \quad \Theta \equiv \begin{pmatrix} \boldsymbol{\Theta}_{x,\varepsilon} & \boldsymbol{\Theta}_{x,\nu} \\ \boldsymbol{\Theta}_{z,\varepsilon} & \boldsymbol{\Theta}_{z,\nu} \end{pmatrix}$$

- Our graphical explorations relied on **two key inputs**:

  1. **Non-policy**: causal effects of $\boldsymbol{\varepsilon}$ under base rule $\{\boldsymbol{x}(\boldsymbol{\varepsilon}) = \boldsymbol{\Theta}_{x,\varepsilon} \times \boldsymbol{\varepsilon}, \boldsymbol{z}(\boldsymbol{\varepsilon}) = \boldsymbol{\Theta}_{z,\varepsilon} \times \boldsymbol{\varepsilon}\}$
  2. **Policy**: causal effects of all current *and news* shocks $\boldsymbol{\nu}$ to the base rule, $\{\boldsymbol{\Theta}_{x,\nu}, \boldsymbol{\Theta}_{z,\nu}\}$
     - This is multi-dimensional—each column gives the IRF to a particular policy shock
     - First column = contemp. shock, later columns = news shocks

individual **VARs/LPs** give $\{\boldsymbol{x}(\boldsymbol{\varepsilon}), \boldsymbol{z}(\boldsymbol{\varepsilon})\}$ & *(avg's of) columns* of $\{\boldsymbol{\Theta}_{x,\nu}, \boldsymbol{\Theta}_{z,\nu}\}$

From policy shocks to counterfactuals

Proposition

For any $\{\tilde{A}_x, \tilde{A}_z\}$ that induces a unique eq'm, we can recover the counterfactuals $\tilde{\boldsymbol{x}}(\boldsymbol{\varepsilon})$ and $\tilde{\boldsymbol{z}}(\boldsymbol{\varepsilon})$ as the impulse responses under the baseline rule to the shocks $\{\boldsymbol{\varepsilon}, \tilde{\boldsymbol{\nu}}\}$, where $\tilde{\boldsymbol{\nu}}$ solves

$$\tilde{\mathcal{A}}_x \left(\boldsymbol{x}(\boldsymbol{\varepsilon}) + \Theta_{x,\nu} \times \tilde{\boldsymbol{\nu}}\right) + \tilde{\mathcal{A}}_z \left(\boldsymbol{z}(\boldsymbol{\varepsilon}) + \Theta_{z,\nu} \times \tilde{\boldsymbol{\nu}}\right) = \boldsymbol{0} \tag{3}$$

In words: compute IRFs under the baseline rule $\boldsymbol{\varepsilon}$ and an artificial date-0 policy shock vector $\tilde{\boldsymbol{\nu}}$, chosen so that cnfct'l rule holds following $\{\boldsymbol{\varepsilon}, \tilde{\boldsymbol{\nu}}\}$. Note how this is the date-0, vector-of-shocks generalization of Sims-Zha.

- **Intuition**: private sector only cares about (expected) instrument path
  - Select policy shocks to enforce cnfct'l rule. Then same instrument $\rightarrow$ same outcomes.
  - Aside: if only first entry of $\tilde{\boldsymbol{\nu}}$ is non-zero, then this is Sims-Zha!

For the complete proof see McKay-Wolf (2023). There also discussion of eq'm existence/uniqueness.

Identification Results

Scope & Limitations

Discussion

- Results apply to a large **class of macro models**. Where's the **Lucas critique**?
  Recall key asn's: instrument sufficiency & linearity. Consistent with typical RANK, HANK, ...
  - Traditional formulation is in state-space:

    $$\begin{aligned} s_t &= A(\bullet)s_{t-1} + B(\bullet)e_t \\ y_t &= C(\bullet)s_{t-1} + D(\bullet)e_t \end{aligned}$$

    Famous Hansen-Sargent cross-equation restrictions: $\{A, B, C, D\}$ all depend on policy rule
  - Here: policy invariance is at a more primitive level, for the $\mathcal{H}(\bullet)$'s
- There are still some meaningful limitations:
  1. Instrument sufficiency fails in some environments, e.g. in signal extraction problems
     E.g.: in Lucas island economy rule matters above and beyond nominal demand growth
  2. Linearity is for practical feasibility. Restricts to rule changes that don't affect steady state.

Identification Results

Answering Q2 & Q3

Extension to other counterfactuals

- Can we extend this logic to our other two counterfactuals?
  - Suppose that economy is subject to vector of shocks e_t, giving the SVMA(∞)

$$y_t = \sum_{\ell=0}^{\infty} \Theta_\ell e_{t-\ell}, \quad \text{Var}(e_t) = I \tag{4}$$

    where the y_t's are observable macroeconomic outcomes, $y_t = (x_t', z_t')'$

    For each shock, the IRFs Θ_ℓ come from a linear perfect-foresight system like (1) - (2).
  - Contemplate changing the policy rule to $\tilde{A}_x \boldsymbol{x} + \tilde{A}_z \boldsymbol{z} = \boldsymbol{0}$.

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    Q2 **Business-cycle statistics**: cnfct'l IRFs $\tilde{\Theta}_\ell$ give cnfct'l autocovariance function

$$\tilde{\Gamma}_y(\ell) = \sum_{m=0}^{\infty} \tilde{\Theta}_{m+\ell} \tilde{\Theta}_m'$$

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    Q3 **Alternative history**: cnfct'l outcomes at a particular date t would be [ignoring initial cond's]

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$$\tilde{y}_t = \sum_{\ell=0}^{\infty} \tilde{\Theta}_\ell e_{t-\ell}$$

  - Immediate if we can observe e_t, just proceed shock-by-shock. But can we relax that?

Extension to other counterfactuals

Proposition

Suppose that the SVMA(∞) process (4) is ***invertible****. Then a) y_t and its autocovariance f'n $\Gamma_y(\ell)$ and b) policy effects Θ_ν suffice to construct the second and third counterfactuals.*

- Key idea: **invertibility** substitutes for knowledge of the individual shocks $\boldsymbol{e_t}$. Why?
    - By a), we know the Wold representation of y_t. Write it as $y_t = \sum_{\ell=0}^{\infty} \Psi_\ell u_{t-\ell}$.
    - Using b), apply McKay-Wolf (2023) to the Wold innovation IRFs to get the cnfctl's:

$$\sum_{\ell=0}^{\infty} \tilde{\Psi}_\ell u_{t-\ell} = \sum_{\ell=0}^{\infty} \tilde{\Theta}_\ell Q' Q e_{t-\ell} = \sum_{\ell=0}^{\infty} \tilde{\Theta}_\ell e_{t-\ell} = \tilde{y}_t$$

      where we use that $u_t = Q\varepsilon_t$ and $\tilde{\Psi}_\ell = \tilde{\Theta}_\ell Q'$, by invertibility.

- Intuition: predictions based on 1-1 function of e_t = predictions based on the true e_t.

Non-invertibility in practice

Invertibility is a strong assumption. What happens when it is violated?

Visual illustration using Smets-Wouters model as DGP. Implement proposition with different info sets.

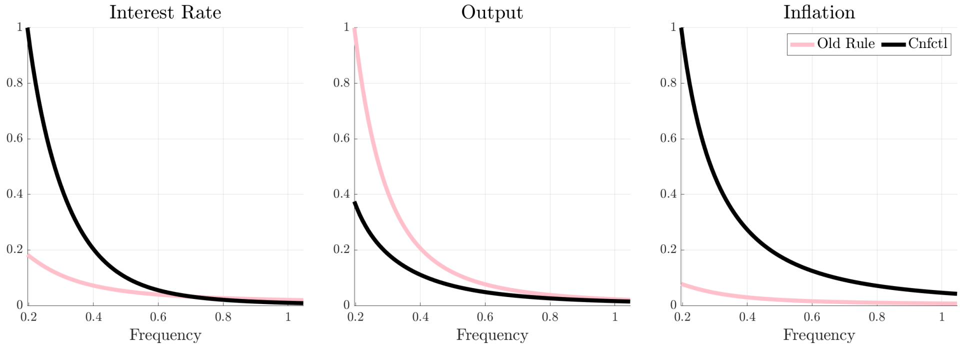

Figure shows baseline and counterfactual (true & predicted) spectral densities.

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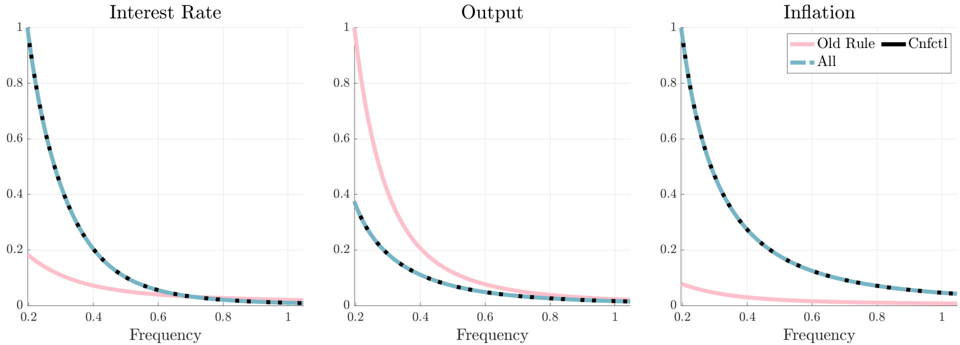

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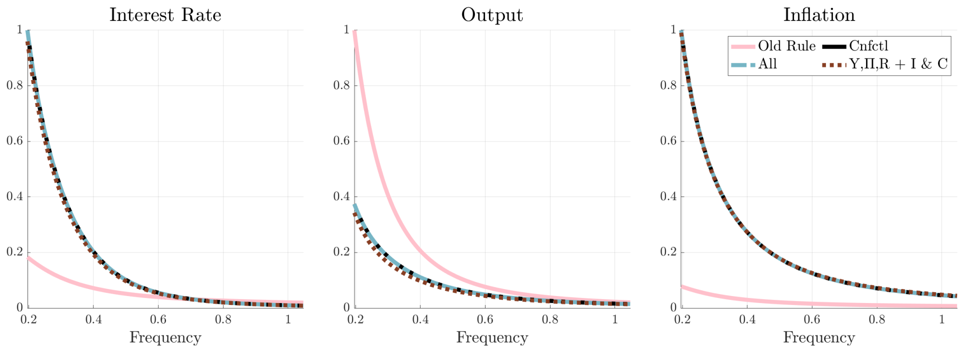

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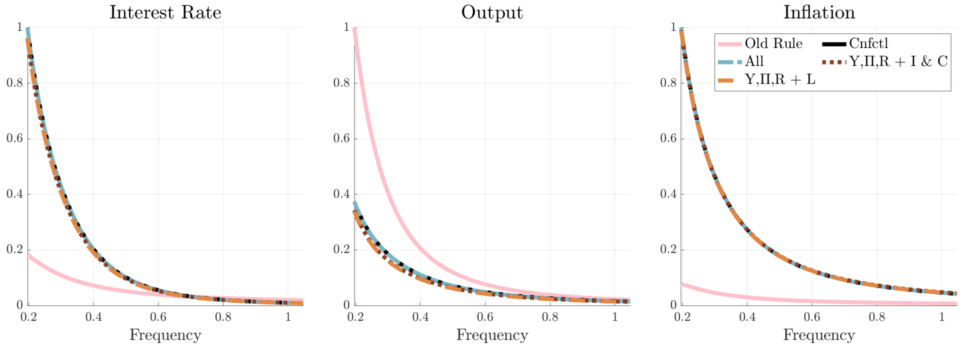

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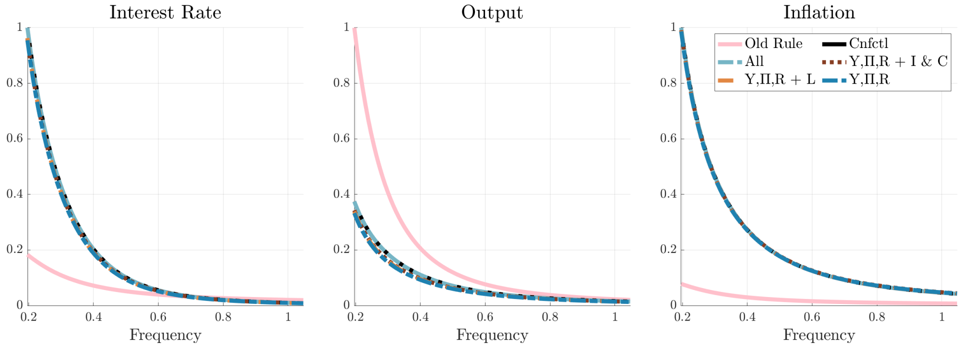

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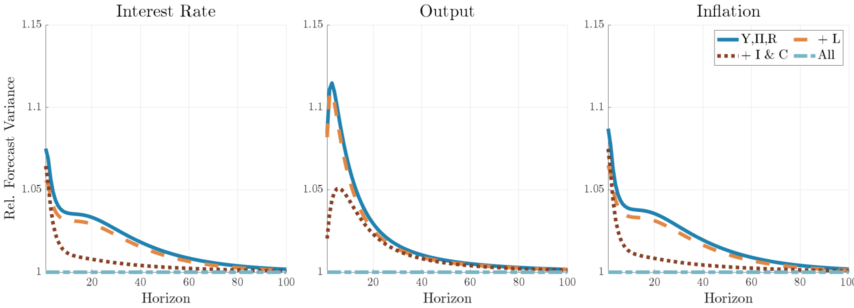
Non-invertibility in practice

Can get close to the truth even when far from **invertibility**. Why?

Key intuition: proof works as long as fcst's based on $\{y_{t-\ell}\}_{\ell=0}^{\infty}$ = fcst's based on $\{e_{t-\ell}\}_{\ell=0}^{\infty}$.



Shows relative forecast uncertainty. Predictions were accurate because addt'l observables don't help much.

Aside: note that invertibility here plays a very different role compared to our identification discussion.

Implementation

Implementation

How can we leverage these **identification results** in practice?

- What we need vs. what we have
  - Focus on Q2 & Q3. Need: a) **autocovariance function** & b) **policy causal effects**
  - What do we have?
    a) Can get **autocovariance function** easily, using reduced-form time series tools
    b) Use **policy shock** VARs/LPs to learn about Θ_ν
- Next few slides: focus on b)
  1. What exactly do policy shock regressions give us? instrument space vs. shock space
  2. What – if anything – can we do if we don't know all of Θ_ν?
  3. Supplementing the data: empirics + structure hybrid to learn about Θ_ν

Implementation

Interpreting Policy Shock Regressions

Instrument sufficiency: shock space vs. instrument space

- To connect with empirics, let's begin by studying the role of the initial rule $\mathcal{A}_x, \mathcal{A}_z$
  - Θ_ν is defined relative to that rule. But argument would also work if we observed shock effects relative to a different rule. Rule is the "basis" w.r.t. which causal effects are defined.
  - What if the rule was $\mathcal{A}_x = \mathbf{0}$, $\mathcal{A}_z = -I$? Then shocks ν = policy instrument z. From (1):

$$\boldsymbol{x} \;=\; \underbrace{-\mathcal{H}_x^{-1}\mathcal{H}_z}_{\equiv \Theta_{x,z}} \times \boldsymbol{z}$$

    $\Theta_{x,z}$ gives the causal effects of any instrument *path* on macro outcomes. The basis is now not an arbitrary rule, but the policy instrument itself. **Shock space** vs. **instrument space**.

- Next two slides:
  1. Quick illustration of the **basis change** using the familiar 3-equation NK model
  2. Using the **instrument space** to interpret **policy shock** empirical evidence

NK model illustration

- Consider a simple NK model with iid shocks:

$$y_t = -\frac{1}{\gamma}(i_t - \underbrace{\mathbb{E}_t \pi_{t+1}}_{=0}) + \underbrace{\mathbb{E}_t y_{t+1}}_{=0}, \quad \pi_t = \kappa y_t + \beta \underbrace{\mathbb{E}_t \pi_{t+1}}_{=0}, \quad i_t = \phi_\pi \pi_t + \nu_t$$

- Solving for the mapping to endogenous outcomes:
  - In shock space:

$$y_t = -\frac{1}{\gamma + \phi_\pi \kappa}\nu_t, \quad \pi_t = -\frac{\kappa}{\gamma + \phi_\pi \kappa}\nu_t, \quad i_t = \frac{\gamma}{\gamma + \phi_\pi \kappa}\nu_t$$

  - In instrument space:

$$y_t = -\frac{1}{\gamma} i_t, \quad \pi_t = -\frac{\kappa}{\gamma} i_t$$

Note how the instrument space mapping depends only on the private-sector block, not the policy rule.

Interpreting empirical evidence

- What do **LP/VAR** strategies for **policy shocks** actually recover?
  - Policy is multi-dimensional in practice, and thus so are [presumably] policy shocks. E.g.,

    $$i_t = f(\Omega_t) + \nu^m_{0,t} + \nu^m_{1,t-1} + \nu^m_{2,t-2} + \dots$$

    Sometimes revision to short end of the yield curve, sometimes to long end.
  - A valid **policy IV** w_t revises policy, but does not correlate w/ any other macro shocks:

    $$w_t = \alpha_0 \nu^m_{0,t} + \alpha_1 \nu^m_{1,t} + \alpha_2 \nu^m_{2,t} + \dots + \text{noise}$$

    LPs/VARs then simply report regressions of macro outcomes on w_t.
- How should we interpret that **estimand**? Easiest in **instrument space**:
  1. Regress the policy instrument z_t on the IV w_t. That gives the treatment path $\boldsymbol{z}$.
  2. Regress outcomes x_t on w_t. That gives the associated treatment causal effects $\Theta_{\boldsymbol{x},\boldsymbol{z}} \times \boldsymbol{z}$.

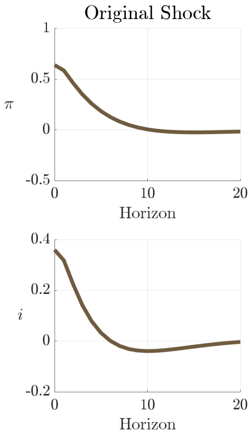
Implementation

Do We Need All of $\Theta_{x,z}$?

In practice a few policy shocks *may* suffice

Q: How would this **forecast** have changed in the absence of a monetary reaction?

Can interpret this IRF as specific shock (for Q1), Wold innovation, or just forecast (for Q2 & Q3).



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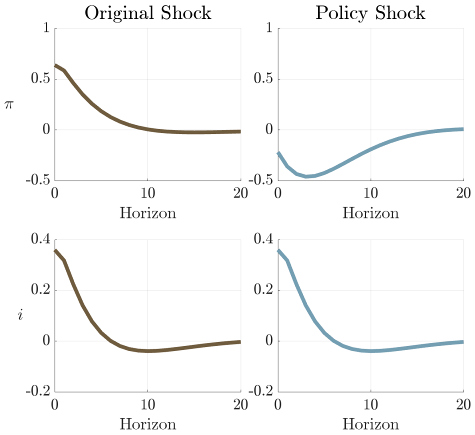

- ID result: find a **monetary shock** inducing the same rate response
  $\Rightarrow$ move $\mathbb{E}_0(i_t)$ just like the **forecast**

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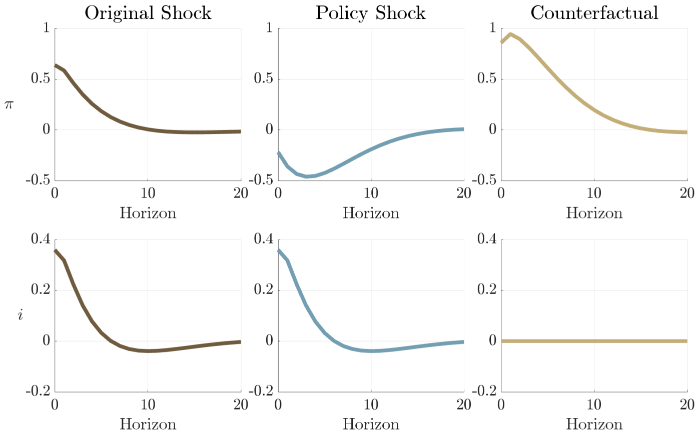

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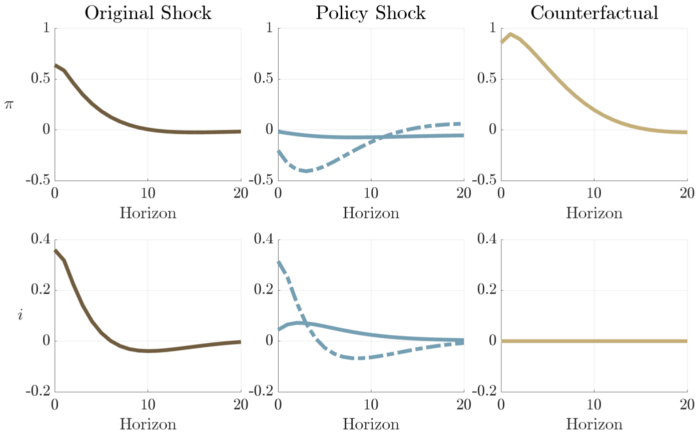

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  [Same result for combo of MP shocks.]

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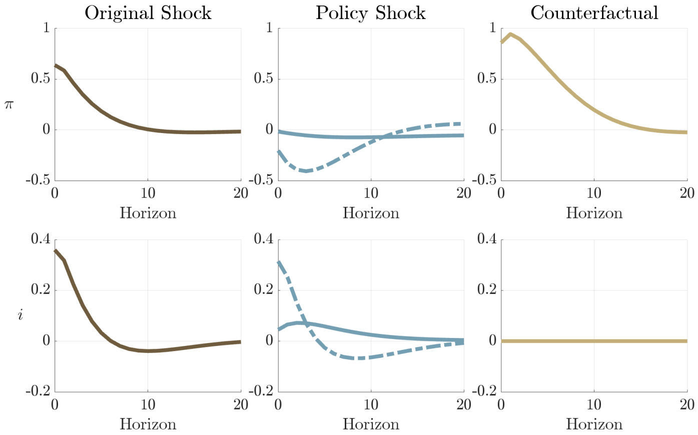

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  $\Rightarrow$ move $\mathbb{E}_0(i_t)$ just like the **forecast**
- $\Longrightarrow$ subtract **(2)** from **(1)** to get **(3)**
  [Same result for combo of MP shocks.]
- Thus: for any given application, a small **# of shocks** may suffice to enforce the desired **cnfct'l**
  In practice: construct best approximation. Is it accurate enough?

Implementation

Structural Models

Models as extrapolation devices

What if the counterfactual of interest is not spanned by **policy shock** evidence?

- Obvious solution: use model structure to **extrapolate**
  - Suppose empirics give $\theta_{x,z} \subset \Theta_{x,z}$. Build model matching this evidence, then extrapolate.
  - How much model structure do we need for this?

    $\rightarrow$ Need to specify $\mathcal{H}_x$ and $\mathcal{H}_z$ – the non-policy block

    $\rightarrow$ Policy rule $\mathcal{A}_\bullet$ or non-policy shocks $\boldsymbol{\varepsilon}$ instead don't matter at all
    Sidesteps concerns about "dubiously structural" shocks. Just not needed for extrapolation.

  It's just impulse response matching! This + **autocovariance function** is all we need.

- We will illustrate this approach through the application in Angeletos-Lian-Wolf (2026)

Re-interpreting full structural approaches

What about conventional full-blown **likelihood-based approaches**?

E.g., as in Smets-Wouters (2007) or Bocola-Dovis-Jørgensen-Kirpalani (2025).

- Through the lens of the **sufficient statistics** result:
    - **Second moments** matched [more or less] by construction, no direct discipline on **policy causal effects** [but often reported and compared with evidence]
    - So is it a problem if the shocks are "dubiously structural"? Only if:
        1. Having incorrect shocks distorts inference on **policy causal effects**
        2. We care about the nature of the shocks *per se*, e.g., for welfare reasons
- vs. just using a model for **extrapolation**: familiar efficiency vs. robustness trade-off
    - Previous slide: need to specify less, in particular can be silent on hidden shock processes
    - But: if everything is correctly specified, then full-information approach is more efficient

Application

Angeletos-Lian-Wolf (2026)

Q: Does **slow fiscal** adjustment help or hurt an inflation-targeting central bank?

- Angeletos-Lian-Wolf (2026) show that the answer is ambiguous. Main theoretical results:
    1. *Positively*, slow fiscal adjustment meaningfully boosts output & inflation
       Forward guidance-like mechanism: dynamically amplify static automatic stabilizers.
    2. *Normatively*, stabilization may or may not be desirable for the central bank
       Depends on strength of automatic stabilizers, shock mix that hits the economy, tax distortions, ...
- Thus inherently **quantitative**. How can proceed?
    - Conventional strategy: estimate structural general equilibrium model, evaluate central bank loss under different assumptions on fiscal policy
    - Now instead: try to leverage our **sufficient statistics** results

Application

Measurement Strategy

The policy counterfactual problem

- Consider a **central bank** with reduced-form objective function

$$\mathcal{L}_{CB} = \frac{1}{2}\mathbb{E}\left[\sum_{t=0}^{\infty}\beta^t\left\{\lambda_\pi \pi_t^2 + \lambda_y y_t^2 + \lambda_i i_t^2\right\}\right] \tag{5}$$

First two terms are standard dual mandate objective, third term is concern for rate stability.

- Next turn to **fiscal policy**:
  - Consider fiscal rule that maps $\{\pi_t, y_t, i_t\}$ into gov't debt [equivalently taxes]:

$$\boldsymbol{d} = \mathcal{D}_y \boldsymbol{y} + \mathcal{D}_\pi \boldsymbol{\pi} + \mathcal{D}_i \boldsymbol{i} \tag{6}$$

  - Can write Leeper (1991)-style rules in this way. Parameterize debt-to-tax feedback by $\tau_d \in (0,1)$ = fiscal adjustment speed. (6) gives $\{\mathcal{A}_x, \mathcal{A}_z\}$ in the previous notation.
- **Objective**: compute eq'm process for $\{\pi_t, y_t, i_t\}$ – and thus also the central bank loss – when fiscal policy follows (6) and monetary policy minimizes (5)

Evaluating the central bank loss

This fits (almost) exactly into our policy evaluation structure from before:

- Need two **inputs**:
  a) **Autocovariance function** for $\{y_t, \pi_t, i_t, d_t\}$, get through direct estimation
  b) **Causal effects** of changes in two policy instruments: interest rates and taxes/debt
     Get through model of fiscal/monetary propagation, consistent with empirical shock evidence.

- **Implementation details** – two steps:
  1. Previous slide is the cnfct'l fiscal rule $\{\mathcal{A}_x^f, \mathcal{A}_z^f\}$. What's the monetary rule $\{\mathcal{A}_x^m, \mathcal{A}_z^m\}$?
     → Denote monetary policy causal effects given the τ_d rule by $\Theta_{\bullet,m}^{\tau_d}$ for all $\{\pi, y, i, d\}$
     → Let $W = \text{diag}(1, \beta, \beta^2, \dots)$. Then minimizing (5) gives an implicit targeting rule with

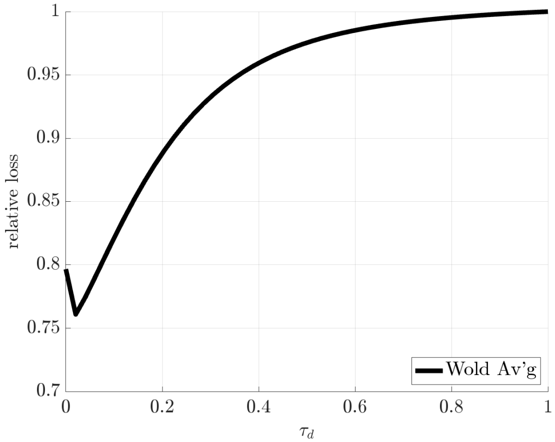
$$\mathcal{A}_\pi^m = \lambda_\pi(\Theta_{\pi,m}^{\tau_d})'W, \quad \mathcal{A}_y^m = \lambda_y(\Theta_{y,m}^{\tau_d})'W, \quad \mathcal{A}_i^m = \lambda_i(\Theta_{i,m}^{\tau_d})'W, \quad \mathcal{A}_d^m = \mathbf{0}.$$

  2. Now proceed as before: two instruments, set through cnfct'l rules $\{\mathcal{A}_x^f, \mathcal{A}_z^f\}$ & $\{\mathcal{A}_x^m, \mathcal{A}_z^m\}$

Application

Results

Very slow fiscal adjustment appears desirable

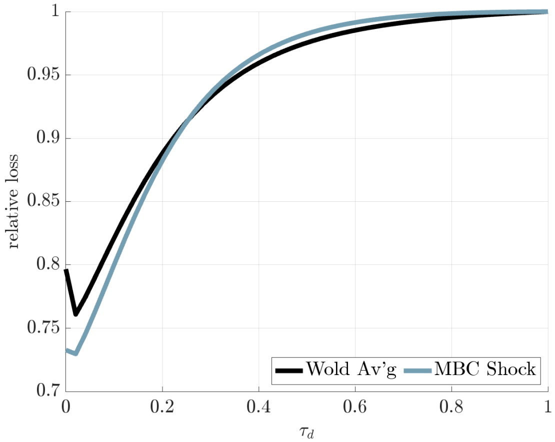


- Main result: **very small τ_d** desirable

  Minimal loss for debt half-life of around 8 years.

  - Baseline Wold: loss largely monotone

Very slow fiscal adjustment appears desirable



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  - Even steeper for "main business-cycle shock" = demand-type shock

    And this shock dominates second moments.

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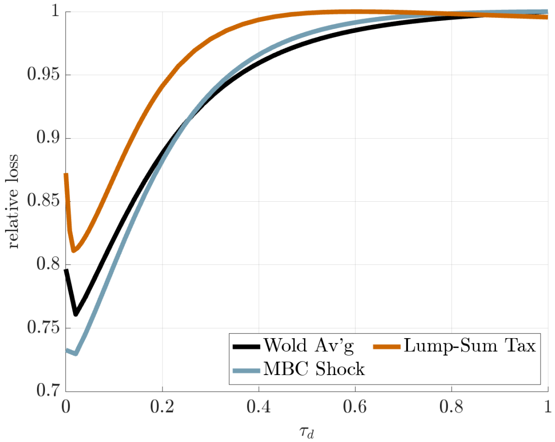

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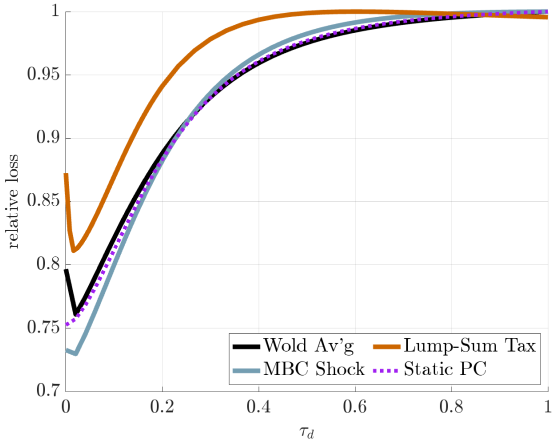
  Minimal loss for debt half-life of around 8 years.

  - Baseline Wold: loss largely monotone
  - Even steeper for "main business-cycle shock" = demand-type shock

    And this shock dominates second moments.
  - Distortionary taxes play secondary role

Very slow fiscal adjustment appears desirable



- Main result: **very small τ_d** desirable

  Minimal loss for debt half-life of around 8 years.

  - Baseline Wold: loss largely monotone
  - Even steeper for "main business-cycle shock" = demand-type shock

    And this shock dominates second moments.
  - Distortionary taxes play secondary role

Further robustness: NKPC + different objective.

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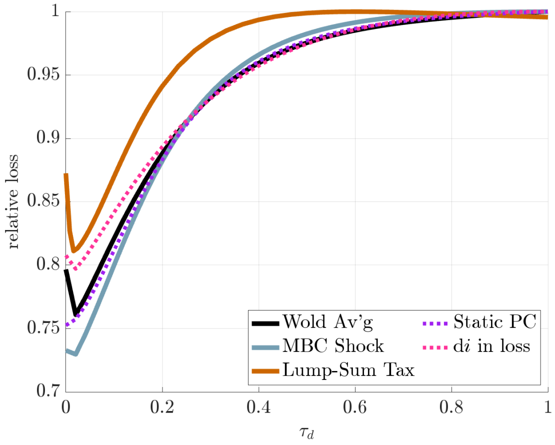

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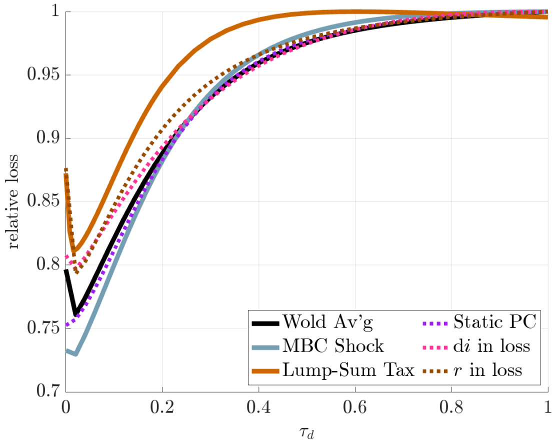

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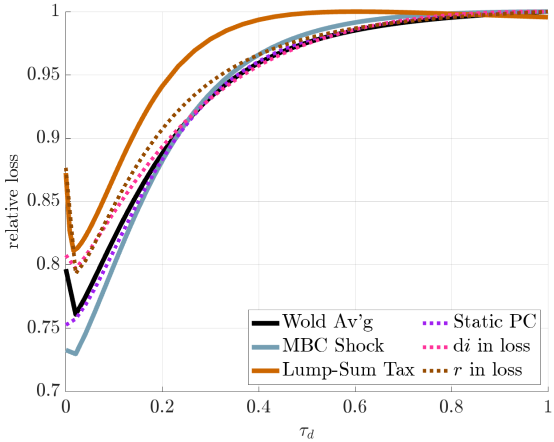

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- Overall: result driven by **two inputs**
  a) Business cycles look **demand-driven**
  b) Fiscal adjustment delays are **stabilizing**

Takeaways

Policy evaluation takeaways

- This conclues my block, on **policy evaluation**. Main conceptual lessons:
  1. Identification results: cond's such that **policy rules** $=$ **policy shocks**
     "Instrument sufficiency": irrelevant *why* instrument is set to a given value, whether rule or shock.
  2. **Instrument space** to connect with empirical evidence: think of policy as high-dimensional treatment. Regressions on policy shocks isolate a particular treatment path.
  3. Key role of model structure: policy causal effect **extrapolation**
- Illustration for **fiscal-monetary interactions**: optimal monetary policy *given* fiscal rule
  Reduce results to **autocovariance f'n** $+$ **policy causal effects**. Transparent measurement exercise.

Thank you!

Model examples

1. **HANK model**
   - Generalized IS curve
   $$\boldsymbol{c} = \mathcal{C}(\boldsymbol{y}, \boldsymbol{\pi}, \boldsymbol{i}, \boldsymbol{\varepsilon}^d) = \mathcal{C}_y \boldsymbol{y} + \mathcal{C}_\pi \boldsymbol{\pi} + \mathcal{C}_i \boldsymbol{i} + \boldsymbol{\varepsilon}^d$$
2. **Behavioral models**
   - Various behavioral frictions correspond to simple adjustments of the matrices in $\mathcal{H}$
   - Example: sticky information in consumption decisions
   $$\tilde{\mathcal{C}}_p(t,s) = \sum_{q=1}^{\min(t,s)} [\mathcal{E}(q,s) - \mathcal{E}(q-1,s)] \mathcal{C}_p(t-q+1, s-q+1)$$
   where $\mathcal{E}(0,s) = 0$ and
   $$\mathcal{E} = \begin{pmatrix} 1 & 1-\theta & 1-\theta & \dots \\ 1 & 1 & 1-\theta^2 & \dots \\ 1 & 1 & 1 & \dots \\ \vdots & \vdots & \vdots & \ddots \end{pmatrix}$$

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