# Innovation Powered Narrative Inference

Regis Barnichon (FRB San Francisco)
Geert Mesters (Universitat Pompeu Fabra, BSE & CREI)

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# Dynamic causal effects

Key task in macro: estimate $\theta_h$ 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

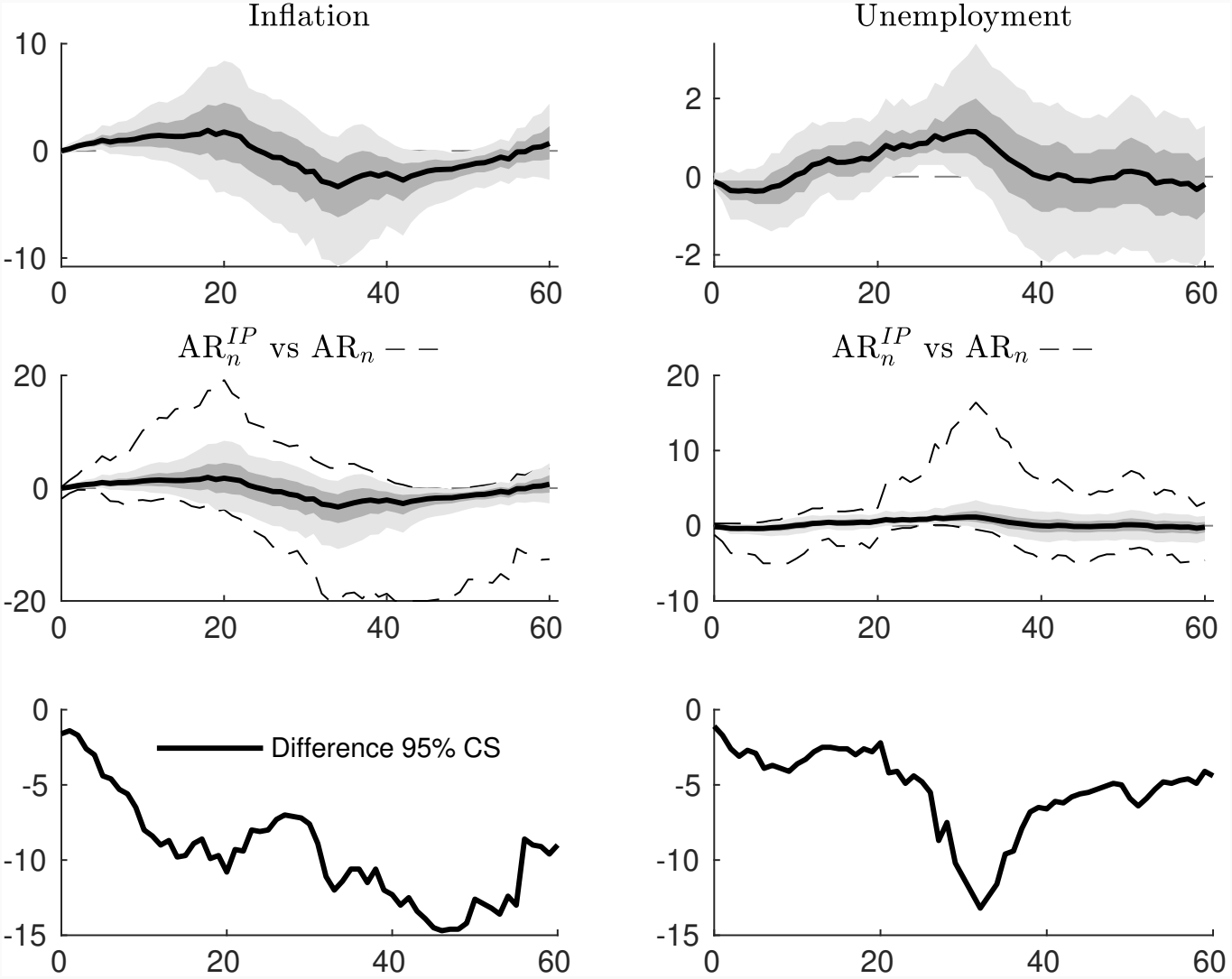
$$z_t = \begin{cases} f(\varepsilon_t) & \text{if} \quad t \in \mathcal{G} = \text{good periods: narrative is clear} \\ \text{missing} & \text{if} \quad t \in \mathcal{B} = \text{bad periods: narrative is inconclusive} \end{cases}$$

  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

# 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 specifying 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 $\theta$ 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

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

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-on-observables 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 $\zeta_t$
- Allows $s_t$ function of structural shocks $\boldsymbol{\eta}_t$
- Assume $\pi_t$ 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 $z_t = f(\epsilon_t) + \zeta_t$ 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 conditions

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

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 $\theta_h$ 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. $\varepsilon_t$ 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 $\kappa$ is known function differentiable wrt $\gamma_{\pi}$

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-*$\alpha$ *quantile of the* $\chi^2(1)$ *distribution*

**(a)** Illustrative static example

**(b)** Innovation powering in a dynamic macro environment

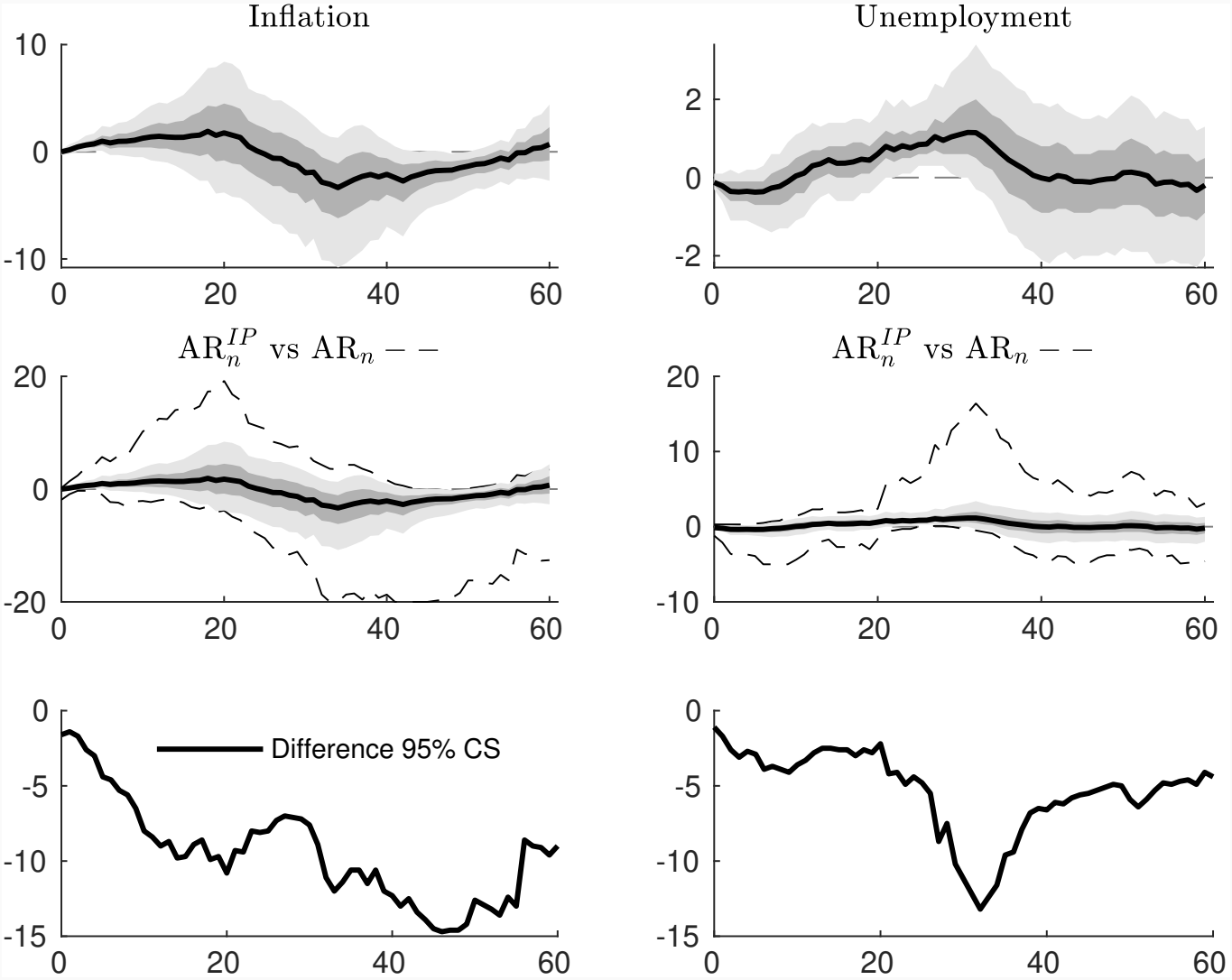
**(c)** Empirical evidence US monetary policy

# 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/speech occurred
  - all else is missing ... implying $n_{\mathcal{G}} = 156$, or 79%
- 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

**(b)** Innovation powering in a dynamic macro environment

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**(d)** Appendix

# Simulation design

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

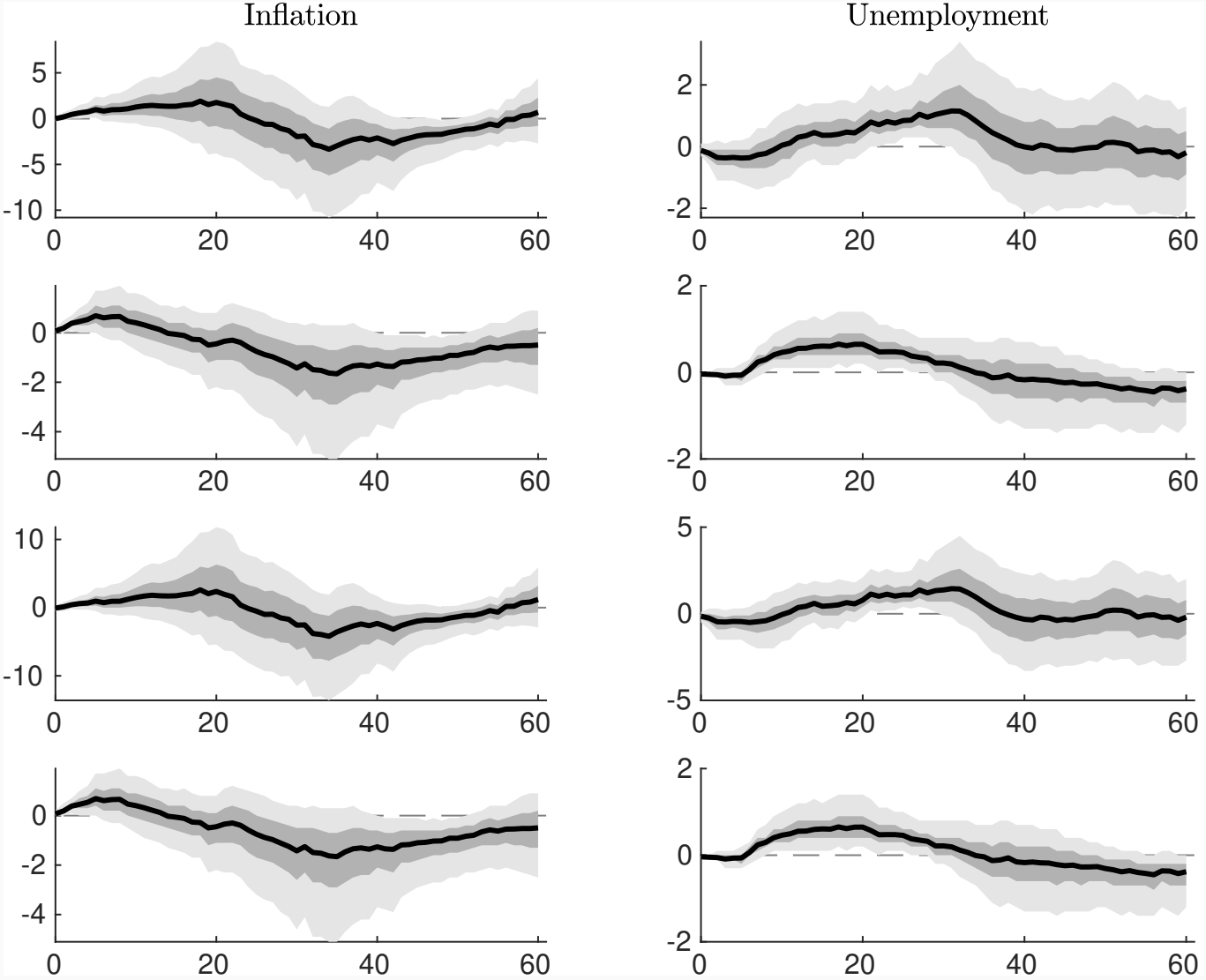
- Fit SVAR(4) to US data from 1959M1-2007M4, short run id
- Simulate data from fitted SVAR for different $n, n_{\mathcal{G}}$
- Compare
  - Zeroes IV
  - IP-GMM-(i): $\mathbf{v}_t = i_t^\perp$
  - IP-GMM-(ii): $\mathbf{v}_t = g_t^\perp$

# Simulation results

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

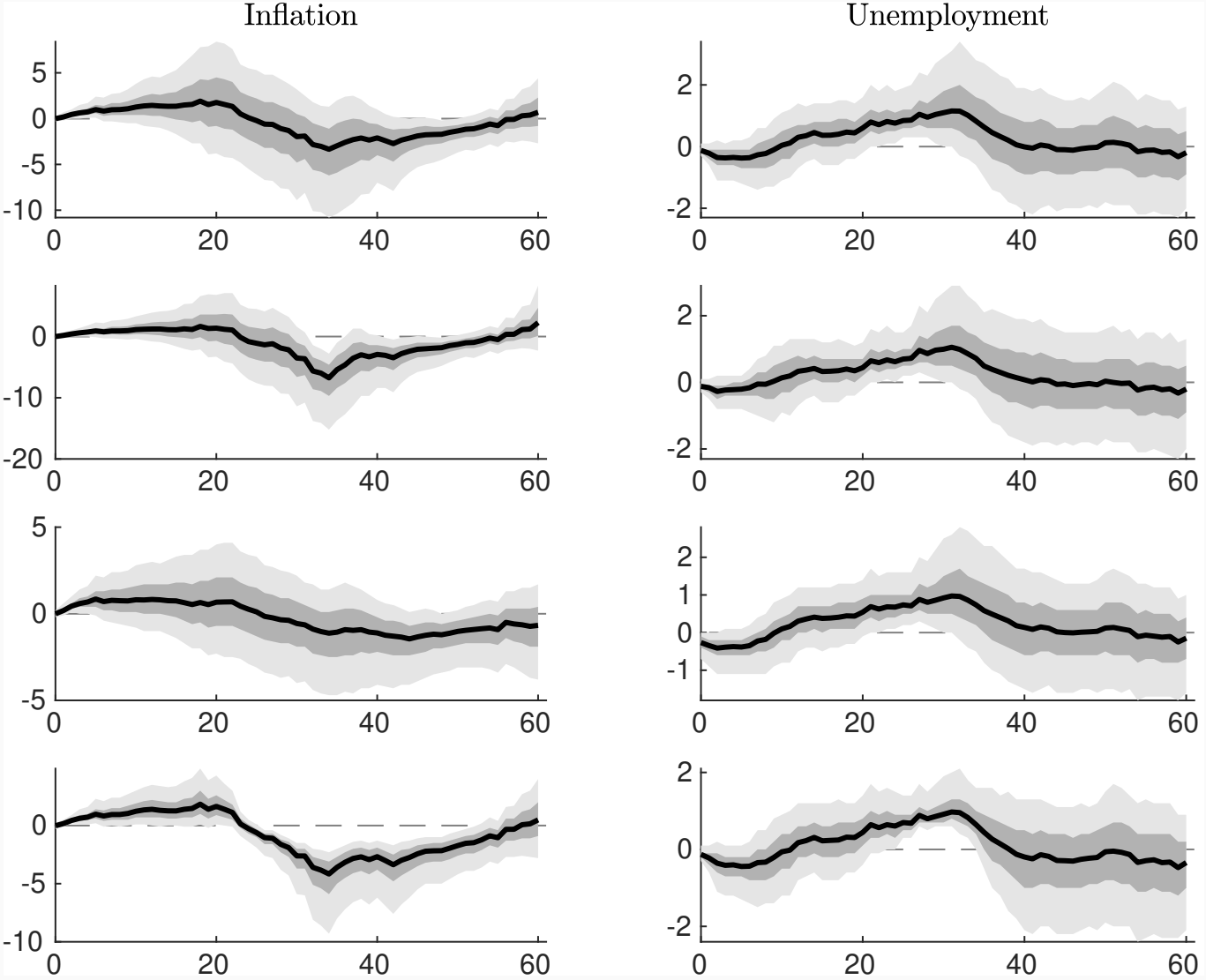
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# Alternative Narrative Treatments




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# Alternative Selection and Innovation models




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