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: $\text{cov}(p_t, u_{t+h}) \neq 0$

- 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 $\longrightarrow$ 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

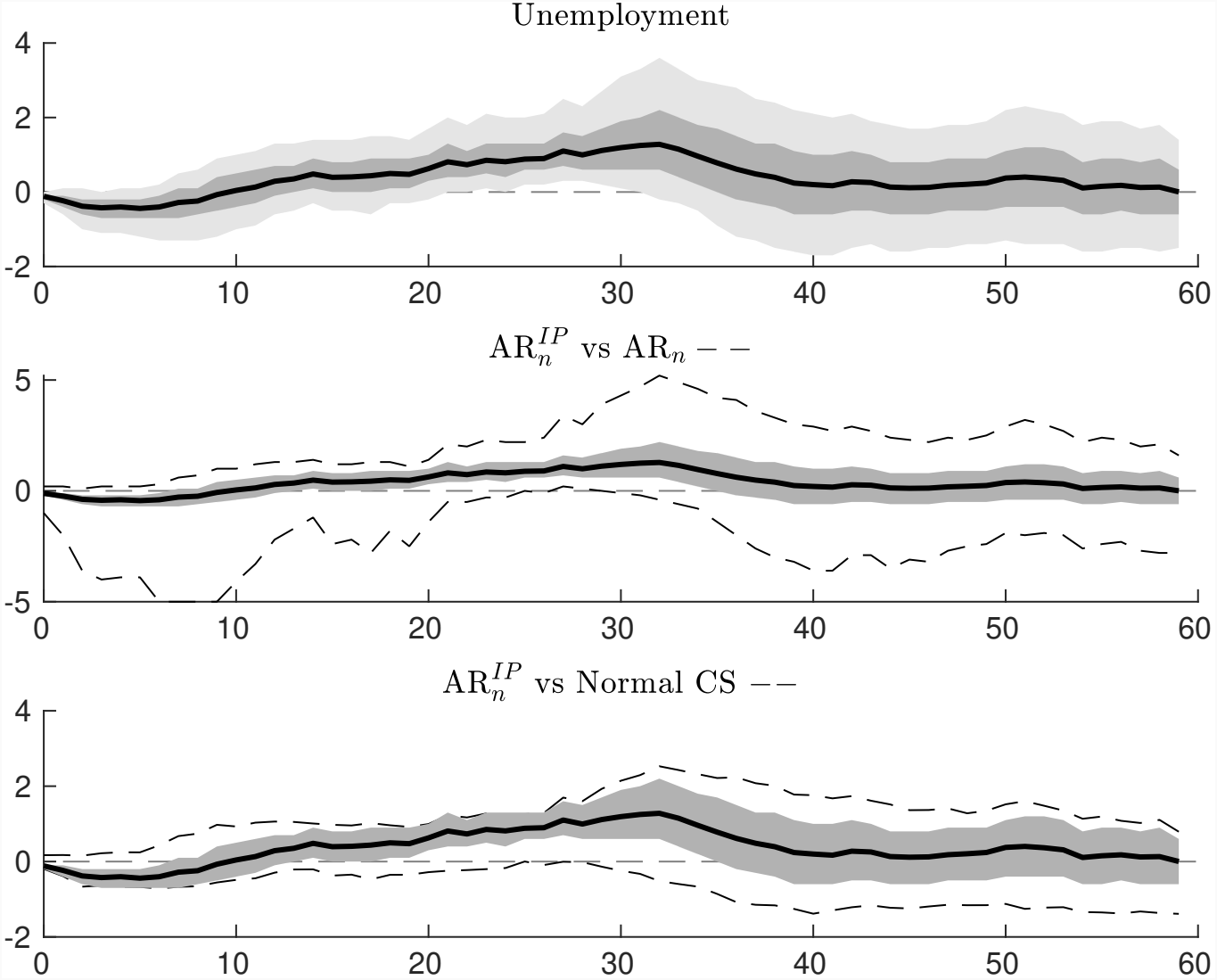
This paper: underlying idea

- 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

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

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

$$P(s_t = 1|\eta_t, \zeta_t) = P(s_t = 1|\eta_t) \equiv \pi_t > 0$$

- No selection on measurement error ζ_t
- Allows s_t function of structural shocks η_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

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

$\Rightarrow$ 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

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

$\Rightarrow$ 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

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

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

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

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

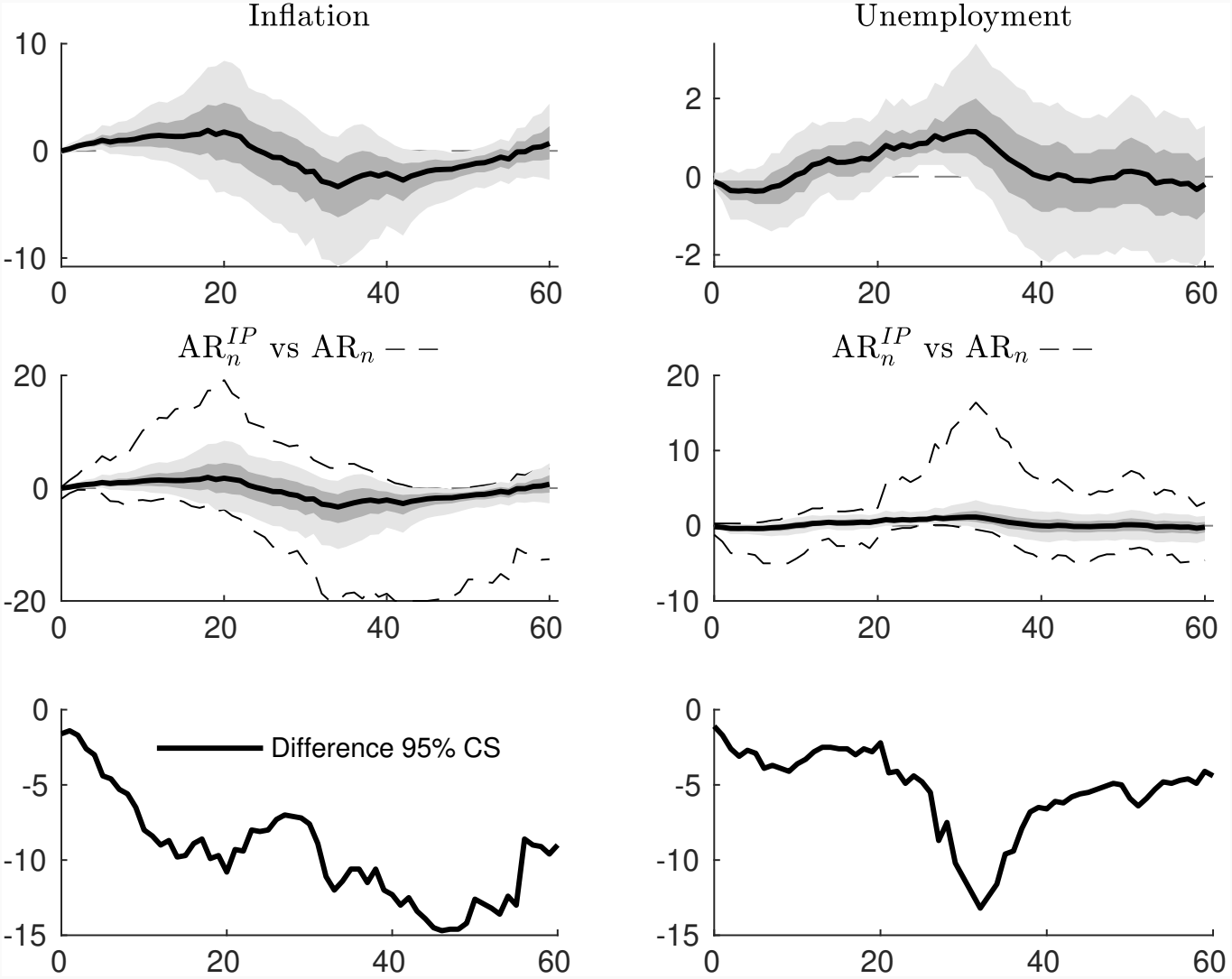
(c) Empirical evidence US monetary policy

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

(a) Illustrative static example

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(d) Appendix

Simulation design

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

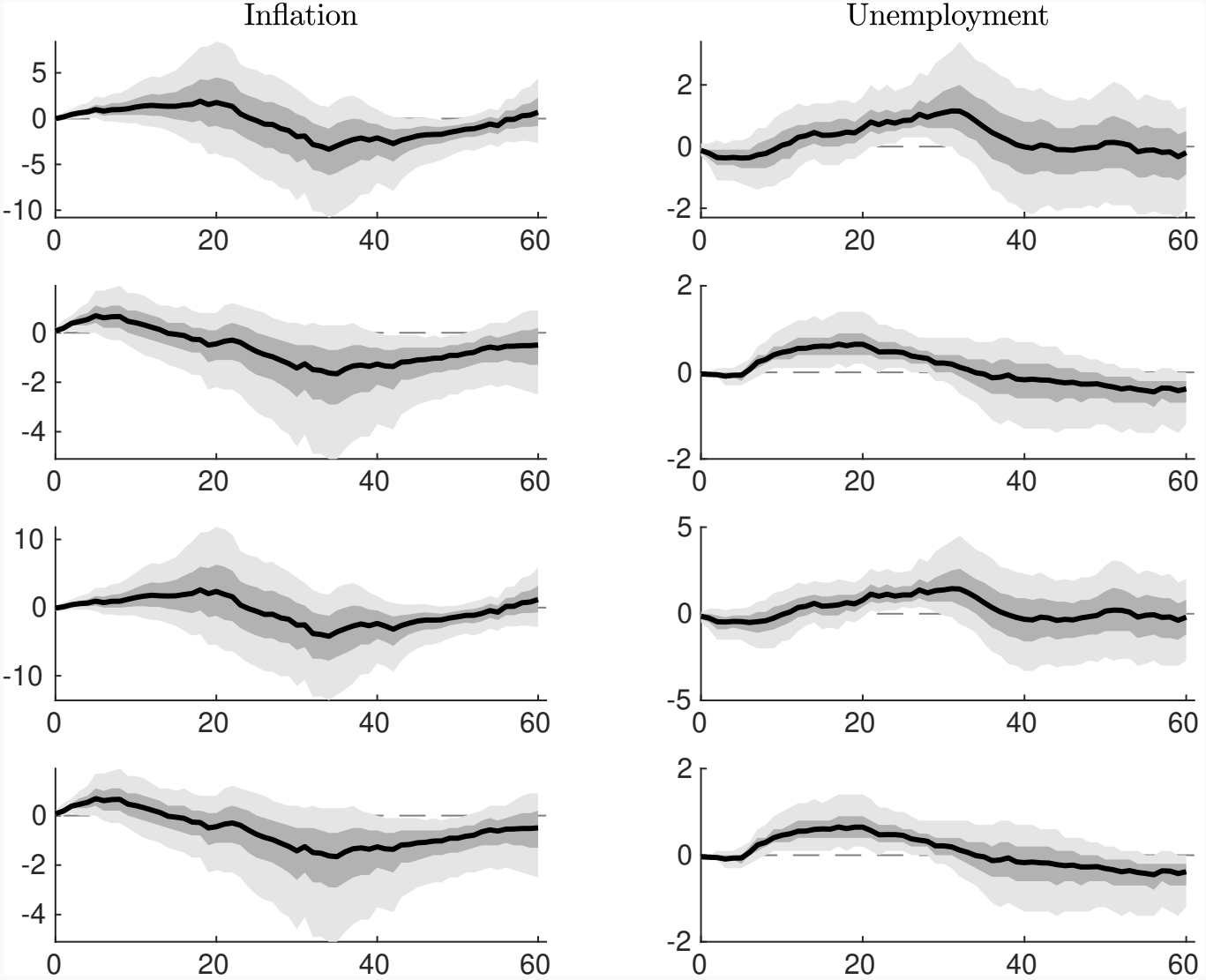
- Fit SVAR(12) to US data from 1959M1-2007M4, short run id
- Simulate data from fitted SVAR for different $n, n_{\mathcal{G}}$
- Compare
  - Zeroes IV
  - IP-GMM-(i): $\mathbf{v}_t = i_t^\perp$
  - IP-GMM-(ii): $\mathbf{v}_t = g_t^\perp$

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

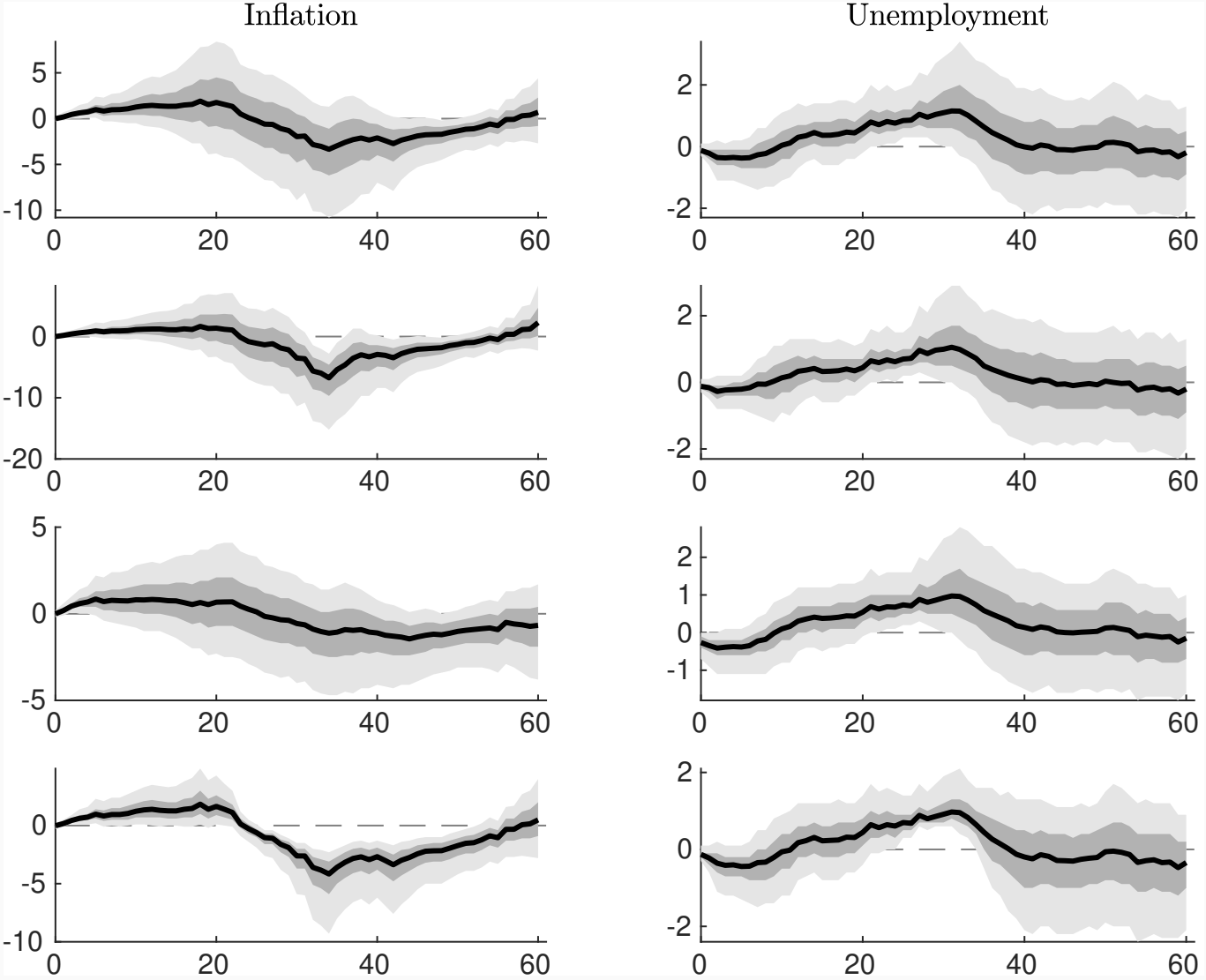
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Alternative Narrative Treatments



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Alternative Selection and Innovation models



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