Innovation Powered Narrative Inference

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Dynamic causal effects

Key task in macro: estimate θ_h from

$$y_{t+h} = c + \theta_h p_t + u_{t+h} \ , \qquad \text{for} \quad t \in \mathcal{N}$$

where

- y_{t+h} outcome variable h periods ahead
- p_t, e.g., interest rate, spending, tax, etc

General concern is endogeneity: $\mathrm{cov}(p_t, u_{t+h}) \neq 0$

- ordinary least squares is biased
- some identification strategy is needed

The Narrative Method in Macroeconomics

An empirical technique where one gathers systematic evidence from contemporaneous qualitative sources (such as newspapers, government reports, and policy meeting transcripts), and incorporates it into statistical analysis to establish causal relationships

Romer & Romer 2023

- Narrative records to construct series z_t: exogenous changes in p_t
- Use z_t as instrumental variable to avoid endogeneity bias

Classic Narrative Series z_t

- Hamilton (1985) – oil price
- Romer and Romer (1989, 2023) – monetary policy
- Ramey and Shapiro (1998) – defense spending news
- Romer and Romer (2000) – tax
- Reinhart and Rogoff (2009) – financial shocks
- and many more recent ones:

  Ramey (2011), De Vries et al (2011), Cloyne (2013), Jalil (2015), Romer and Romer (2017), Ramey and Zubairy (2018), Alesina, Favero and Giavazzi (2019), Gil et al (2019), Carriere-Swallow, David, and Leigh (2021), Rojas, Vegh and Vuletin (2022), Drechsel (2023), Cloyne, Dimsdale and Postel-Vinay (2023), Bi and Zubairy (2023), Fieldhouse and Mertens (2023), ...

A less noticed feature

Paper	# obs	# zeros	**% zeros**
Bi and Zubairy (2023)	590	464	79%
Carriere-Swallow, David and Leigh (2021)†	28	22	81%
Cloyne (2013)	248	94	38%
Cloyne, Dimsdale and Postel-Vinay (2023)	89	69	77%
Fieldhouse and Mertens (2023)	292	228	78%
Guajardo, Leigh and Pescatori (2014)†	32	22	68%
Gil et al. (2019)	120	87	72%
Hamilton (1985)	140	121	86%
Jalil (2015)	90	83	92%
Ramey and Shapiro (1998)	200	197	98%
Ramey (2011)	280	194	69%
Ramey and Zubairy (2018)	504	396	79%
Romer and Romer (2023)	852	842	99%
Romer and Romer (1989)	852	845	99%
Romer and Romer (2010)	252	207	82%
Romer and Romer (2017)†	91	81	88%
Rojas, Vegh and Vuletin (2022)†	106	86	81%
Average			**80%**

Implications of many Zeros

(i) zeros are not informative

- weaker instruments $\rightarrow$ larger confidence bands

$\Rightarrow$ efficiency problem

(ii) small number of non-zeros

- finite sample correlation with other structural shocks

  e.g. Hoover & Perez 1994 monetary - oil relationship

$\Rightarrow$ possible endogeneity problem

This paper

- Conceptually: treat uninformative/endogenous z_t as missing

$$z_t = \begin{cases} f(\varepsilon_t) & \text{if} \quad t \in \mathcal{G} = \text{good periods: narrative is clear} \\ \text{missing} & \text{if} \quad t \in \mathcal{B} = \text{bad periods: narrative is inconclusive} \end{cases}$$

  adopt ideas from *missing data* literature

- Innovation Powered (IP) Inference
  - **Objective**: reduce variance conventional (zeroes-IV) estimates
  - **Approach**:
    - (i) Compute innovations v_t using time series model/identification
      e.g. short-run, long-run, max-share ...
    - (ii) v_t to compute **inconsistent** but **low variance** IV estimate/test
    - (iii) Use z_t and v_t on $\mathcal{G}$ to correct endogeneity bias

$\Rightarrow$ Innovation Powered Anderson-Rubin test

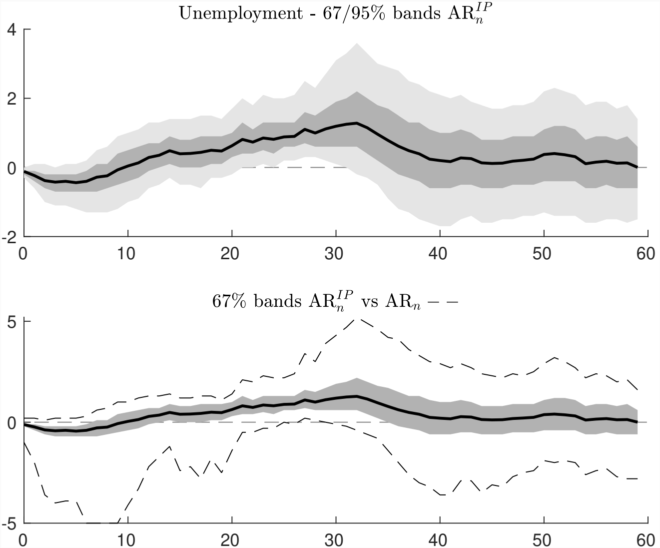
This paper: underlying idea

- Macro has little uncontroversial exogenous variation
  - small bits of narrative evidence seem convincing
- At the same time there is a wealth of great time series methods
  - identification: short-run, long-run, heteroskedasticity, non-Gaussian, structural, ...
  - model: svar, svarma, state space, dsge ...

  can use to **predict** shocks – relaxes identification/modeling

$\Rightarrow$ Paper: combine clean narrative evidence with powerful time series

US Monetary Policy — Romer & Romer (1989,2023)



Literature

- **Narrative methods**: Ludvigson, Ma & Ng (2017), Antolin-Diaz & Rubio-Ramirez (2018), Giacomini, Kitagawa & Read (2022,2023), Plagborg-Møller (2022)
  - we do not require correctly specified svar model
  - narrative can be contaminated by measurement error
  - narrative events are not assumed to arrive randomly

- **Missing data**: Robins, Rotnitzky & Zhao (1994), Robins & Rotnitzky (1995), Kang and Schafer (2007), Chaudhuri & Guilkey (2016), Abrevaya & Donald (2017), Little & Rubin (2019)
  - instruments z_t are missing not y, x
  - many time series opportunities for constructing v_t
  - allow for weak identification

(a) Illustrative static example

(b) Innovation powering in a dynamic macro environment

(c) Empirical evidence US monetary policy

Toy model

Object of interest is θ in

$$\underbrace{\begin{pmatrix} p_t \\ y_t \end{pmatrix}}_{=\mathbf{w}_t} = \underbrace{\begin{pmatrix} 1 & \rho \\ \theta & 1 \end{pmatrix}}_{=\mathbf{A}} \underbrace{\begin{pmatrix} \varepsilon_t \\ u_t \end{pmatrix}}_{\boldsymbol{\eta}_t} \qquad \boldsymbol{\eta}_t \overset{iid}{\sim} (0, \mathbf{D}) \qquad t \in \mathcal{N}$$

with $\mathbf{A}$ non-singular and $n = |\mathcal{N}|$

Narrative series

$$z_t = f(\varepsilon_t) + \zeta_t \ , \qquad \mathbb{E}(\zeta_t) = 0 \ , \qquad \zeta_t \perp (\varepsilon_t, u_t)$$

Implies

$$y_t = \theta p_t + e_t \ , \qquad \mathbb{E}(z_t e_t) = 0 \ , \qquad \mathbb{E}(z_t p_t) \neq 0$$

Missing instruments

Indicator for z_t valid and informative instrument

$$s_t = \begin{cases} 0 & \text{if} \quad t \in \mathcal{B} = \{t \in \mathcal{N} : z_t \text{ missing}\} \\ 1 & \text{if} \quad t \in \mathcal{G} \end{cases},$$

Selection assumption

$$P(s_t = 1 | \boldsymbol{\eta}_t, \zeta_t) = P(s_t = 1 | \boldsymbol{\eta}_t) \equiv \pi_t > 0$$

- No selection on measurement error ζ_t
- Allows s_t function of structural shocks $\boldsymbol{\eta}_t$
- Assume π_t is known, for now ...

Simple estimator

Simple IV moment condition

$$\mathbb{E}(z_t(y_t - \theta p_t)) = \mathbb{E}(s_t z_t(y_t - \theta p_t)/\pi_t) = 0$$

We get **consistent** IV estimate

$$\hat{\theta}_{\mathcal{G}} = \frac{\sum_{t\in\mathcal{G}} z_t y_t/\pi_t}{\sum_{t\in\mathcal{G}} z_t p_t/\pi_t} \qquad \text{but } \textbf{high variance}\text{: } \mathrm{var}(\hat{\theta}_{\mathcal{G}}) = O(n_{\mathcal{G}}^{-1})$$

$\Rightarrow$ uses only $\mathcal{G}$ periods !!!

Innovations

Construct prediction for $z_t = f(\varepsilon_t) + \zeta_t$ using observables $\mathbf{w}_t$, e.g.

$$v_t = p_t - \beta y_t \qquad \text{i.e. innovation in policy equation}$$

- Generally v_t depends on u_t and is not exogenous instrument
- Therefore we refer to v_t as an **innovation**, not a shock

Leads to **inconsistent** IV estimate

$$\hat{\theta}^*_{\mathcal{N}} = \frac{\sum_{t \in \mathcal{N}} v_t y_t}{\sum_{t \in \mathcal{N}} v_t p_t} \qquad \text{but } \textbf{low variance}\text{: } \mathrm{var}(\hat{\theta}^*_{\mathcal{N}}) = O(n^{-1})$$

$\Rightarrow$ uses all $\mathcal{N}$ periods, but not correct shocks !!!

Innovation powering

$$\hat{\theta}_{IP} = \underbrace{\frac{\sum_{t\in\mathcal{N}} v_t y_t}{\sum_{t\in\mathcal{N}} v_t p_t}}_{=\hat{\theta}^*_{\mathcal{N}}} + \underbrace{\underbrace{\frac{\sum_{t\in\mathcal{G}} z_t y_t/\pi_t}{\sum_{t\in\mathcal{G}} z_t p_t/\pi_t}}_{=\hat{\theta}_{\mathcal{G}}} - \underbrace{\frac{\sum_{t\in\mathcal{G}} v_t y_t/\pi_t}{\sum_{t\in\mathcal{G}} v_t p_t/\pi_t}}_{=\hat{\theta}^*_{\mathcal{G}}}}_{=\text{bias correction}}$$

- $\hat{\theta}^*_{\mathcal{N}}$: IV estimate using v_t on $\mathcal{N}$
- $\hat{\theta}_{\mathcal{G}}$: IV estimate using z_t on $\mathcal{G}$
- $\hat{\theta}^*_{\mathcal{G}}$: IV estimate using v_t on $\mathcal{G}$

Innovation powering: consistency

$$\hat{\theta}_{IP} = \underbrace{\frac{\sum_{t\in\mathcal{G}} z_t y_t/\pi_t}{\sum_{t\in\mathcal{G}} z_t p_t/\pi_t}}_{=\hat{\theta}_{\mathcal{G}}} + \underbrace{\frac{\sum_{t\in\mathcal{N}} v_t y_t}{\sum_{t\in\mathcal{N}} v_t p_t}}_{=\hat{\theta}^*_{\mathcal{N}}} - \underbrace{\frac{\sum_{t\in\mathcal{G}} v_t y_t/\pi_t}{\sum_{t\in\mathcal{G}} v_t p_t/\pi_t}}_{=\hat{\theta}^*_{\mathcal{G}}} \xrightarrow{p} \theta$$

- Simple IV estimate is consistent $\hat{\theta}_{\mathcal{G}} \xrightarrow{p} \theta$
- Biases of second and third term cancel:

$$\hat{\theta}^*_{\mathcal{N}} - \hat{\theta}^*_{\mathcal{G}} \xrightarrow{p} b - b = 0$$

Innovation powering: variance reduction

$$\hat{\theta}_{IP} = \underbrace{\frac{\sum_{t \in \mathcal{N}} v_t y_t}{\sum_{t \in \mathcal{N}} v_t p_t}}_{=\hat{\theta}^*_{\mathcal{N}}} + \underbrace{\frac{\sum_{t \in \mathcal{G}} z_t y_t / \pi_t}{\sum_{t \in \mathcal{G}} z_t p_t / \pi_t}}_{=\hat{\theta}_{\mathcal{G}}} - \underbrace{\frac{\sum_{t \in \mathcal{G}} v_t y_t / \pi_t}{\sum_{t \in \mathcal{G}} v_t p_t / \pi_t}}_{=\hat{\theta}^*_{\mathcal{G}}}$$

- $\hat{\theta}^*_{\mathcal{N}}$ has low variance $\rightarrow$ uses all observations
- but

$$\hat{\theta}_{\mathcal{G}} - \hat{\theta}^*_{\mathcal{G}} = \frac{\sum_{t \in \mathcal{G}} z_t y_t / \pi_t}{\sum_{t \in \mathcal{G}} z_t p_t / \pi_t} - \frac{\sum_{t \in \mathcal{G}} v_t y_t / \pi_t}{\sum_{t \in \mathcal{G}} v_t p_t / \pi_t}$$

  can also have low variance if $z_t \approx v_t$, i.e. good predictions

Ensuring efficiency via method of moments

Underlying innovation powered IV are moment conditions:

$$\underbrace{\mathbb{E}(s_t z_t(y_t - \theta p_t)/\pi_t) = 0}_{\text{conventional IV}} \quad \text{and} \quad \underbrace{\mathbb{E}((1 - s_t/\pi_t)v_t(y_t - \theta p_t)) = 0}_{\text{innovation powering}}$$

- combine moments optimally to ensure improvements over zeros IV

Can show estimator based on

$$\mathbb{E}(s_t z_t(y_t - \theta p_t)/\pi_t + \gamma(1 - s_t/\pi_t)v_t(y_t - \theta p_t)) = 0$$

with $\gamma = \mathbb{E}(v_t^2)^{-1}\mathbb{E}(v_t z_t)$ has minimal variance if

$$\mathbb{E}(z_t|\mathbf{w}_t) = \gamma v_t$$

Summary : Innovation Powering

1. Construct innovation: $v_t = p_t - \beta y_t$

2. IP Moment condition

$$\mathbb{E}(\underbrace{s_t z_t (y_t - \theta p_t)/\pi_t}_{\text{clean narrative}} + \gamma \underbrace{(1 - s_t/\pi_t) v_t (y_t - \theta p_t)}_{\text{powerful time series}}) = 0$$

3. Build estimators/tests

   - GMM estimate

   - Anderson-Rubin test

$\Rightarrow$ 2. and 3. are similar in general dynamic environment

(a) Illustrative static example

(b) Innovation powering in a dynamic macro environment

(c) Empirical evidence US monetary policy

Dynamic environment

Interested in θ_h in

$$y_{t+h} = \theta_h p_t + \boldsymbol{\beta}_h' \mathbf{x}_t + u_{t+h} \ , \qquad \text{for } t \in \mathcal{N}$$

Project out controls

$$y_{t+h}^{\perp} = \theta_h p_t^{\perp} + u_{t+h}^{\perp} \ , \qquad \text{for } t \in \mathcal{N}$$

Missing indicator

$$s_t = \begin{cases} 0 & \text{if} \quad t \in \mathcal{B} = \{t \in \mathcal{N} : z_t \text{ missing}\} \\ 1 & \text{if} \quad t \in \mathcal{G} \end{cases}$$

How to construct innovations?

Determine $\mathbf{v}_t$ with common sense:

- What do structural shocks predict? e.g. ε_t monetary

$$i_{t+h} = \beta_h \varepsilon_t + \text{controls}_t + \text{error}_t$$

reverse regression

$$\varepsilon_t = \gamma_h i_{t+h} + \text{controls}_t + \text{error}_t$$

use **current/future** interest rate residuals, i.e. $\mathbf{v}_t = (i_t^{\perp}, \ldots, i_{t+H}^{\perp})'$

In general

$$\mathbf{v}_t = (v_{1t}, \ldots, v_{d_v t})' \ , \quad v_{it} \in \{\mathbf{w}^s_{t+h} - \text{Proj}(\mathbf{w}^s_{t+h} | \mathbf{x}^s_t), h = 0, 1, \ldots, H\} \ .$$

includes several time series models/identification strategies

Main Assumptions

1. **Narrative:** $\mathbb{E}(z_t^{\perp} u_{t+h}^{\perp}) = 0$ for all t

2. **Missings:** Let $\mathbf{d}_t^{\pi} = (y_{t+h}^{\perp}, p_t^{\perp}, \mathbf{v}_t')'$. We have

$$\pi_t \equiv P(s_t = 1 | \mathbf{d}_t^{\pi}) = P(s_t = 1 | \mathbf{d}_t^{\pi}, z_t^{\perp}) \ ,$$

   and $\pi_t > 0$ with probability 1. Further,

$$\pi_t = \kappa(\mathbf{d}_t^{\pi}; \gamma_{\pi}) \ ,$$

   where κ is known function differentiable wrt γ_{π}

3. **Innovations:** $\mathbb{E}(\mathbf{v}_t(z_t^{\perp} - \gamma_v' \mathbf{v}_t)) = \mathbf{0}$ for all t

IP-GMM estimate

Let $\boldsymbol{\psi} = (\theta_h, \gamma_\pi, \gamma_v)$ and

$$g(\boldsymbol{\psi}; \mathbf{d}_t) = \begin{bmatrix} s_t z_t^\perp (y_{t+h}^\perp - \theta_h p_t^\perp)/\pi_t + (1 - s_t/\pi_t)\gamma_v' \mathbf{v_t} (y_{t+h}^\perp - \theta_h p_t^\perp) \\ s_t \mathbf{v}_t (z_t^\perp - \gamma_v' \mathbf{v}_t)/\pi_t \\ \kappa^{(1)}(\mathbf{d}_t^\pi; \gamma_\pi)(s_t - \pi_t)/(\pi_t(1 - \pi_t)) \end{bmatrix}$$

with $\kappa^{(1)}(\mathbf{d}_t^\pi; \gamma_\pi) = \partial\kappa(\mathbf{d}_t^\pi; \gamma_\pi)/\partial\gamma_\pi$

$$(\hat{\theta}_{nh}^{\mathrm{IP}}, \hat{\gamma}_\pi, \hat{\gamma}_v) = \operatorname*{argmin}_{\tilde{\boldsymbol{\psi}} \in \Psi} \widehat{g}_n(\tilde{\boldsymbol{\psi}})' \widehat{\Omega}_n^{-1}(\tilde{\boldsymbol{\psi}}) \widehat{g}_n(\tilde{\boldsymbol{\psi}})$$

with

- $\widehat{g}_n(\boldsymbol{\psi}) = \frac{1}{n} \sum_{t=1}^n g(\boldsymbol{\psi}; \mathbf{d}_t)$
- $\widehat{\Omega}_n(\boldsymbol{\psi})$ consistent HAC for $\Omega_n(\boldsymbol{\psi}) = \mathrm{Var}(n^{-1/2} \sum_{t=1}^n g(\boldsymbol{\psi}; \mathbf{d}_t))$

Subvector IP-AR test

To get weak-IV robust confidence bands, we test

$$H_0 : \theta_h = \bar{\theta}_h \qquad \text{against} \qquad H_1 : \theta_h \neq \bar{\theta}_h$$

IP-AR test statistic

$$\mathrm{AR}_n^{\mathrm{IP}}(\bar{\theta}_h) = \min_{\tilde{\gamma} \in \Gamma} n\widehat{g}_n(\bar{\theta}_h, \tilde{\gamma})' \widehat{\Omega}_n^{-1}(\hat{\theta}_h, \tilde{\gamma}) \widehat{g}_n(\hat{\theta}_h, \tilde{\gamma}) \ ,$$

Proposition
Given assumptions 1-3 + regularity conditions we have that under H_0

$$\lim_{n \to \infty} P_\psi(\mathrm{AR}_n^{\mathrm{IP}}(\bar{\theta}_h) > c_{\chi^2(1),\alpha}) = \alpha$$

where $c_{\chi^2(1),\alpha}$ denotes the 1-α quantile of the $\chi^2(1)$ distribution

(a) Illustrative static example

(b) Innovation powering in a dynamic macro environment

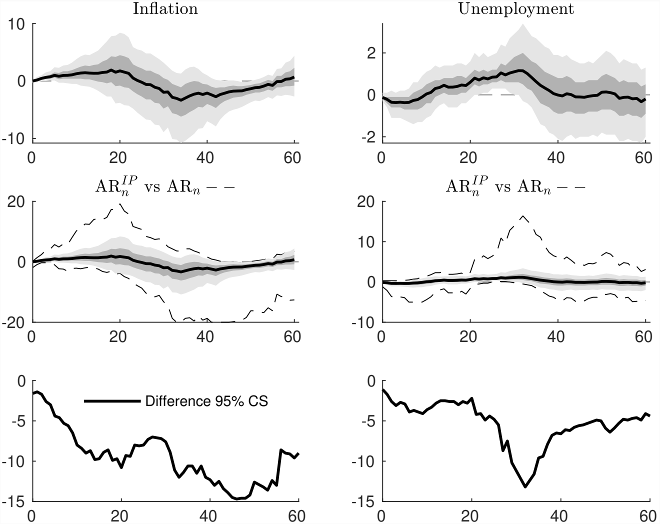
(c) Empirical evidence US monetary policy

Empirical study: US monetary policy

Revisit Romer & Romer (1989, 2023)

- Sample 1954M7-2016M12, $n = 749$, z_t as RR, but
  - set missing coincidental monetary-oil events
  - only zero if no meeting occurred
  - all else is missing ... implying 79% zeros
- Model $y_{t+h} = \theta_h p_t + \text{controls} + u_t$ with
  - y_{t+h} unemployment or CPI inflation
  - p_t is fed funds rate
  - controls is constant + 12 lags of y_t, p_t
- Model selection probability: logit with $\mathbf{d}_t^{\pi} = (1, y_{t+h}^{\perp}, p_t^{\perp})$
- Innovations: $v_t = (1, p_t^{\perp})'$

US Monetary Policy — Romer & Romer (1989,2023)



Robustness checks

- Simulation study ▸ link
- Alternative narrative treatments ▸ link
- Alternative innovation models ▸ link
- Alternative selection models ▸ link

Conclusion

- Narrative classification is difficult:
  - many zeros lead to inefficiency
  - and possible endogeneity bias
- We introduce **Innovation Powered** inference
  - combines narrative evidence with time series evidence
  - improve the power of conventional narrative methods
- Empirically we document
  - accurate dynamic causal effects of US monetary policy
  - despite many missing narrative shocks

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(d) Appendix

Simulation design

Consider $\mathbf{w}_t = (g_t, \pi_t, i_t)'$ and $\boldsymbol{\varepsilon}_t = (\varepsilon_t^g, \varepsilon_t^\pi, \varepsilon_t^{mp})'$

- Fit SVAR(12) to US data from 1959M1-2007M4, short run id
- Simulate data from fitted SVAR for different n, $n_{\mathcal{G}}$
- Compare
    - Zeroes IV
    - IP-GMM-(i): $\mathbf{v}_t = i_t^\perp$
    - IP-GMM-(ii): $\mathbf{v}_t = g_t^\perp$

Simulation results

Monthly Monetary VAR – $n = 400$, $p = 12$						
	π_t^1			π_t^2		
	$h = 0$	$h = 20$	$h = 40$	$h = 0$	$h = 20$	$h = 40$
MAE						
$\hat{\theta}_{hn}^{\mathrm{IV}}$	0.039	1.333	1.668	0.033	1.103	1.400
$\hat{\theta}_{hn}^{\mathrm{IP}} - (i)$	0.041	0.560	0.701	0.044	0.591	0.685
$\hat{\theta}_{hn}^{\mathrm{IP}} - (ii)$	0.039	1.329	1.758	0.034	1.169	1.506
ERP						
$\mathrm{AR}_n(\bar{\theta}_h)$	0.041	0.048	0.049	0.042	0.047	0.052
$\mathrm{AR}_n^{\mathrm{IP}}(\bar{\theta}_h) - (i)$	0.049	0.054	0.042	0.047	0.054	0.045
$\mathrm{AR}_n^{\mathrm{IP}}(\bar{\theta}_h) - (ii)$	0.055	0.058	0.067	0.043	0.061	0.066
wCS						
CS_{nh}	0.338	2.296	2.603	0.301	2.122	2.374
$\mathrm{CS}_{nh}^{\mathrm{IP}} - (i)$	0.231	1.251	1.416	0.239	1.255	1.395
$\mathrm{CS}_{nh}^{\mathrm{IP}} - (ii)$	0.257	1.977	2.267	0.227	1.811	2.045

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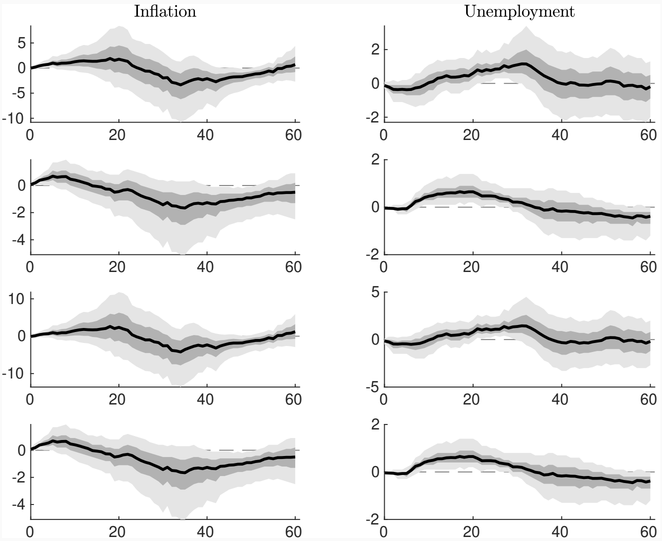
Alternative Narrative Treatments



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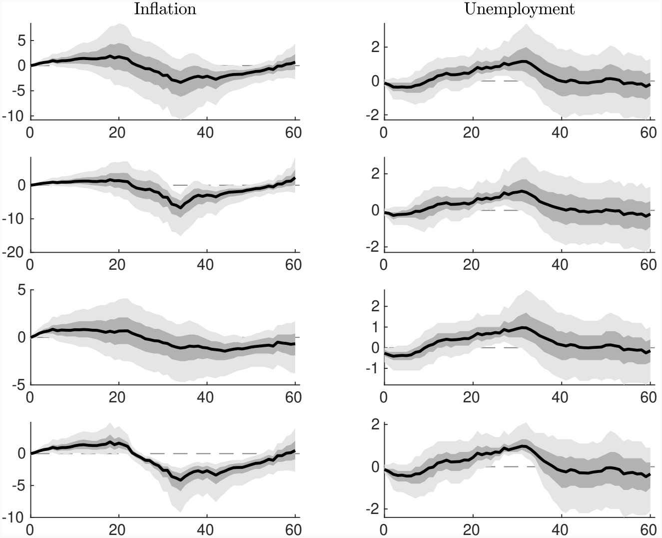
Alternative Selection and Innovation models



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