Evaluating policy makers' performance a reaction function test

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Introduction

- How can we evaluate and compare the performance of policy makers after their term in office?

Naive approach

Compare realized outcomes, e.g,

	Bernanke	Yellen	Powell
$(\pi - 2)^2$	0.29	0.06	2.77
$(\text{output gap})^2$	10.37	5.16	10.82

- but PMs faced different initial conditions, different shocks, different "environments", etc ...

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- but PMs faced different initial conditions, different shocks, different "environments", etc ...
- Yellen was "lucky" compared to Bernanke: good shocks vs bad shocks
- Powell faced bad shocks (covid) *and* a different economy (e.g., lockdowns)

Ideal experiment

Create controlled environment for all policy makers with

- same initial conditions
- same underlying economic structure
- same sequence of shocks...

then compare their average performance

As a first step ...

- Same sequence of non-policy shocks does not happen ...
- Instead, project macro objectives Y on some non-policy shocks ξ and evaluate performance in that space
- Compares the same *average* scenario
- Equalizes initial conditions and the type of shocks

Still leaves open ...

- Policy makers face different environments ...
- pending environment it is easier/harder to offset shocks ...
- need to know what PM **could have done** given environment

This paper (1)

1. Set-up
    - Summarize all actions of PM in reaction function
    - Aggregate economic variables Y in some loss function
2. Measure distance to optimal reaction function in the direction of response to (some) non-policy shocks
    - Conditions on non-policy shocks (as above)
    - Distance is comparable across environments
3. Compare policy makers based on distance to optimality

This paper (2)

- Boils down to
  - Compute rescaled gradient of loss function with respect to PM's *response to non-policy shocks*
  - Gradient depends on:

    (i) impulse response of Y to non-policy shocks
    (ii) impulse response of Y to policy shocks
- IRs can be estimated without having to specify explicitly reaction function or structural economic model

Main result

1. Under optimal reaction function

$$\mathcal{R}_i'\Gamma_k = 0 \qquad \text{for any} \quad i, k$$

2. Distance reaction function to optimal response to ξ_k

$$\tau^* = -(\mathcal{R}_i'\mathcal{R}_i)^{-1}\mathcal{R}_i'\Gamma_k$$

where

- $\mathcal{R}_i$ IRF of ith policy shock on objectives under ϕ
- Γ_k IRF of kth non-policy shock on objectives under ϕ

Holds in broad class of forward looking macro models; LREMs, time-varying parameters, state dependence, etc...

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  $\rightarrow$ we emphasize the importance of examining performance *conditional on* same non-policy shocks

Some literature on policy evaluation

- Fair (1978) naive (unconditional) approach is not appropriate
- Blinder & Watson (2016) *project out* contribution of non-policy shocks
  $\rightarrow$ we emphasize the importance of examining performance *conditional on* same non-policy shocks
- Structural modeling approach: evaluate the reaction function in the context of a model (e.g. Gali & Gertler 2007 and many others...)
- Or simpler, estimate a simple policy rule and verify whether Taylor principle holds (e.g. Clarida, Gali, Gertler 1999, Bullard, 2022, and many others...)

A concern ...

- Reaction function are complex
  - "Even with many such modifications, it is difficult to see how...algebraic policy rules could be sufficiently encompassing" **Taylor, 1993**
  - "Taylor-type rules are too restrictive and mechanical, not taking into account all relevant information, and the ability to handle the complex and changing situations faced by policy makers". **Svensson, 2017**

$\Rightarrow$ there exists a reaction function, but we do not know it

This talk

1. Explain intuition in SVAR
2. Illustrate how it generalizes to forward looking models
3. Empirical results for US monetary policy

(i) SVAR model

Set up under SVAR

- Variables $Y_t \in \mathbb{R}^K$ in loss function

$$\mathcal{L}_t = Y_t' Y_t \ ,$$

- Economy for $X_t = (Y_t', W_t', p_t)'$ is given by

$$A(L) X_t = e_t \ , \qquad e_t = (\xi_t, v_t', \varepsilon_t)'$$

  where p_t scalar policy instrument

  - ξ_t scalar non-policy shock
  - v_t vector unidentified shocks
  - ε_t scalar policy shock

Details

Policy equation

$$a_{pp}p_t + a_{py}Y_t + a_{pw}W_t = a_{px}X_{t-1:t-q} + \varepsilon_t$$

- reaction function $\phi = \{a_{pp}, a_{py}, a_{pw}, a_{px}\}$
- environment $\mathcal{A} = \{\text{all other coefficients}\}$
- To make it interesting suppose ...
    - can only identify policy shock ε_t and non-policy shock $\zeta_t \rightarrow$ cannot estimate ϕ

Optimal reaction functions

- Φ set of reaction functions SVAR is invertible, i.e. $\phi \in \Phi$

$$Y_t = \Gamma(L)\xi_t + \mathcal{R}(L)\varepsilon_t + D(L)v_t$$

- Optimal reaction functions:

$$\phi^{\mathrm{opt}} \in \arg\min_{\phi \in \Phi} \mathbb{E}\mathcal{L}_t \quad \text{s.t.} \quad \text{SVAR}$$

- for presentation: ϕ^{opt} is unique

Questions

Q1: Suppose a PM uses ϕ^0, is $\phi^0 = \phi^{\text{opt}}$?

Q2: How far is ϕ^0 from ϕ^{opt} in direction of response to ξ_t?

Q3: How do we compare PMs with $\phi^1, \ldots, \phi^p$?

A thought experiment

- What if PM responded τ more to ξ_t, i.e.

$$a^0_{pp} p_t + a^0_{py} Y_t + a^0_{pw} W_t = a^0_{px} X_{t-1:t-q} + \tau \xi_t + \varepsilon_t$$

- If ϕ^0 optimal, there is no $\tau \neq 0$ that lowers $\mathbb{E}\mathcal{L}_t$

Modified VMA

Under thought experiment VMA for Y_t becomes

$$Y_t = \left(\Gamma^0(L) + \tau\mathcal{R}^0(L)\right)\xi_t + \mathcal{R}^0(L)\varepsilon_t + D(L)v_t$$

To see this note that

$$A^0(L)X_t = \begin{bmatrix} \xi_t \\ v_t \\ 0 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}\epsilon_t + \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}\tau\xi_t$$

- $\tau\xi_t$ is just another innovation to p_t
- equilibrium effect on Y_t is $\mathcal{R}^0(L)$

Score test

Use

$$Y_t = \left(\Gamma^0(L) + \tau\mathcal{R}^0(L)\right)\xi_t + \mathcal{R}^0(L)\varepsilon_t + D(L)v_t$$

to compute gradient

$$\begin{aligned} \nabla_\tau \mathbb{E}\mathcal{L}_t\big|_{\tau=0} &= \sigma_\xi^2 \mathcal{R}^{0'}(\Gamma^0 + \mathcal{R}^0\tau)\Big|_{\tau=0} \\ &= \sigma_\xi^2 \mathcal{R}^{0'}\Gamma^0 \end{aligned}$$

As gradient $= 0$ if $\phi^0 = \phi^{\text{opt}}$ we get

$$\mathcal{R}^{0'}\Gamma^0 \neq 0 \qquad \Longrightarrow \qquad \phi^0 \neq \phi^{\text{opt}}$$

Shades of intuition (1)

Two inputs

1. Γ^0 captures effect of non-policy shock ξ_t under ϕ^0
2. $\mathcal{R}^0$ (under ϕ^0)
   a. captures effect of policy shock
   b. also proportional to effect of PM responding differently to ξ_t

Combining

- Use $\mathcal{R}^0$ to offset effect of non-policy shock Γ^0
- At optimum $\mathcal{R}^{0'}\Gamma^0 = 0$, nothing can be done to offset Γ^0

Shades of intuition (2)

1. Compute OPP statistic of BM (2021):

$$\delta_t^* = -(\mathcal{R}^{0\prime}\mathcal{R}^0)^{-1}\mathcal{R}^{0\prime}\mathbb{E}_t Y_{t:t+\infty}$$

   measures distance of policy instrument to optimality at time t

2. How much of the time t distances can be explained by ξ_t

$$\delta_t^* = \beta \times \xi_t + \text{error}$$

   If response to ξ_t was optimal $\beta = 0$ implies $\mathcal{R}^{0\prime}\Gamma^0 = 0$

Both work...

$$\mathcal{R}^{0\prime}\Gamma^{0} = 0$$

Two routes

- What PM did vs what could have been done
- How much of PM's optimization failures can be explained on average by (some) non-policy shocks

Computing the distance

Additionally, we can solve

$$\nabla_\tau \mathbb{E}\mathcal{L}_t = \sigma_\xi^2 \mathcal{R}^{0\prime}(\Gamma^0 + \mathcal{R}^0 \tau) = 0$$

to get

$$\tau^* = -(\mathcal{R}^{0\prime}\mathcal{R}^0)^{-1}\mathcal{R}^{0\prime}\Gamma^0$$

- τ^* measures the distance of ϕ^0 to the reaction function that responds optimally to ξ_t

Regression in impulse response space

Boils down to

$$\Gamma^0 = -\mathcal{R}^0 \tau + \text{error}$$

- Goal: minimize Γ^0 using adjustment τ to reaction function
- Solution:

$$\tau^* = -(\mathcal{R}^{0\prime}\mathcal{R}^0)^{-1}\mathcal{R}^{0\prime}\Gamma^0$$

Comparing policy makers

Now suppose we have d policy makers with

- Reaction functions ϕ^j
- Environments A^j

For each compute distances

$$\tau_j^* = -(\mathcal{R}^{j\prime}\mathcal{R}^j)^{-1}\mathcal{R}^{j\prime}\Gamma^j \qquad \text{for } j = 1, \ldots, d$$

- Rank $|\tau_j^*|$'s smallest to largest (best PM to worst)

Comparisons work...

$$\tau_j^* = -(\mathcal{R}^{j'}\mathcal{R}^j)^{-1}\mathcal{R}^{j'}\Gamma^j$$

Distances are comparable

- $\mathcal{R}^j$ response to one-unit increase in ε_t
- Γ^j response to one-unit increase in ξ_t
- Same units across policy makers !!!

Key take away

- All information relevant for evaluating reaction functions is *encoded* in IRFs
- Main mechanism:
  - IRF to non-policy shocks capture:
    What the policy maker did to offset shocks
  - IRF to policy shocks capture:
    What the policy maker could have done to offset shocks

In practice

- We can estimate $\mathcal{R}^0$ and Γ^0 using any desired method
- Compute joint distribution (asy/boot/bay approx)

1. Test

$$\mathcal{R}^{0\prime}\Gamma^0 = 0$$

2. Evaluate

$$\tau^* = -(\mathcal{R}^{0\prime}\mathcal{R}^0)^{-1}\mathcal{R}^{0\prime}\Gamma^0$$

3. Compare

$$-(\mathcal{R}^{j\prime}\mathcal{R}^j)^{-1}\mathcal{R}^{j\prime}\Gamma^j \ , \quad j = 1, 2, \ldots$$

If you have proxies for shocks ...

Consider

$$\xi_t = -\epsilon_t \times \tau + \text{error}_t$$

- τ^* is equal to population GMM estimator where
  - Instruments are Y_t
  - Weighting matrix $W = I$
- Replace ξ_t and ϵ_t with good proxy variables
- Use observed variables to estimate $\hat{\tau}^*$

(ii) General framework

Result holds far beyond SVAR models

- Forward looking macro models with time-varying parameters, state dependence, etc...
- Practical requirement: need to be able to estimate IRFs
- Builds on recent works that show IRFs can be used as a testbed to evaluate policy decisions or construct policy rule counter-factuals in a broad class of models

  e.g. McKay & Wolf 2022, BM 2022

Policy objectives, loss function and instruments

- Policy objectives: $\boldsymbol{Y}_t = (Y_t', Y_{t+1}', \ldots)'$ where $Y_t = (y_{1,t}, \ldots, y_{M_y,t})'$
- Loss function:
$$\mathcal{L}_t = \frac{1}{2}\mathbb{E}_t \boldsymbol{Y}_t' \mathcal{W} \boldsymbol{Y}_t$$
with $\mathcal{W} = \mathrm{diag}(\beta \otimes \lambda)$.
- Expected policy paths
$$\mathbb{E}_t \boldsymbol{P}_t = \mathbb{E}_t (p_t', p_{t+1}', \ldots)'$$
with $p_t = (p_{1,t}, \ldots, p_{M_p,t})'$

Generic macro model

$$\begin{cases} \mathcal{A}_{yy}\mathbb{E}_t\boldsymbol{Y}_t - \mathcal{A}_{yw}\mathbb{E}_t\boldsymbol{W}_t - \mathcal{A}_{yp}\mathbb{E}_t\boldsymbol{P}_t & = \mathcal{B}_{y\xi}\mathbb{E}_t\Xi_t \\ \mathcal{A}_{ww}\mathbb{E}_t\boldsymbol{W}_t - \mathcal{A}_{wy}\mathbb{E}_t\boldsymbol{Y}_t - \mathcal{A}_{wp}\mathbb{E}_t\boldsymbol{P}_t & = \mathcal{B}_{w\xi}\mathbb{E}_t\Xi_t \end{cases}$$

where

- $\mathbb{E}_t(\cdot) = \mathbb{E}(\cdot|\mathcal{F}_t)$, with $\mathcal{F}_t$ information set
- $\boldsymbol{W}_t = (w_t', w_{t+1}', \dots)$ path additional endogenous variables
- $\Xi_t = (\xi_t', \xi_{t+1}', \dots)$ structural shocks

Generic reaction function

$$\mathcal{A}_{pp}\mathbb{E}_t\boldsymbol{P}_t - \mathcal{A}_{py}\mathbb{E}_t\boldsymbol{Y}_t - \mathcal{A}_{pw}\mathbb{E}_t\boldsymbol{W}_t = \mathcal{B}_{p\xi}\mathbb{E}_t\Xi_t + \mathbb{E}_t\boldsymbol{\epsilon}_t$$

- $\boldsymbol{\epsilon}_t = (\epsilon_t', \epsilon_{t+1}', \ldots)'$ are current and future policy shocks
- $\mathbb{E}_t\boldsymbol{\epsilon}_t$ are policy news shocks
- Reaction function

$$\phi = \{\mathcal{A}_{pp}, \mathcal{A}_{py}, \mathcal{A}_{pw}, \mathcal{B}_{p\xi}\}$$

Optimal reaction function

The set of optimal reaction functions is given by

$$\Phi^{\text{opt}} = \left\{ \phi \in \Phi : \phi \in \arg\min_{\phi \in \Phi} \mathbb{E}\mathcal{L}_t \quad \text{s.t} \quad \text{Generic Model} \right\}$$

- Φ is subset of reaction functions that give unique equilibrium

Objectives

1. Test $\phi^0 \in \Phi^{\text{opt}}$
2. Evaluate distance ϕ^0 to Φ^{opt} in direction $\mathbb{E}_t \xi_{b,t+h}$
3. Compare ϕ^j's

Main result (1)

Proposition

Given the generic model we have that

$$\mathcal{R}_a^{0\prime}\mathcal{W}\Gamma_b^0 \neq 0 \quad \Longrightarrow \quad \phi^0 \notin \Phi^{\text{opt}} .$$

where

- $\mathcal{R}_a^0$ is any subset or linear combination of IRFs to policy shocks
- Γ_b^0 is any subset or linear combination of IRFs to non-policy shocks

Main result (2)

Corollary

Define for ϕ^j

$$\mathcal{T}^j_{a,b} = -(\mathcal{R}^{j'}_a \mathcal{W} \mathcal{R}^j_a)^{-1} \mathcal{R}^{j'}_a \mathcal{W} \Gamma^j_b$$

Let

$$\phi^* = \left\{ \mathcal{A}^j_{pp}, \mathcal{A}^j_{py}, \mathcal{A}^j_{pw}, \mathcal{B}^j_{p_a \xi_b} + \mathcal{T}^j_{a,b}, \mathcal{B}^j_{p_{-a} \xi_{-b}} \right\}$$

Then

$$\mathbb{E}\mathcal{L}_t(\phi^*) \leq \mathbb{E}\mathcal{L}_t(\phi^j) \qquad \text{and} \qquad \nabla_{\mathcal{B}_{p_a \xi_b}} \mathbb{E}\mathcal{L}_t \Big|_{\phi=\phi^*} = 0$$

Implies

Rank policy makers with $\phi^1, \dots \phi^p$ based on

$$|\mathcal{T}^1_{a,b}| \ , \ \dots \ , \ |\mathcal{T}^p_{a,b}|$$

Compare policy makers ϕ^j and $\phi^{j'}$

$$|\mathcal{T}^j_{a,b}| - |\mathcal{T}^{j'}_{a,b}|$$

(i) Empirical study

Fed reaction function

- Evaluate Fed's reaction function over last 60 years
- Consider different non-policy shocks, e.g. oil price, tfp, etc ...
- Compare performance over sub-periods pre-1985 vs post 1985

Some details

- Loss function

$$\mathcal{L}_t = \|\Pi_{t:t+H}\|^2 + \|U_{t:t+H}\|^2$$

  for $H = 20$.

- SVAR identification using external instruments
  - $\mathcal{R}_{\text{rr}}$: Romer & Romer (2004)
  - Γ_{oil}: Hamilton (2003)
  - Γ_{tfp}: Fernald (2012)

- Report:
  - $\tau^* = -(\mathcal{R}^{0\prime}\mathcal{R}^0)^{-1}\mathcal{R}^{0\prime}\Gamma^0$
  - $\Gamma^0 + \tau^*\mathcal{R}^0$

Figure 1: Impulse responses to an oil shock, pre-1985 data

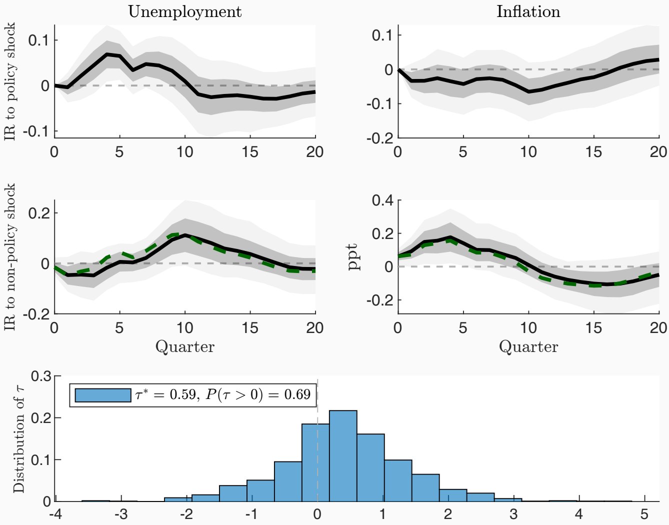


Figure 2: Impulse responses to an oil shock, post-1985 data

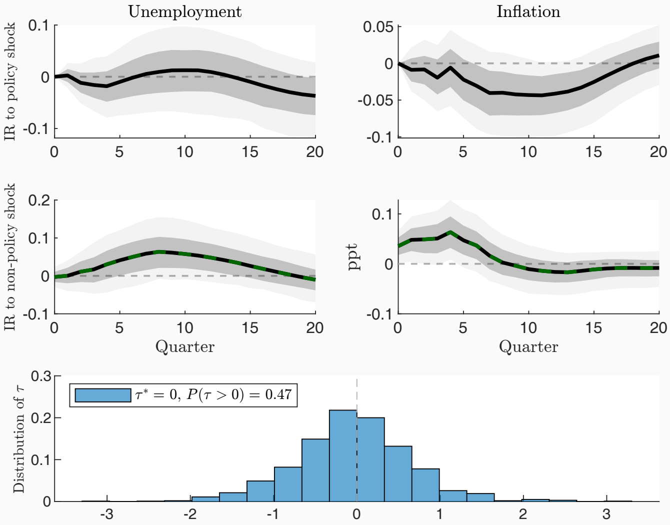


Figure 3: Impulse responses to a TFP shock, pre-1985 data

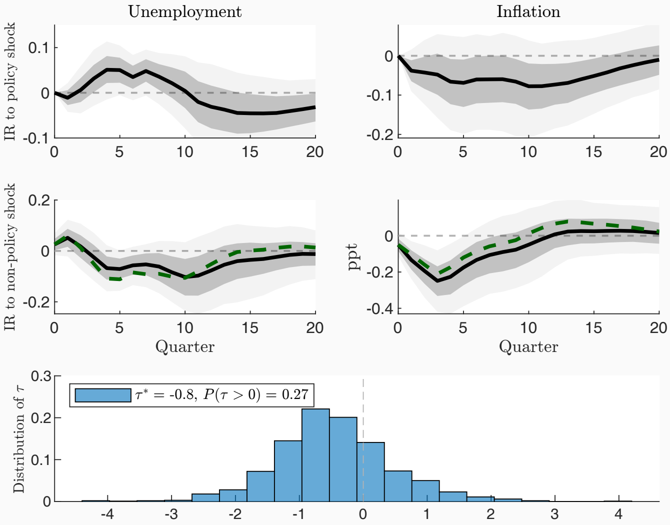
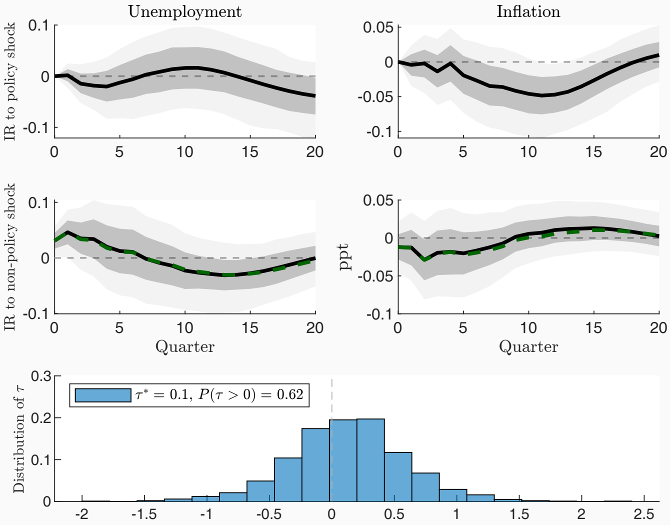


Figure 4: Impulse responses to a TFP shock, post-1985 data



Conclusion

- Propose a methodology for comparing policy makers after their term
- Measure distance to optimal reaction function in the direction of response to (some) non-policy shocks
- Distance depends only on IRFs to policy and non-policy shocks