

Monetary Policy Shocks: Data or Methods?

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The views presented herein are those of the authors and do not necessarily reflect those of the Federal Reserve Board, the Federal Reserve System or their staff.

Intro

Identifying monetary policy is difficult!

- It is endogenous: both responds to and affects the economy

High-frequency changes in asset prices proxy exogenous variation in monetary policy
since Kuttner (2001)

- isolate monetary news by comparing asset prices shortly before and after FOMC announcements
- many possible data and methods → many different monetary policy shocks available
 - Eurodollar and federal funds futures, Treasuries
 - first differences, principal component analysis, Fama-MacBeth regression

Stating the Problem

Problem: the sizes/signs of monetary shock series can vary across data/methods

- correlation as low as 0.3, same sign about 1/2 of the time
- differences starker at the ELB

How do these differences affect estimates of monetary transmission?

What We Do

Compare data/methods of Kuttner (2001), Gertler & Karadi (2015), Nakamura & Steinsson (2018)/Gürkaynak et al. (2005), Bu et al. (2021)

1. shock construction
2. monetary policy transmission

We compare shocks that are

- **high-frequency**, for VAR or narrative comparisons see: Rudebusch (1998), Ettmeier and Kriwoluzky (2019)
- **single series**, for multiple dimensions see: Gürkaynak et al. (2005), Lewis (2023), Swanson (2021, 2023), Acosta (2023), Jarocinski (2023)
- **w/out add-ons**: Miranda-Agrippino and Ricco (2021), Bauer and Swanson (2023, 2022), Jarocinski and Karadi (2020), Nunes et al. (2023), Zhu (2023)

What We Find

Monetary transmission:

- IRFs of LPs and VARs more similar across shock series than forecast revisions
- swapping data/methods → qualitative differences: inference not robust to construction

Bu et al. (2021) shock series:

- unpredictable by economic news
- similar in ELB and non-ELB periods
- mitigates an adversely-signed response in the specifications we study

Attribute to data on long-term rates *and* a method that extract their differential responsiveness relative to short-term rates

- high-frequency shocks pioneered when the FFR was the key policy instrument (and no ELB...); now there is a portfolio of tools

Shock Construction

1. Data Only: MP1 and FF4

MP1: Kuttner (2001)

$$MP1_s = \begin{cases} \frac{D^s}{D^s - d^s} (ff_{s,t}^1 - ff_{s,t-\Delta t}^1) & \text{if } D^s - d^s > 7 \\ ff_{s,t}^2 - ff_{s,t-\Delta t}^2 & \text{otherwise} \end{cases}$$

FF4: Gertler & Karadi (2015), Jarocinski & Karadi (2021)

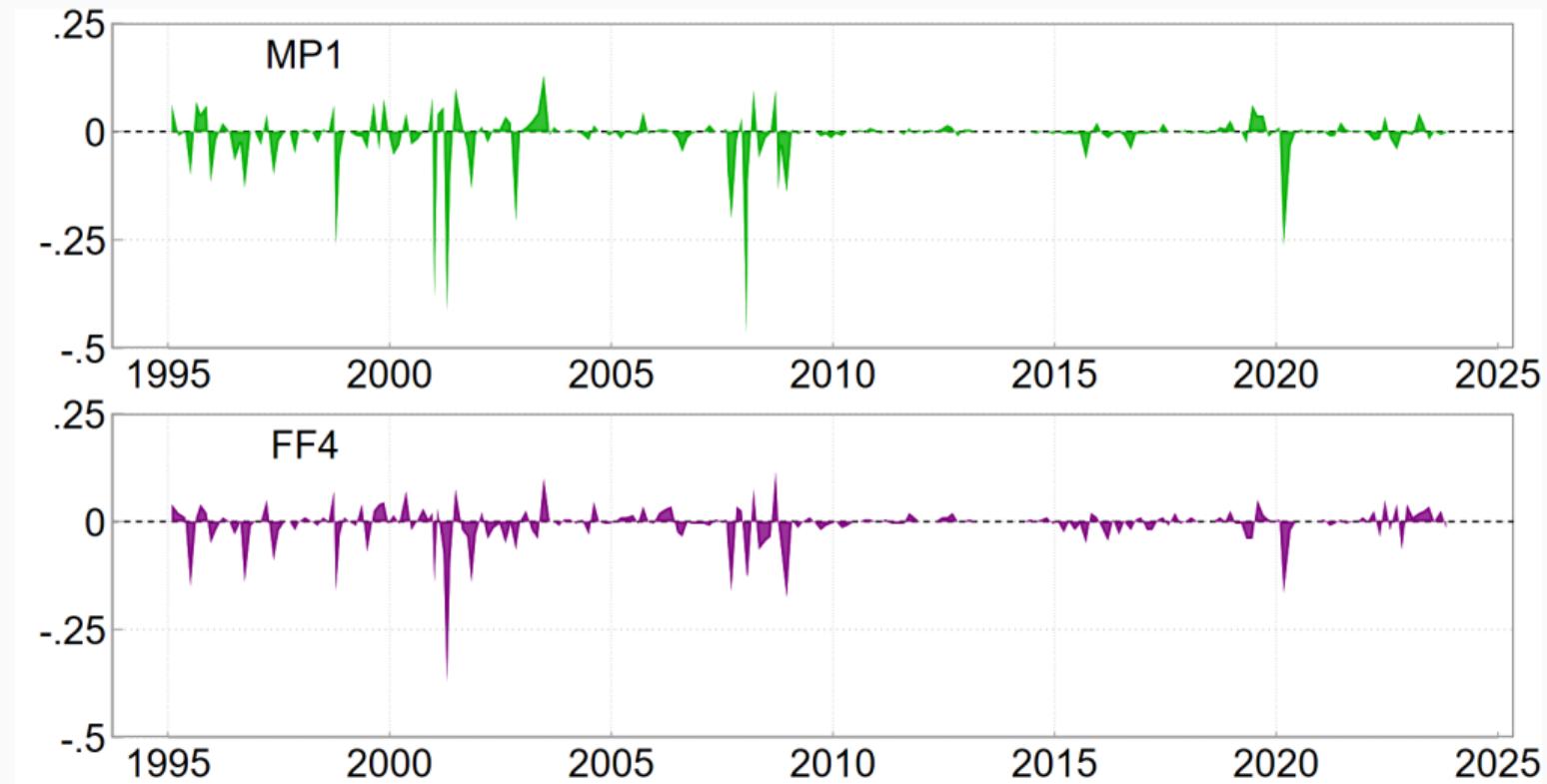
next announcement

$$\Delta ff_s^4 = (ff_{s,t}^4 - ff_{s,t-\Delta t}^4)$$



Data Only: MP1 and FF4

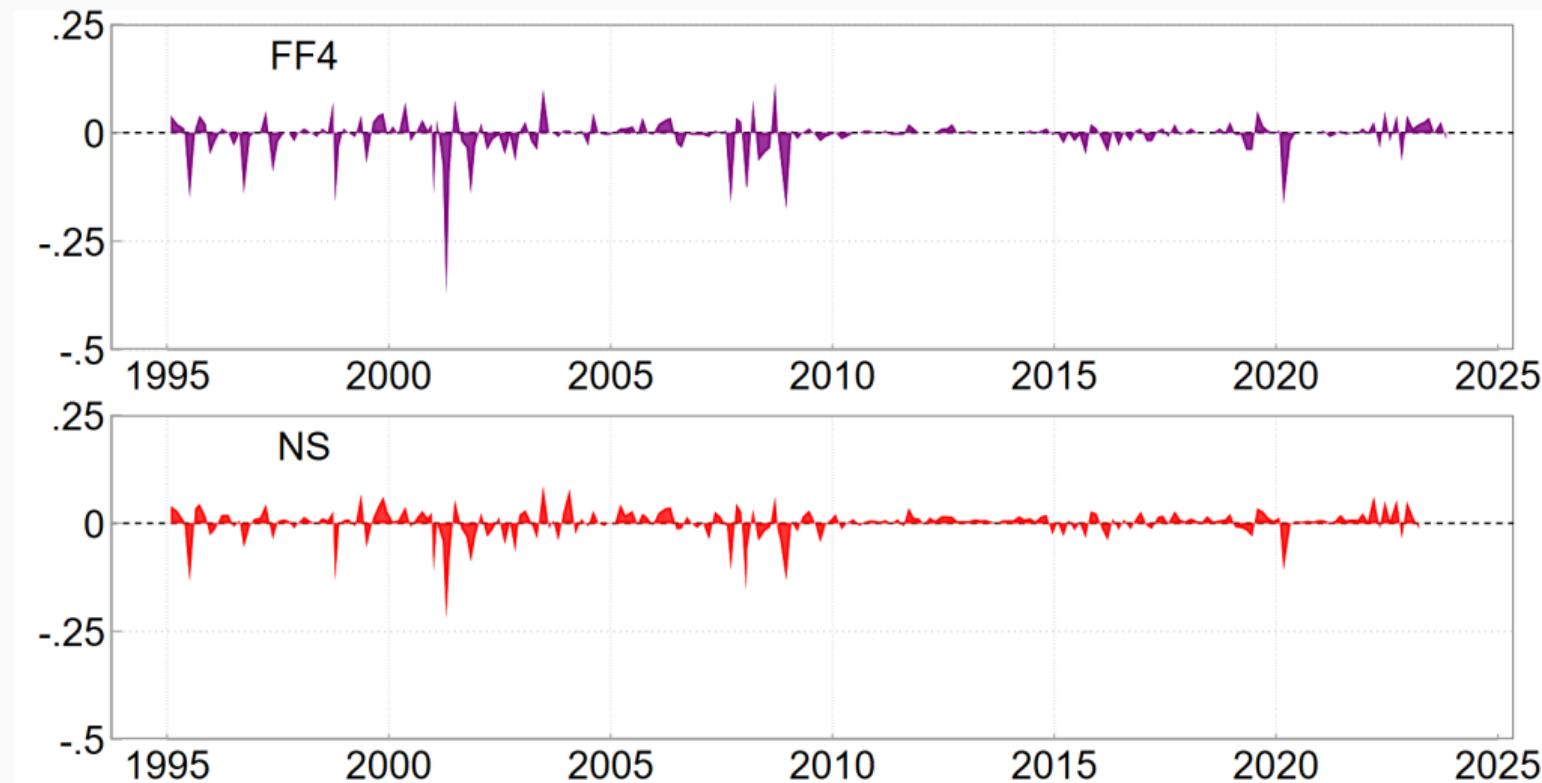
▶ histograms



correlation=0.8 , same-sign=59%

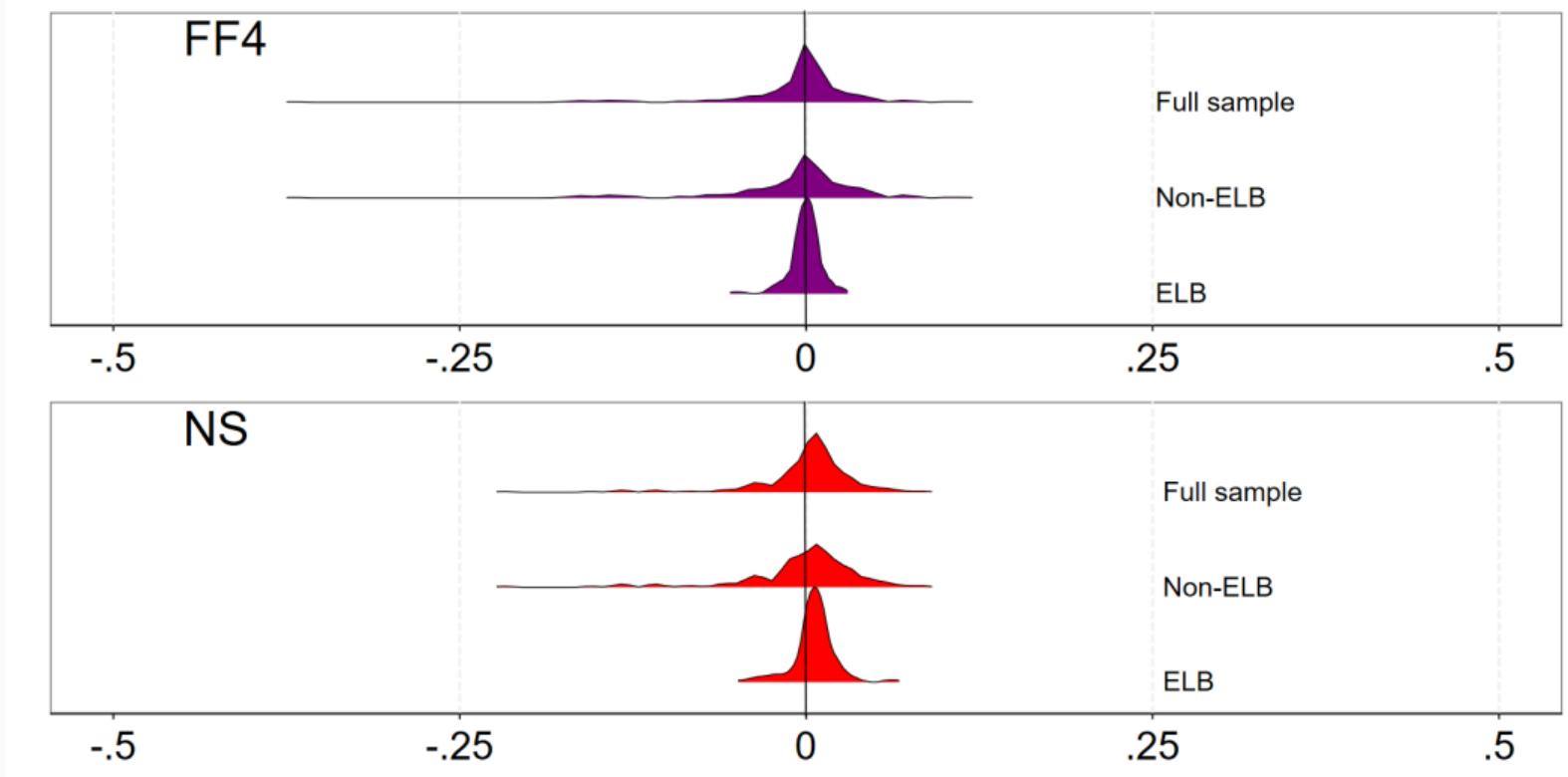
Data & Methods: Nakamura and Steinsson (NS)

▶ NS Construction



correlation=0.92 , same-sign=66%

Data & Methods: Nakamura and Steinsson (NS)



Data and Methods: Bu et al. (2021)

- Fama and MacBeth (1973) regression on Treasury yield curve
- One day window surrounding FOMC announcement s
 1. estimate $\{\hat{\beta}_j\}_{j=1}^{30}$ via separate regressions

$$\begin{aligned}\Delta R_s^1 &= \alpha_1 + \beta_1 \Delta i_s + \epsilon_s^1 \\ &\vdots \\ \Delta R_s^{30} &= \alpha_{30} + \beta_{30} \Delta i_s + \epsilon_s^{30}\end{aligned}$$

assume Δi_s is one-to-one with 2-year yield ΔR_s^2 , so $\Delta i = \Delta R_s^2 - \varepsilon_s^2$. Then,

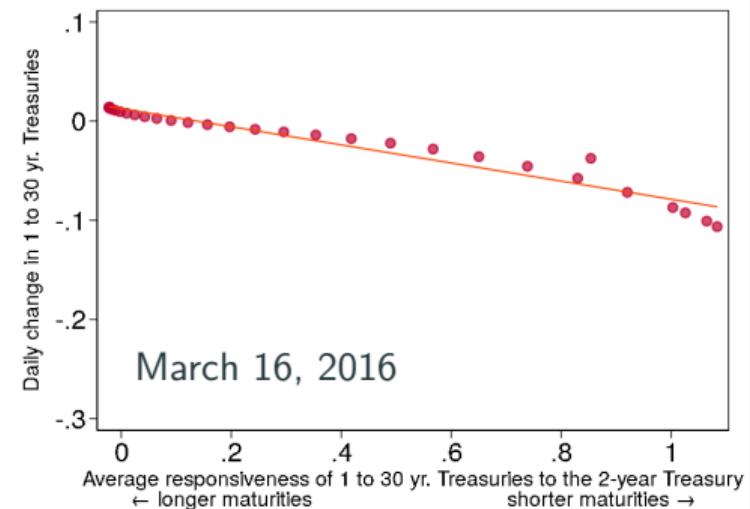
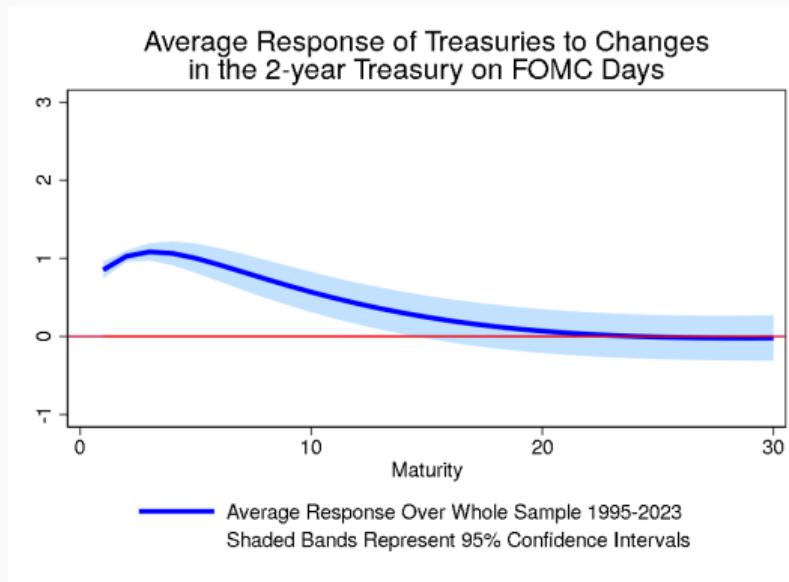
$$\Delta R_s^j = \theta_j + \beta_j \Delta R_s^2 + \underbrace{\epsilon_s^j - \beta_j \varepsilon_s^2}_{\xi_s^j}$$

endogeneity of $\text{corr}(\Delta R_s^j, \xi_s^j) > 0$ reconciled w/ IV or Rigobon (2003) estimator

2. estimate shocks $\Delta \hat{i}_s$ from $s = 1, \dots, T$ cross-sectional reg. of ΔR_s^j on $\{\hat{\beta}_j\}_{j=1}^{30}$

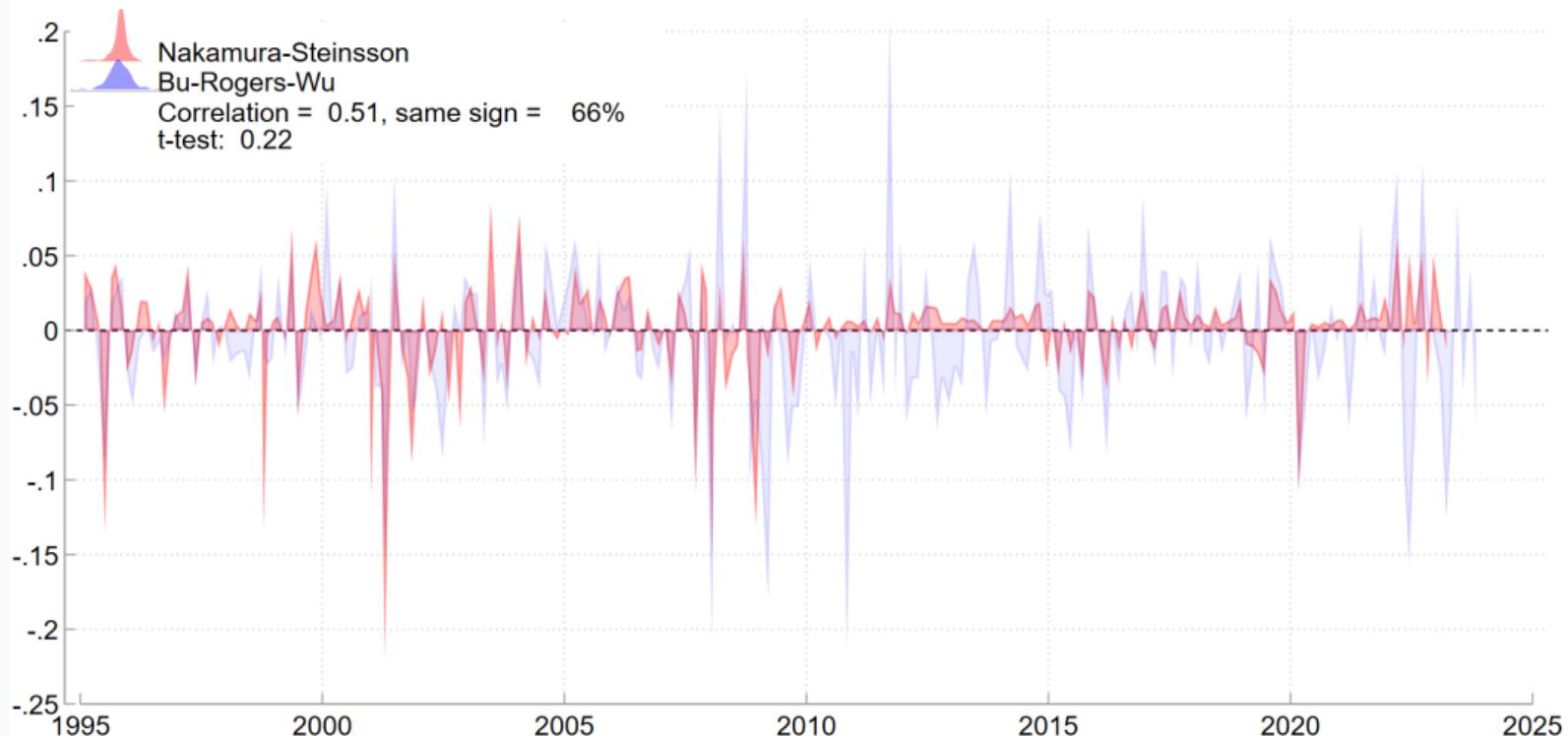
$$\Delta R_s^j = \alpha_j + \Delta \hat{i}_s \hat{\beta}_j + \nu_s^j, \quad s = 1, \dots, T \text{ announcements}$$

3. Re-scale shocks series to ΔR_s^2



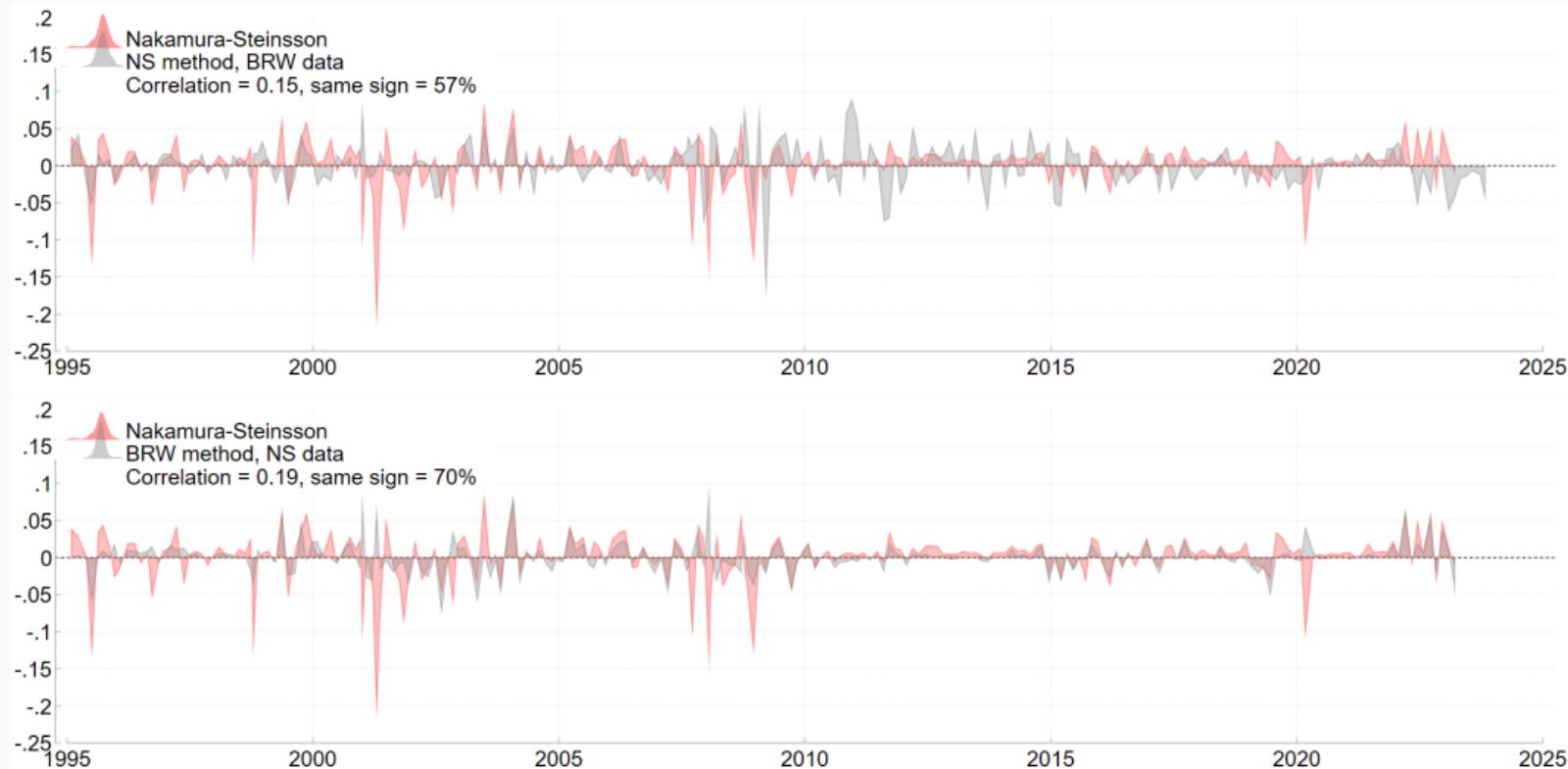
Why the difference?

▶ histograms



3. Swapped shocks: differences due to methods or data?

► BRW compare



Estimating Monetary Transmission

Monthly revisions to Blue-chip forecasts à la Nakamura and Steinsson (2018),
Campbell et al. (2012)

$$\text{Blue Chip GDP Revisions}_T = \beta \varepsilon_t^i + e_T$$

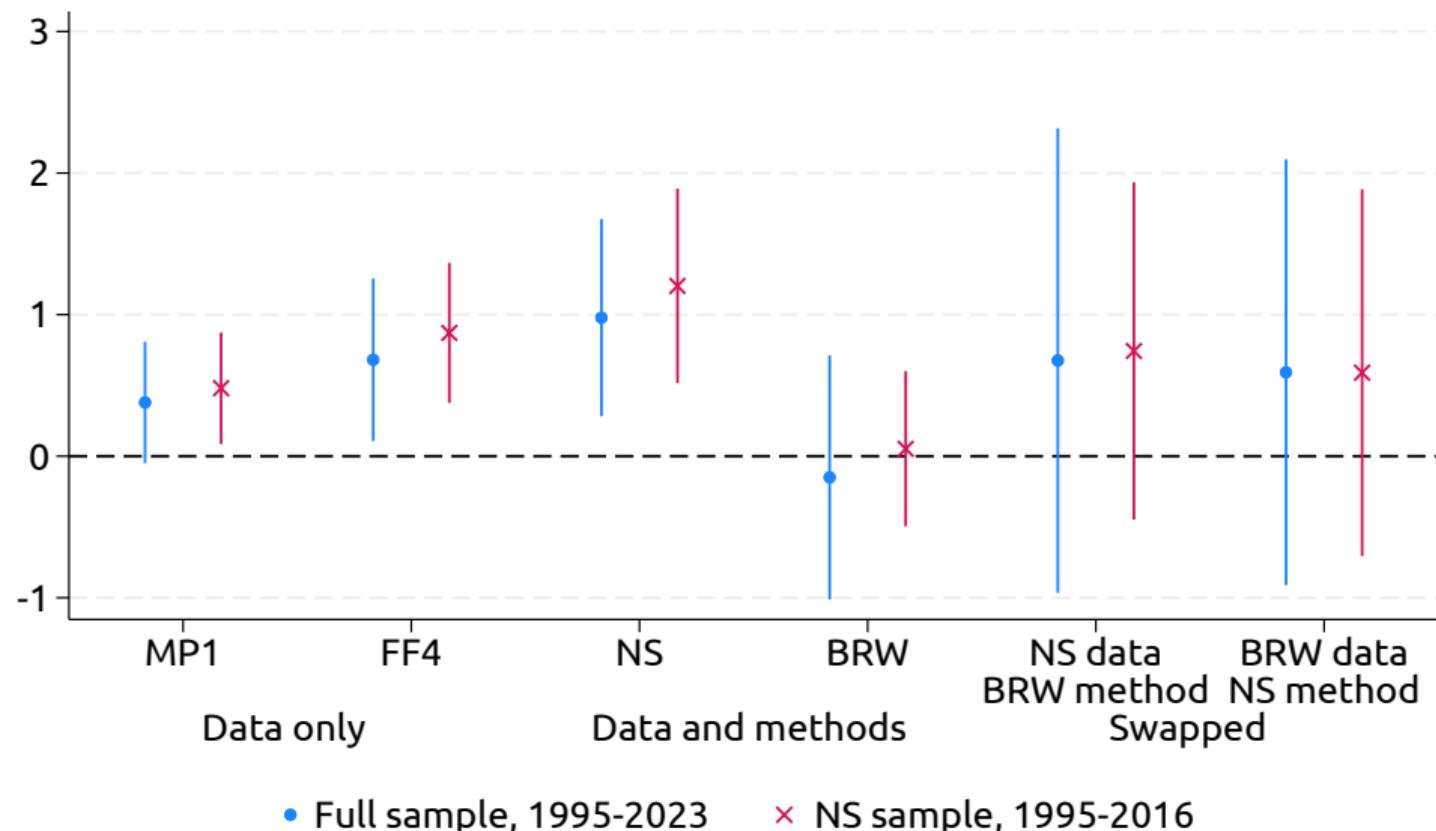
for $i = \text{data, data and methods, swapped}$

- $\hat{\beta}$ often the opposite sign of theoretical predictions

Blue Chip Regression Coefficients, 95% CI

▶ Other samples

▶ ELB



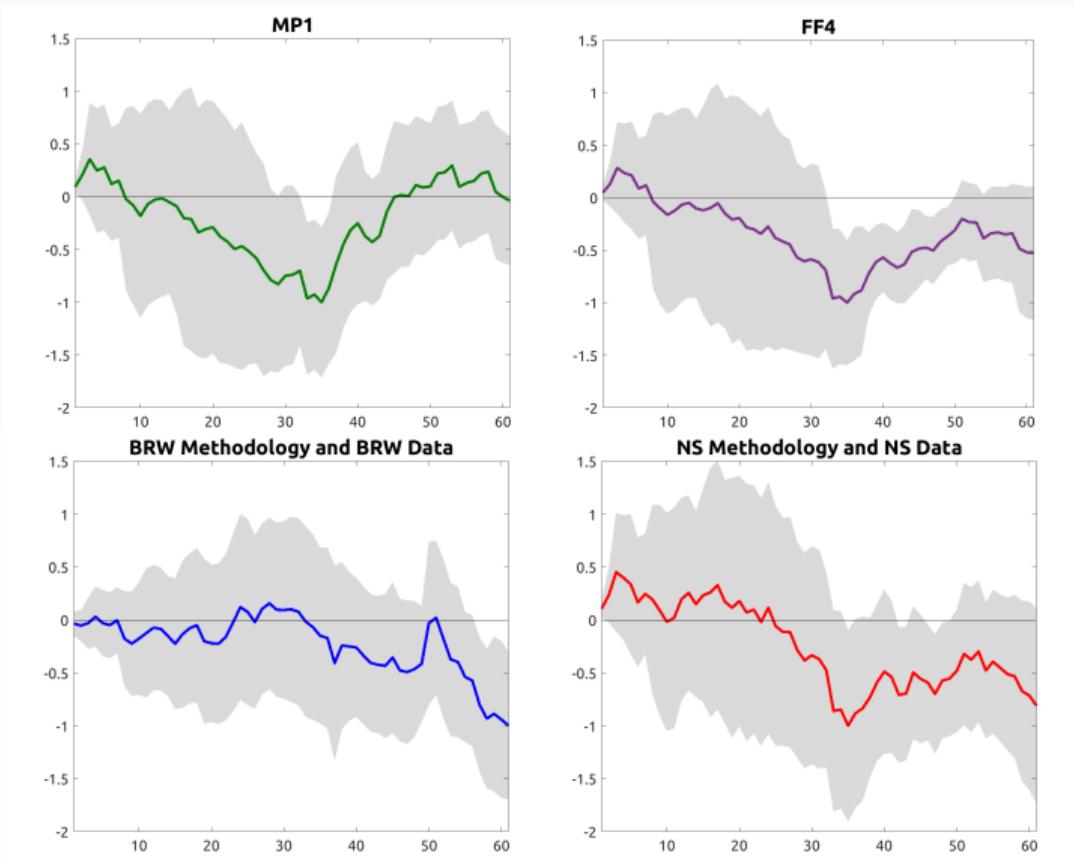
Estimating Monetary Transmission

Billion Prices Project's daily CPI in a local projection for day $t + h$.

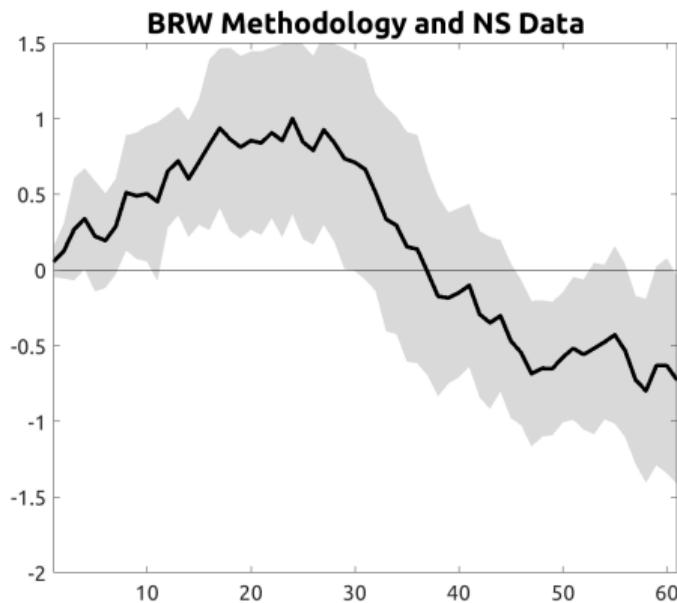
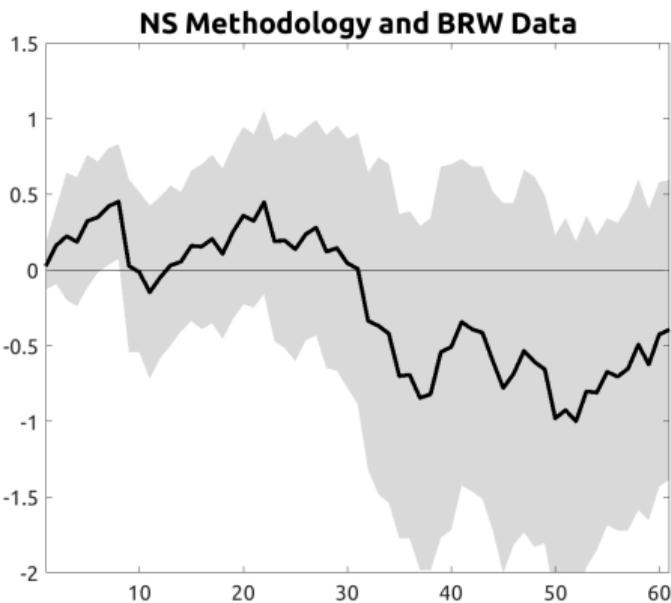
$$\pi_{t+h} = \alpha_{(h)} + \beta_{(h)} \varepsilon_t^i + \Gamma_h z_t + e_t^h$$

- LHS and RHS both high-frequency
- Jacobson et. al (2023): high-frequency LHS mitigates temporal aggregation bias

2. Local Projections 2008-2015, 90% CI



2. Local Projections 2008-2015, 90% CI



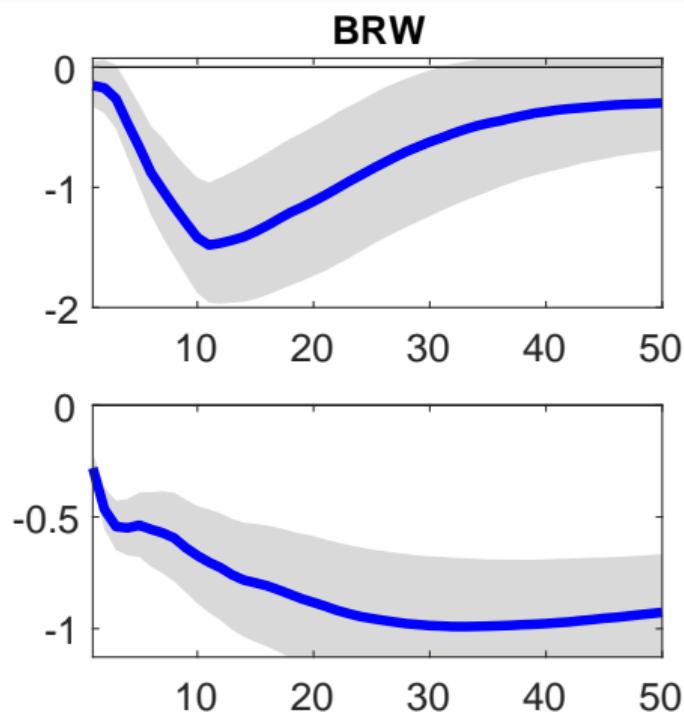
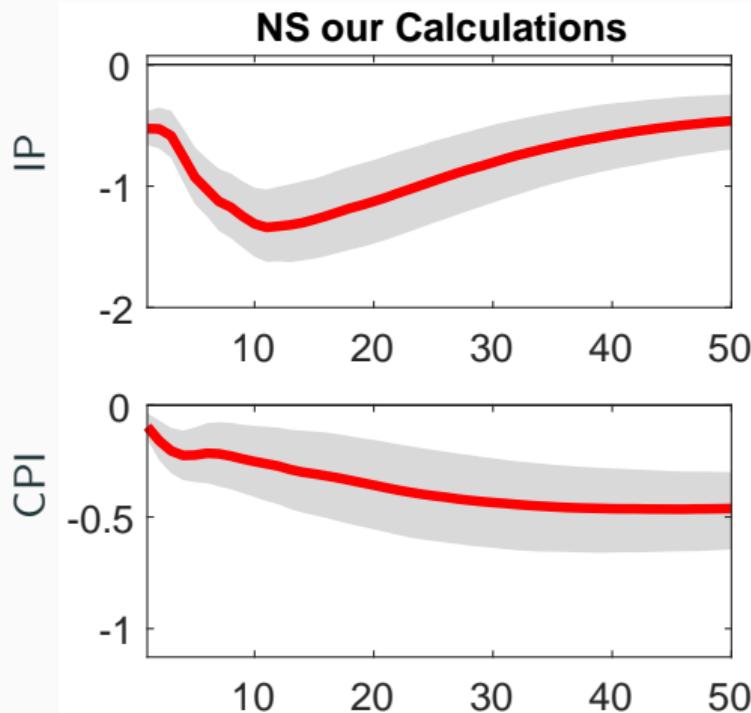
Estimating Monetary Transmission

Gertler and Karadi (2015) VAR with the monetary shock as an external instrument à la Bauer and Swanson (2022)

- 8 lags, 4 variables: IP, CPI, excess bond premium, 2-year Treasury
- VAR: 1973 to Feb. 2020
- External instrument: 1995 to 2019
- Canova & Ferroni Toolbox

VAR IRFs, 25 bps Monetary Shock

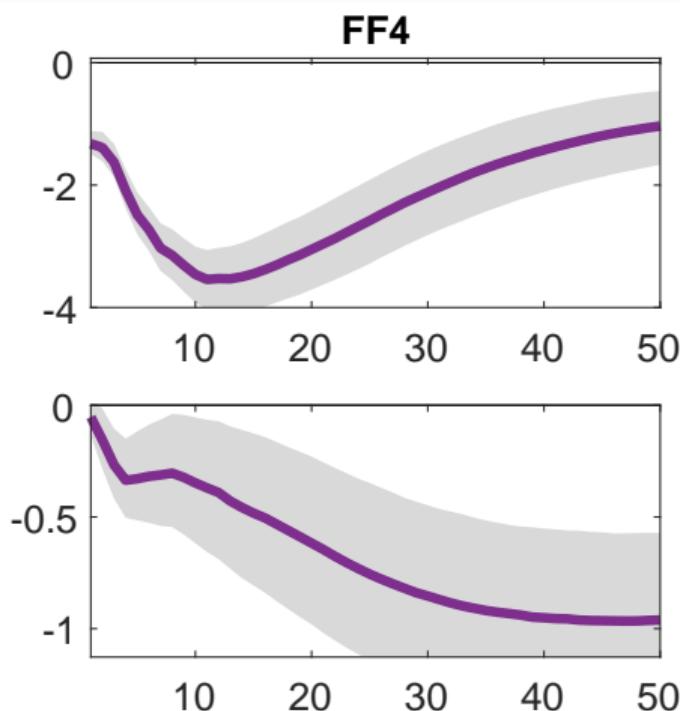
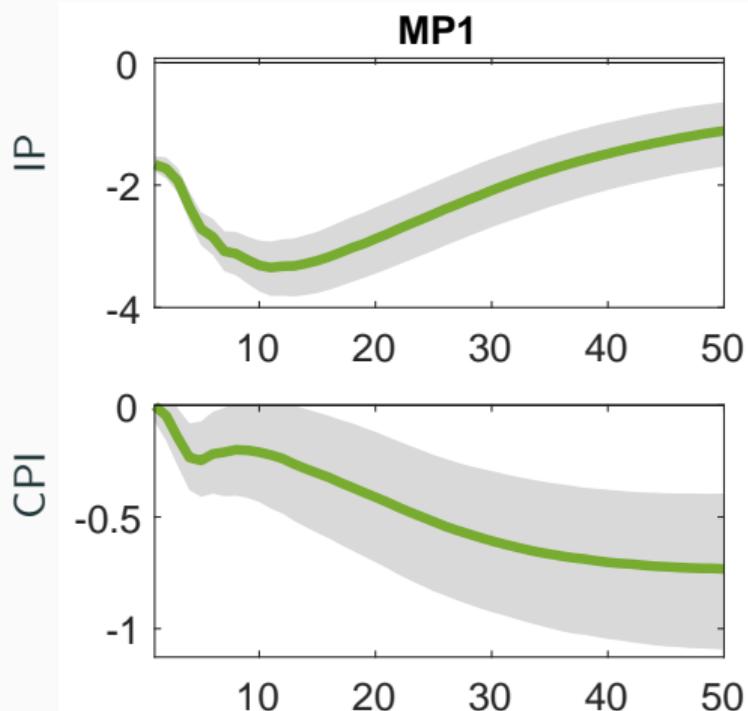
[detailed comparison](#) [financial variables](#)



VAR IRFs, 25 bps Monetary Shock

detailed comparison

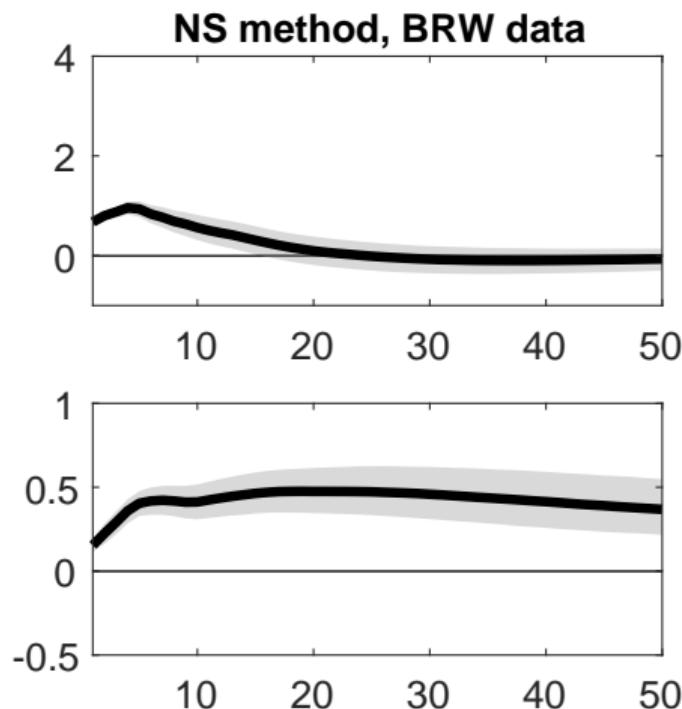
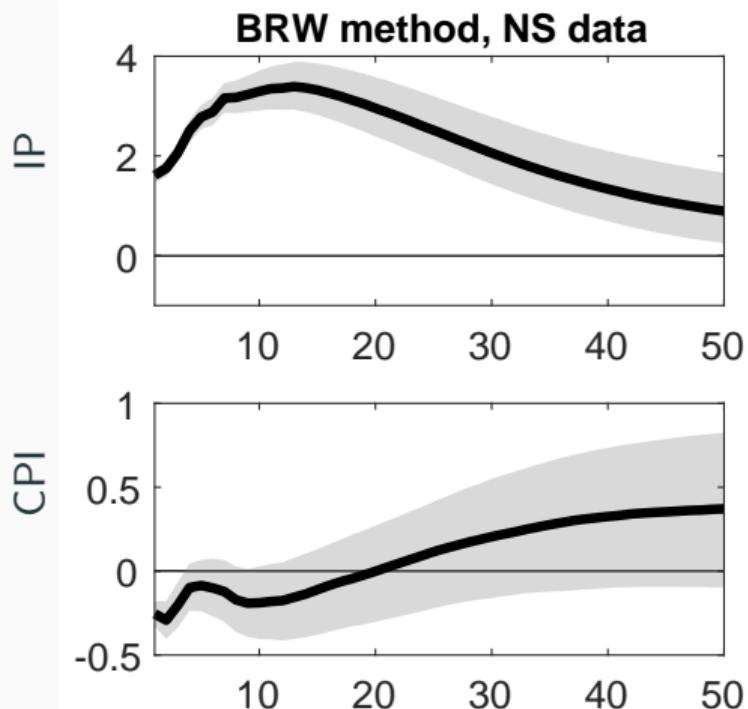
financial variables



VAR IRFs, 25 bps Monetary Shock

[detailed comparison](#)

[financial variables](#)



Conclusion

Document differences in sizes/signs of high-frequency monetary shocks

- starker at the ELB

Attribute differences to both data and methods

- shift away from a single instrument to a portfolio of tools
- exploiting additional information from long-term rates depends on the method

Consequences for inference depends on the specification

- qualitatively similar in some LPs and VARs
- qualitatively different when swapping data/methods, inference may not be robust to all constructions

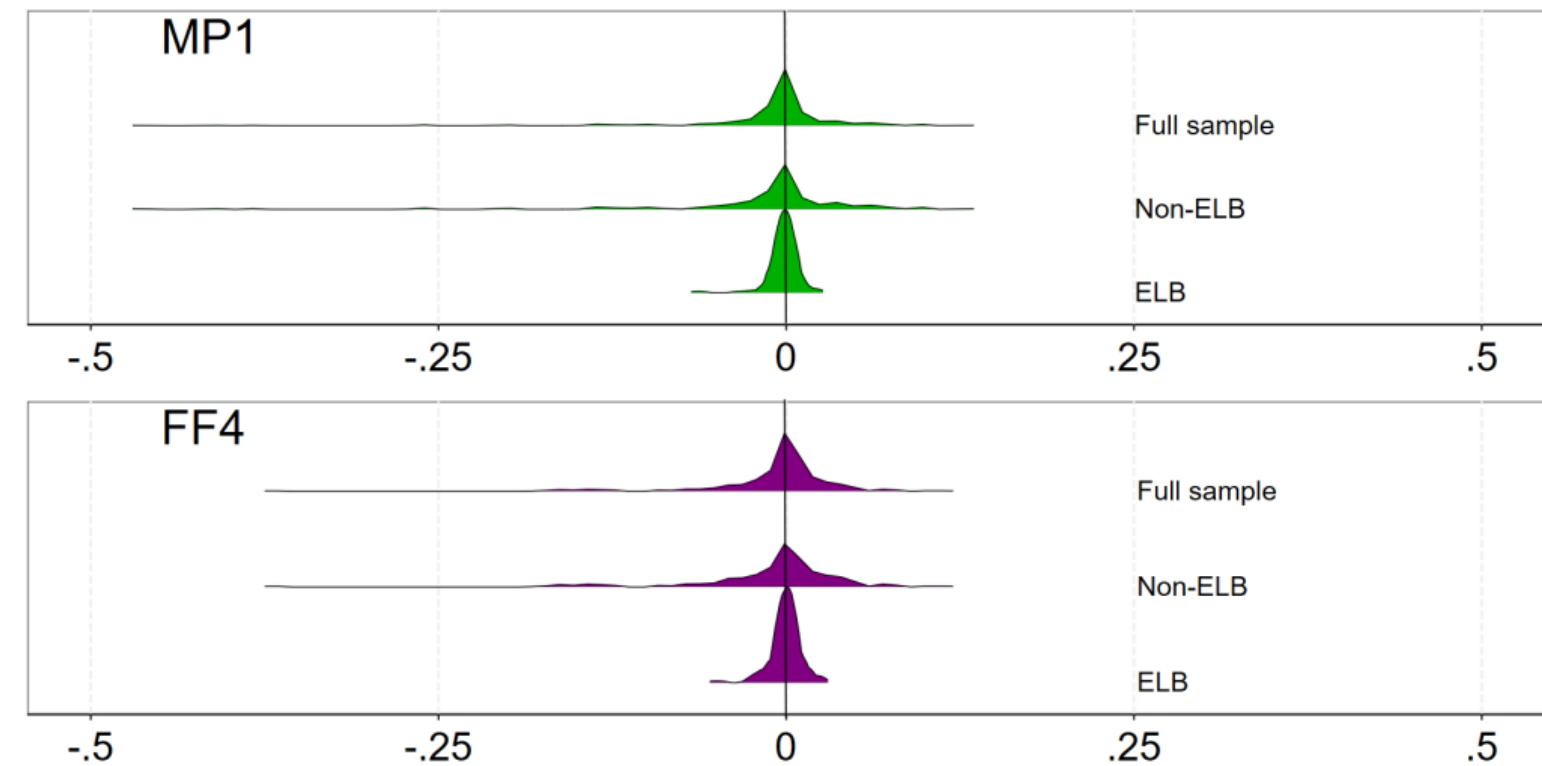
Appendix

Months Ahead of the Next Scheduled FOMC Announcement



Future		Percent	Number
FF1	in current month	2.05%	5
FF2	1-month ahead	50.41%	123
FF3	2-months ahead	47.13%	115
FF4	3-months ahead	0.41%	1
Total			244

1. Data only: High Frequency Monetary Policy Shocks





- First principal component of intraday changes in five futures
- Fed funds futures liquid for ≈ 3 months ahead, eurodollars 4 to 12 months ahead
eurodollars: dollar-denominated deposits at foreign banks
- 30-minute window surrounding FOMC announcement in month s

$MP1_s$ as previously shown

$$MP2_s = \begin{cases} \frac{D^{s'}}{D^{s'} - d^{s'}} \left[(ff_{s',t}^j - ff_{s',t-\Delta t}^j) - \frac{d^{s'}}{D^{s'}} MP1_s \right] & \text{if } D^{s'} - d^{s'} > 7, \quad j \approx 2, 3 \\ ff_{s',t}^{j+1} - ff_{s',t-\Delta t}^{j+1} & \text{otherwise} \end{cases}$$

▶ details

$$edk_q = edk_{q,t} - edk_{q,t-\Delta t}, \quad k = 2, 3, 4 \quad \text{quarters ahead}$$

Construction of Nakamura and Steinsson (2018) Shocks

- expected ffr (r_0) for the month of the FOMC announcement, adjusted elapsed days of the month (d^s) out of total days (D^s)

$$\underbrace{f_{t-\Delta t}^1}_{\text{current month's ffr future prior to FOMC}} = \underbrace{\frac{d^s}{D^s} r_{-1}}_{\text{current month's ffr prior to FOMC}} + \underbrace{\frac{D^s - d^s}{D^s} \mathbb{E}_{t-\Delta t} r_0}_{\text{current month's ffr future prior to FOMC}}$$

$$\underbrace{f_t^1}_{\text{current month's ffr future after FOMC}} = \underbrace{\frac{d^s}{D^s} r_{-1}}_{\text{current month's ffr prior to FOMC}} + \underbrace{\frac{D^s - d^s}{D^s} \mathbb{E}_t r_0}_{\text{current month's ffr future after FOMC}}$$

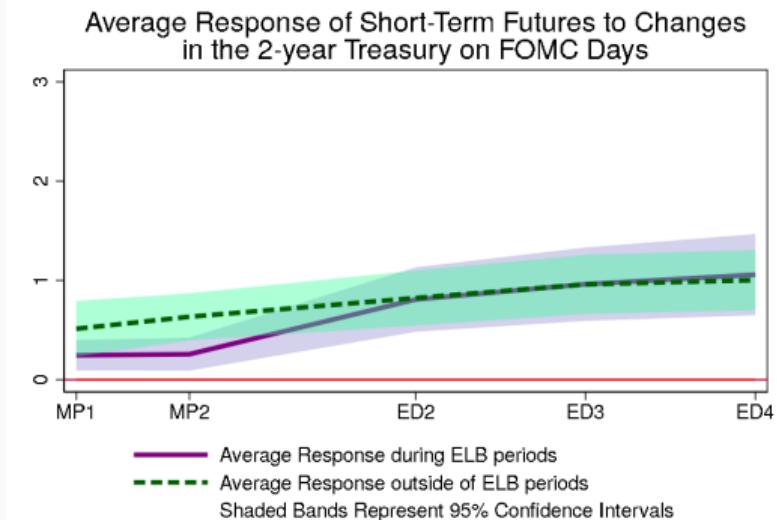
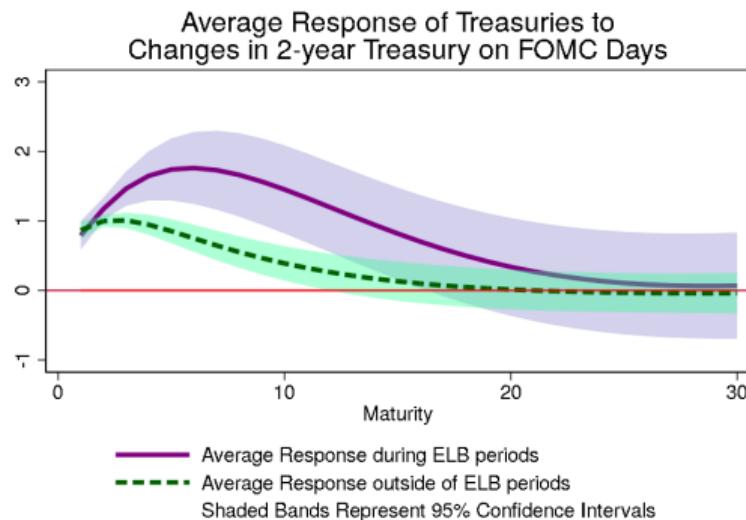
Combining and re-arranging:

$$\underbrace{\mathbb{E}_t r_0 - \mathbb{E}_{t-\Delta t} r_0}_{\text{expected } \Delta \text{ in current month's ffr}} = \frac{D^s}{D^s - d^s} (f_t^1 - f_{t-\Delta t}^1)$$

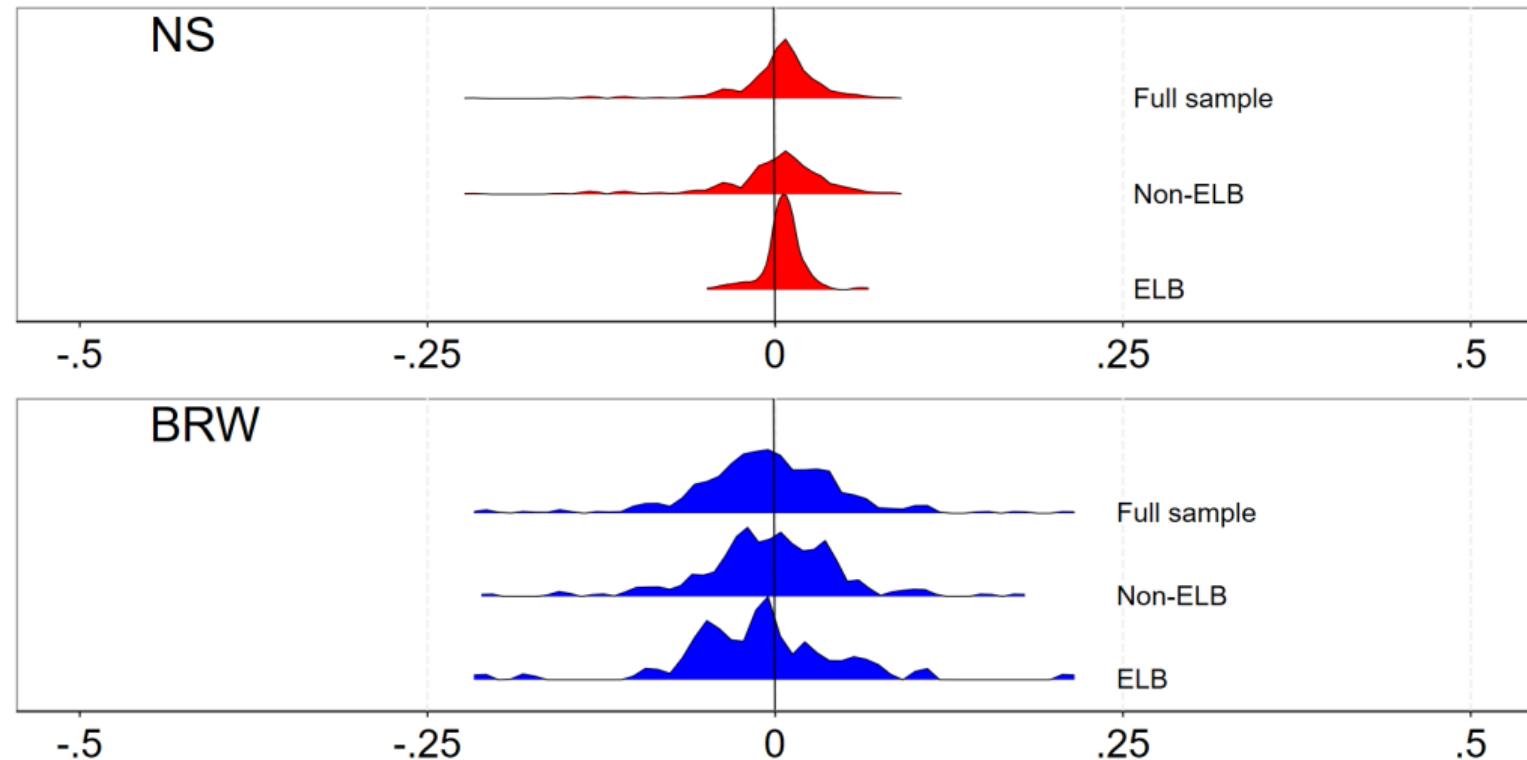
- expected ffr r_1 for the remainder of the month of the next scheduled FOMC announcement

$$\underbrace{\mathbb{E}_t r_1 - \mathbb{E}_{t-\Delta t} r_1}_{\substack{\text{expected } \Delta \text{ in ffr} \\ \text{in month of next FOMC}}} = \frac{d^{s'}}{D^{s'} - d^s} \left[\underbrace{(f_t^n - f_{t-\Delta t}^n)}_{\Delta \text{ in ffr future for next FOMC}} - \underbrace{\frac{d^{s'}}{D^{s'}} (\mathbb{E}_t r_0 - \mathbb{E}_{t-\Delta t} r_0)}_{\text{scaled expected } \Delta \text{ in current month}} \right]$$

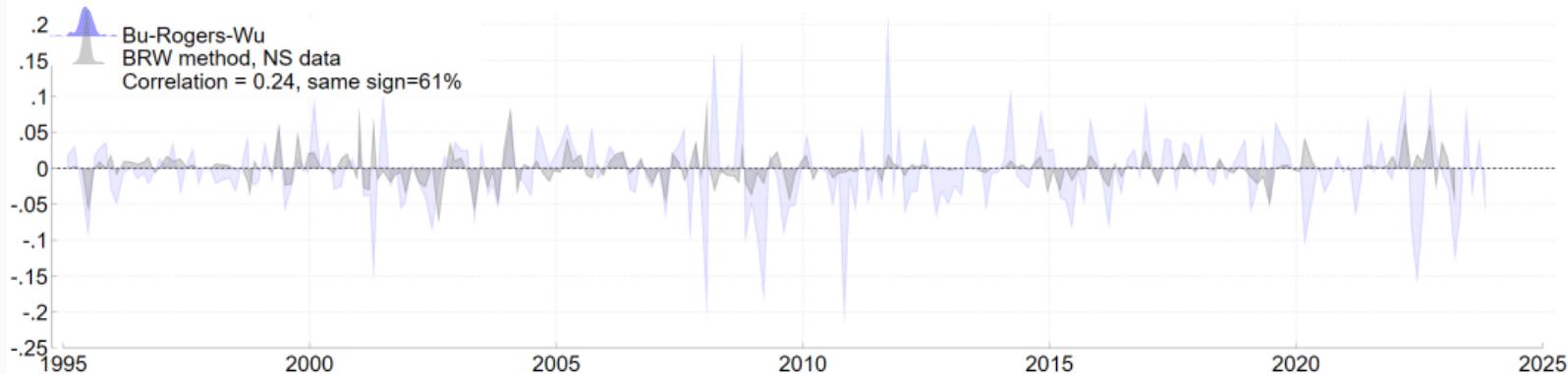
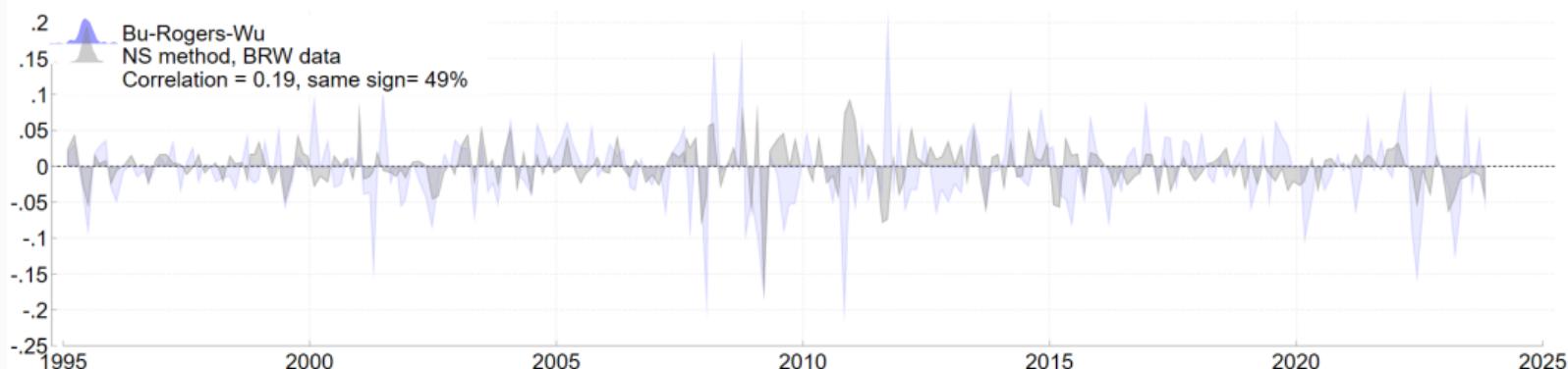
Data and Methods: Bu et al. (2021) ELB Comparison



2. Why the difference?



3. Swapped shocks: differences due to methods or data?



Note: legend markers are data distributions.

Predictability

Karnaukh and Vokata (2022), Sastry (2021), and Bauer and Swanson (2023) show that monetary shocks ε_t^i can be predicted by economic news

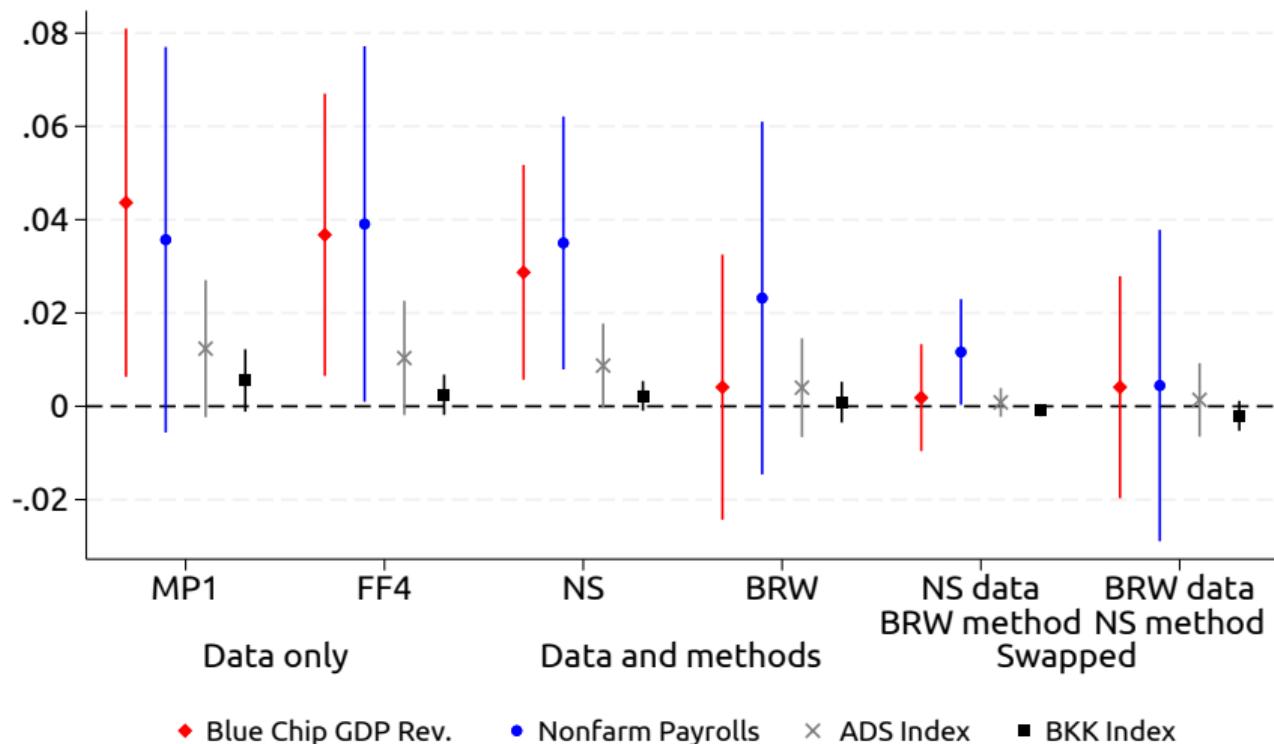
$$\varepsilon_t^i = \alpha + \beta \text{news}_t^k + e_t$$

$$\text{news } k = \left\{ \begin{array}{l} \text{Blue-Chip GDP revisions} \\ \text{Change in non-farm payrolls} \\ \text{Aruoba-Scotti-Diebold index} \\ \text{Brave et. al Index} \end{array} \right.$$

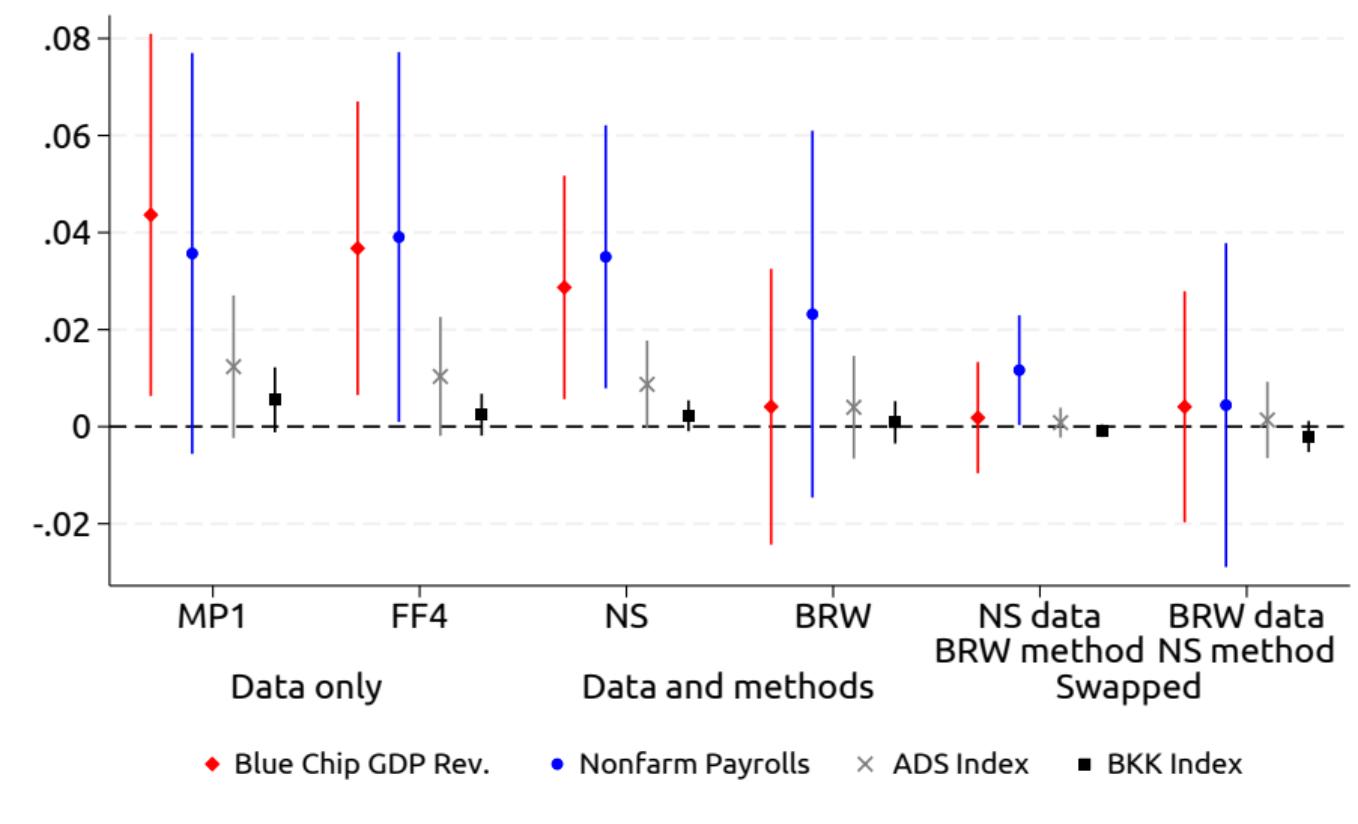
for $i = \text{data, data \& methods, swapped shocks}$

Predictability Coefficients from 1995 to 2023 (ex. Covid), 95% CI

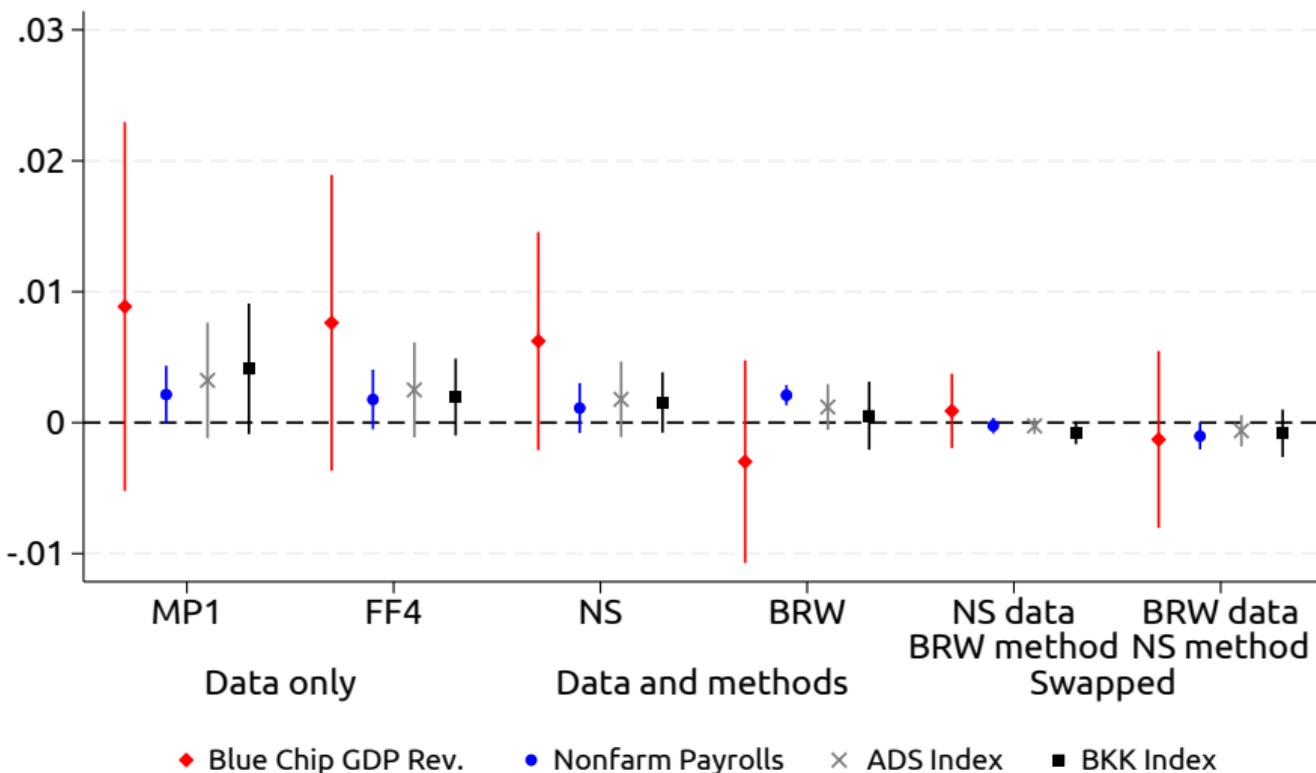
► full sample ► full, ex crisis ► full, ex crisis & covid ► 1995-2016 ► 1995-2016, ex crisis ► ELB ► non-ELB ◀



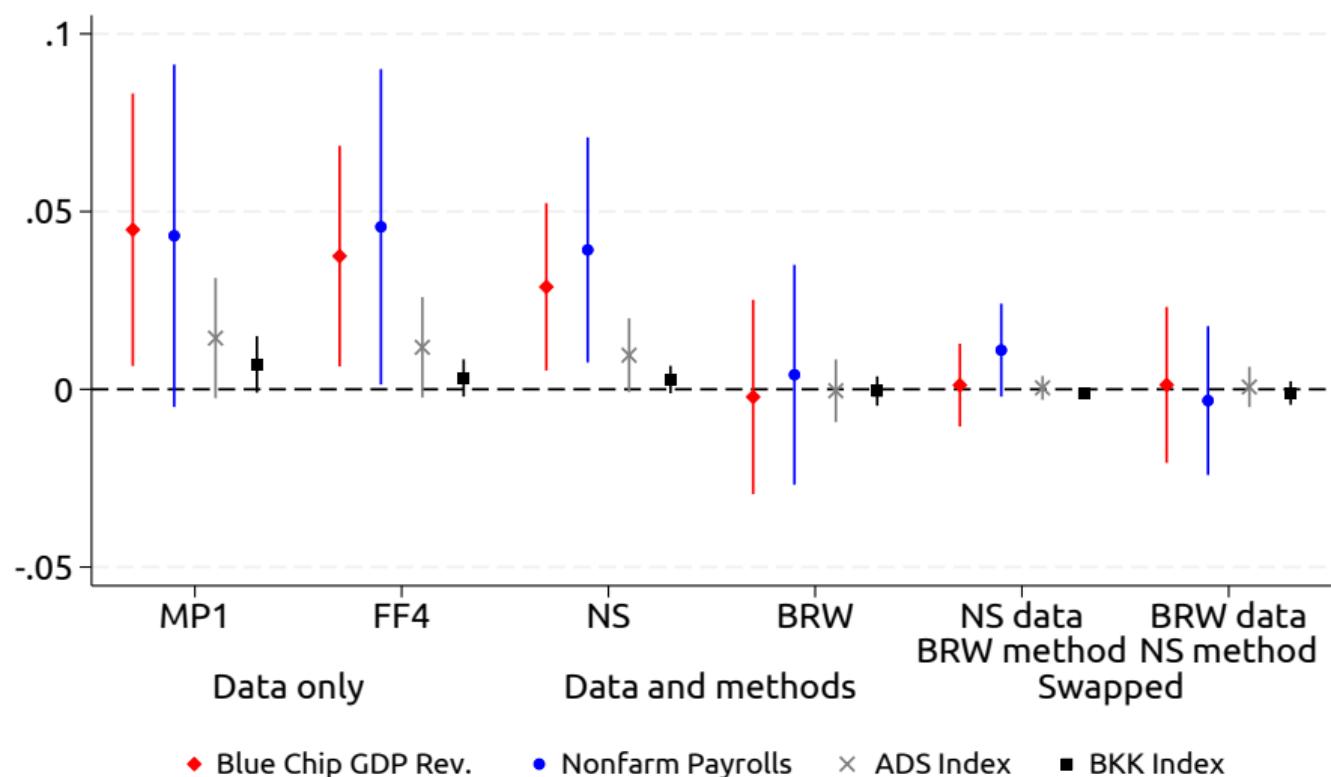
Predictability Coefficients from 1995 to 2023, 95% CI



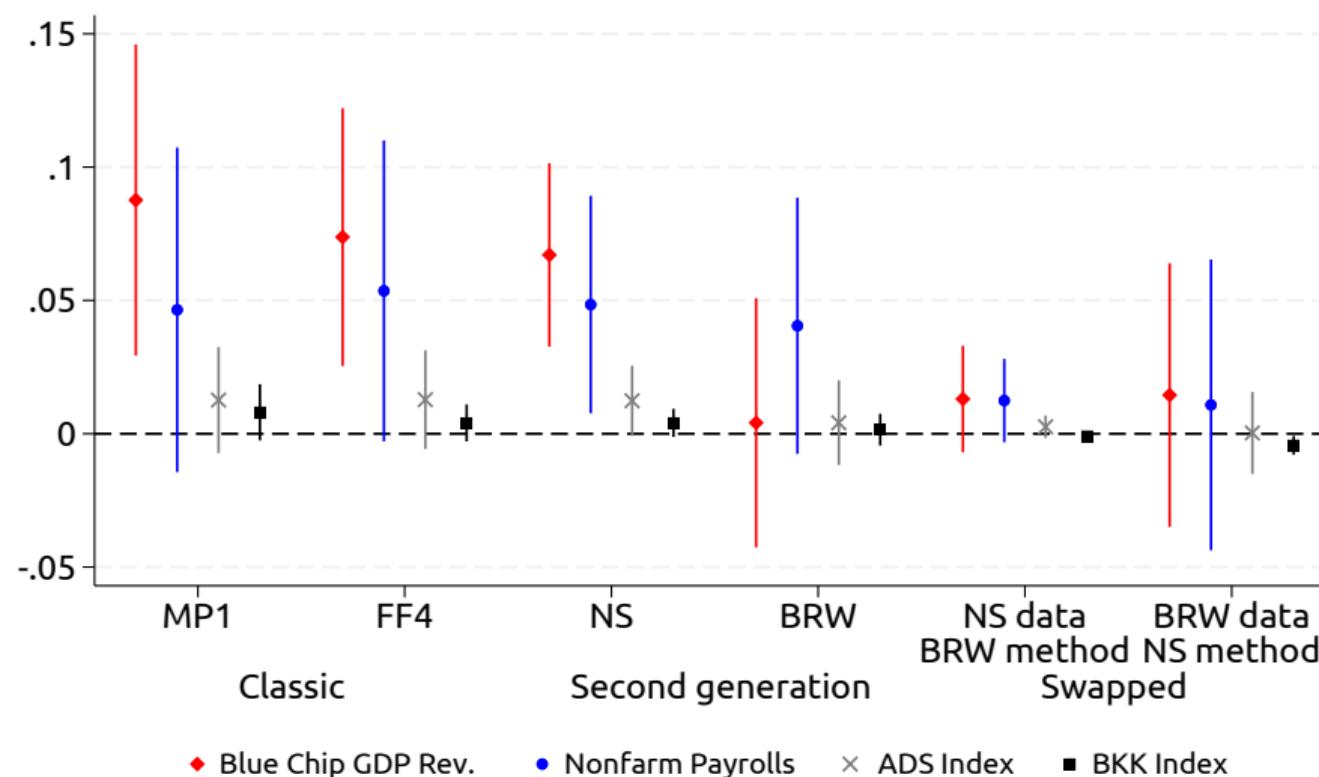
Predictability Coefficients from 1995 to 2023 (ex. crisis), 95% CI



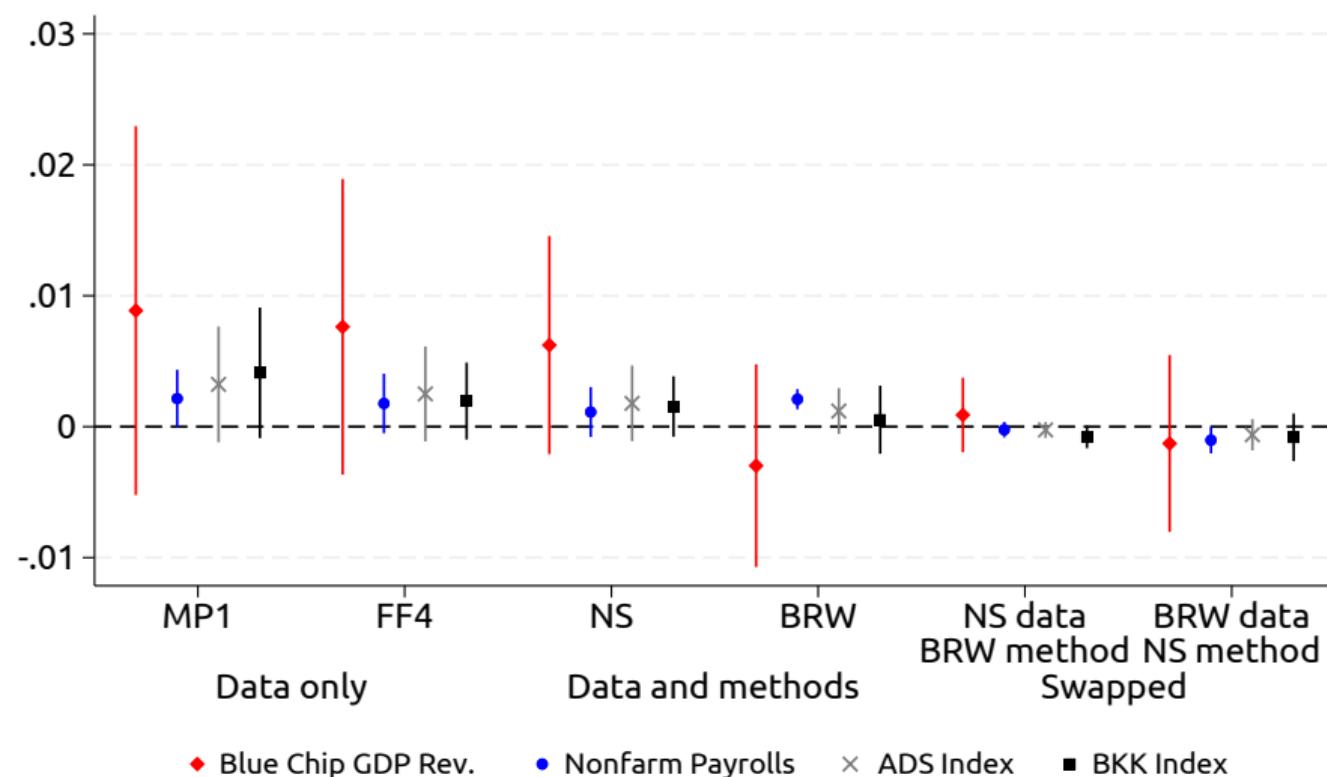
Predictability Coefficients from 1995 to 2023 (ex. crisis & Covid), 95% CI



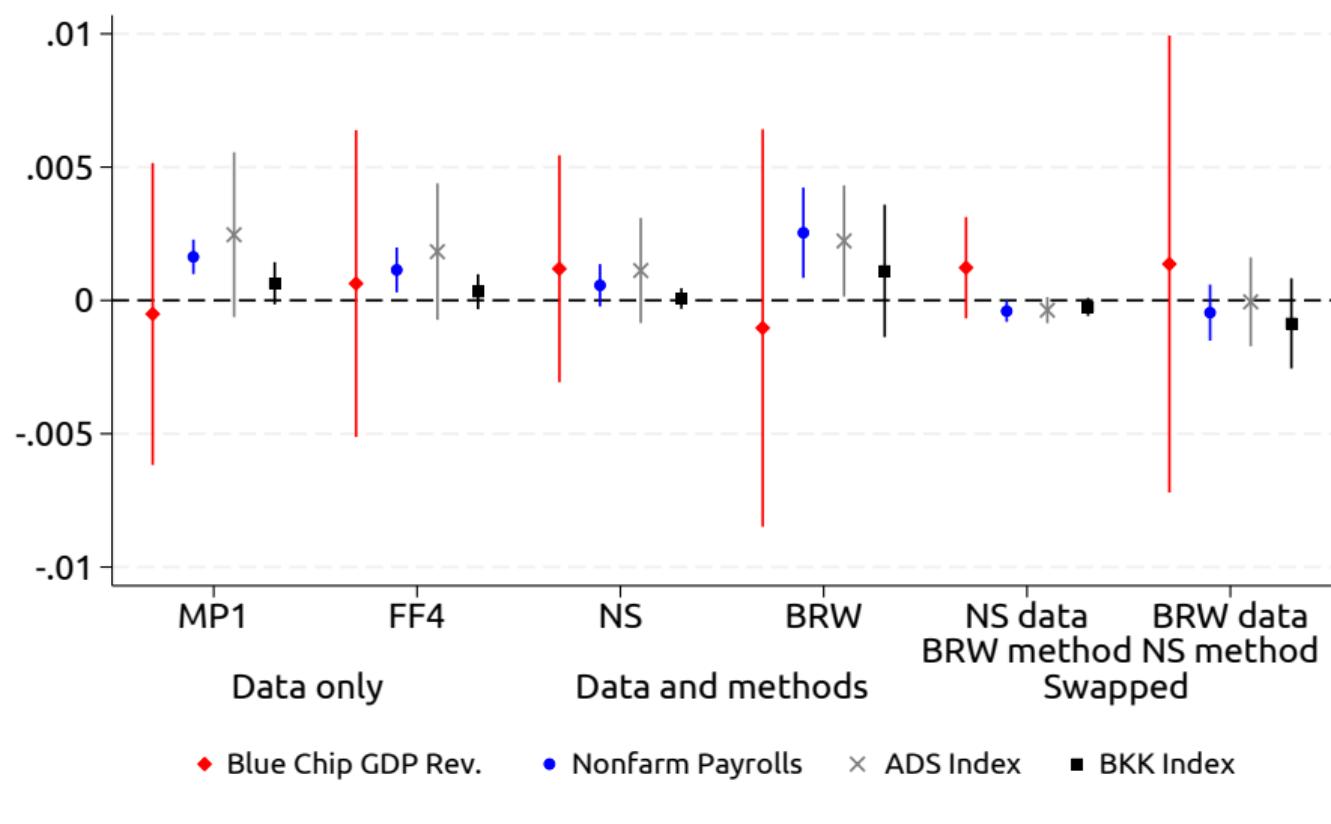
Predictability Coefficients from 1995 to 2016, 95% CI



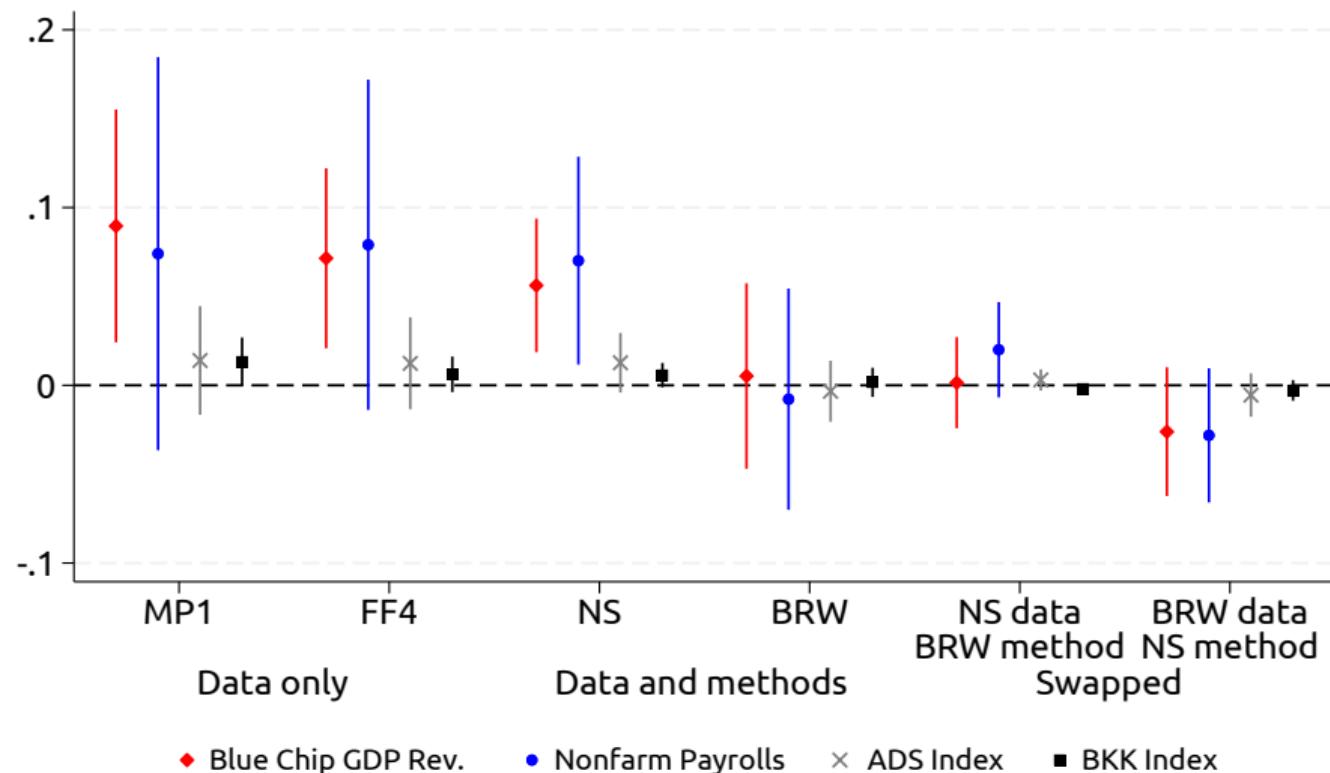
Predictability Coefficients from 1995 to 2016 (ex. crisis), 95% CI



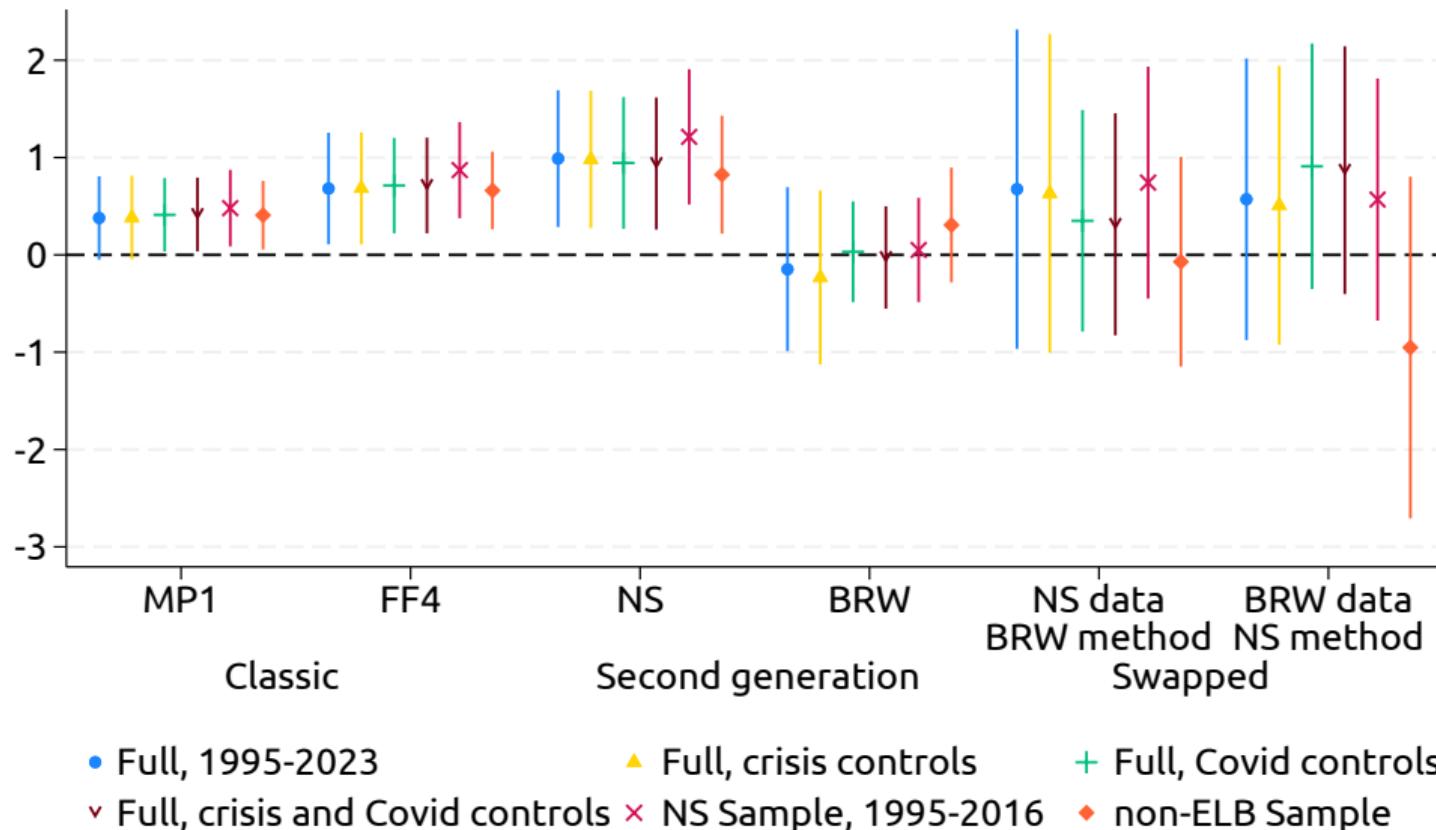
Predictability Coefficients ELB, 95% CI



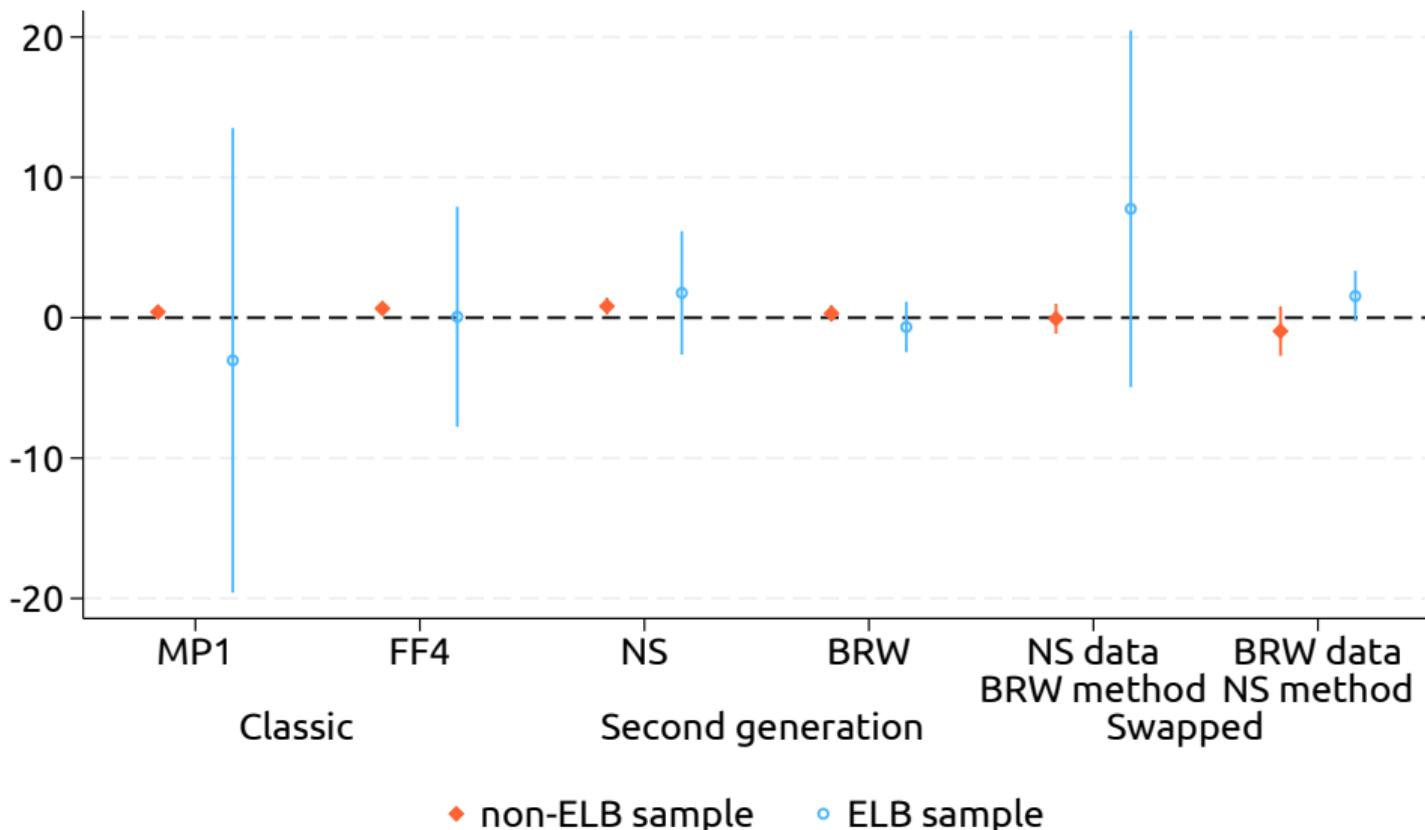
Predictability Coefficients non-ELB, 95% CI



1. Blue Chip Regression Coefficients, 95% CI



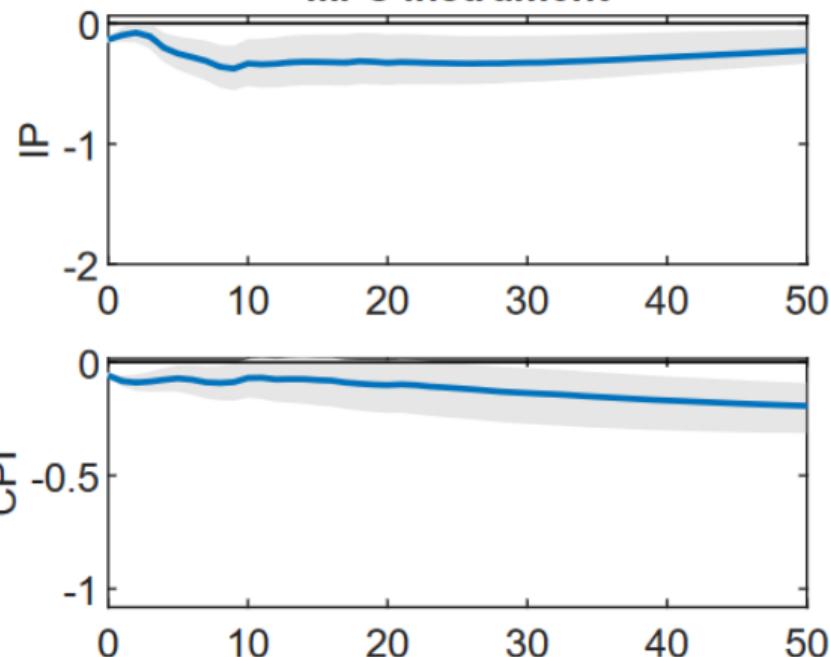
1. Blue Chip Regression Coefficients, 95% CI



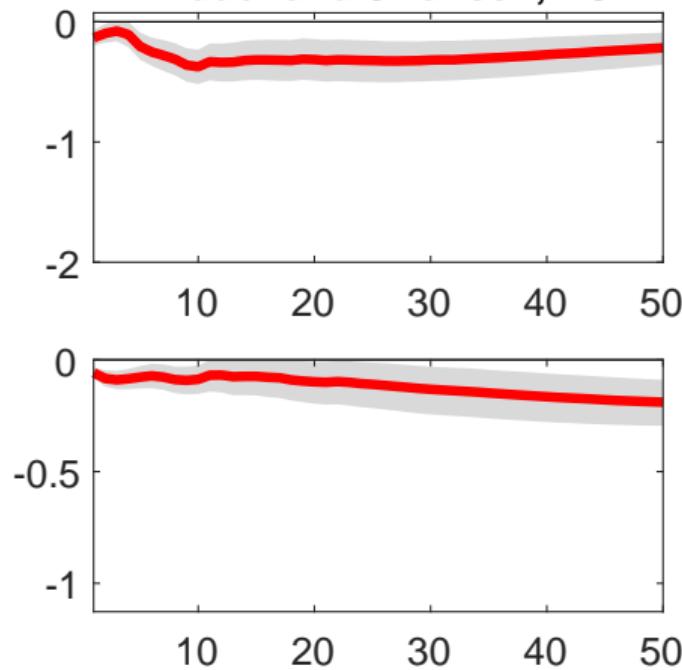
IRFs, 25 bps Monetary Shock

◀ fin. vars ▶ orthogonalized NS

MPS instrument



Bauer and Swanson, NS



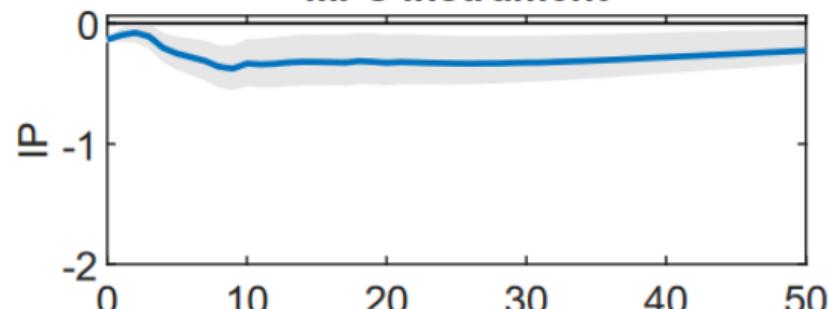
IRFs, 25 bps Monetary Shock, 1995 start, 8 lags



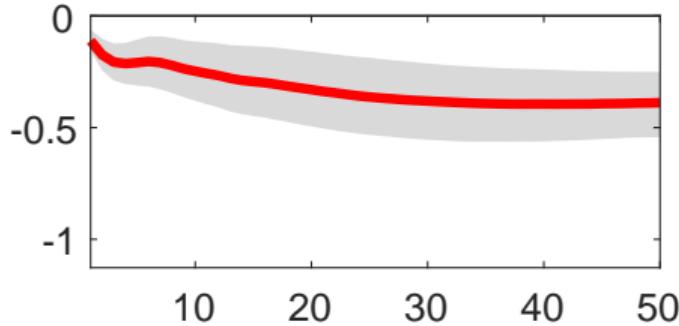
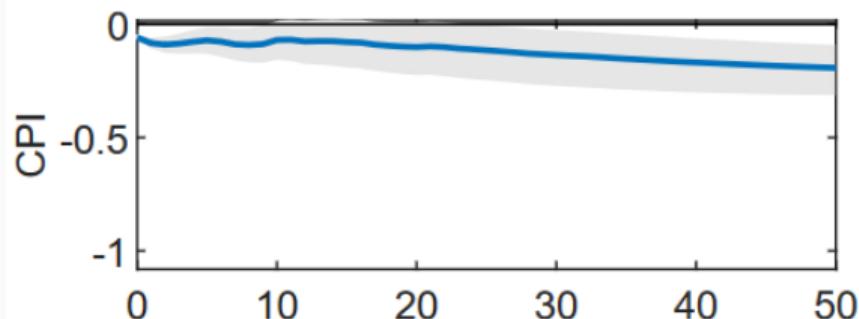
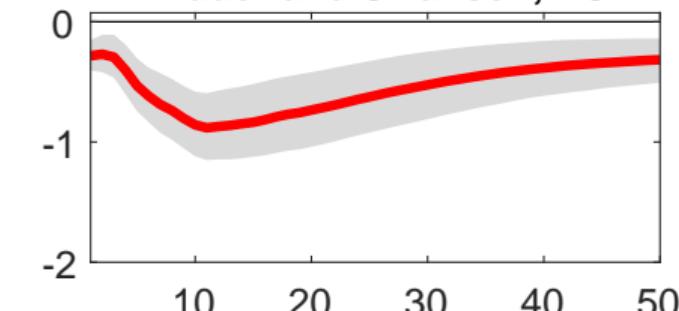
fin. vars

orthogonalized NS

MPS instrument



Bauer and Swanson, NS

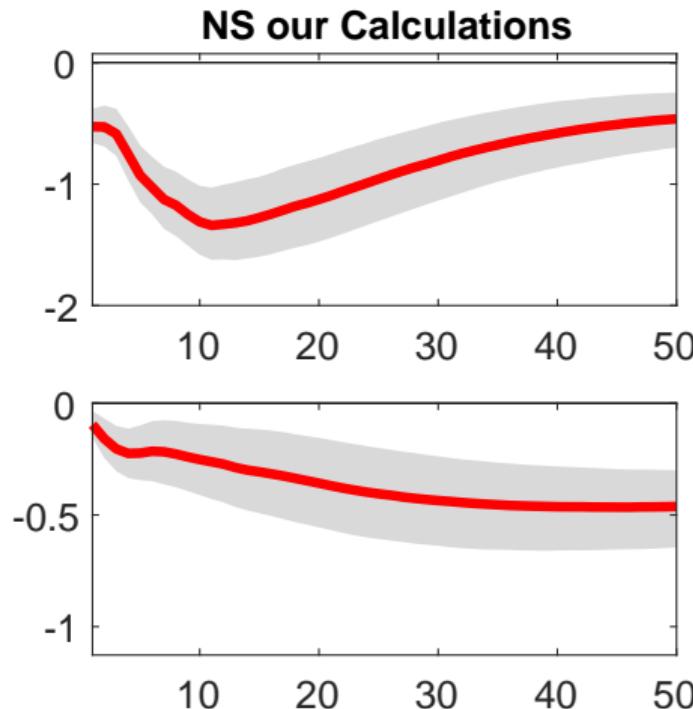
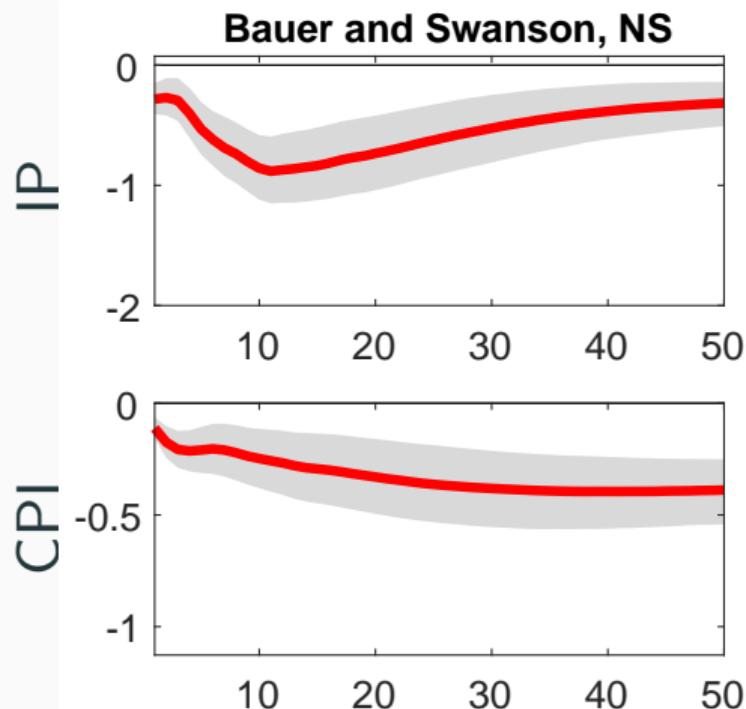


IRFs, 25 bps Monetary Shock, 1995 start, 8 lags



fin. vars

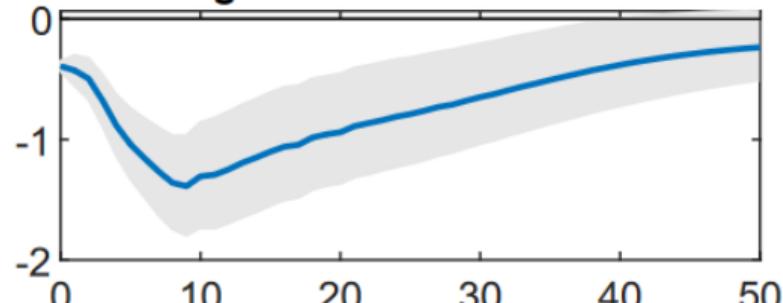
orthogonalized NS



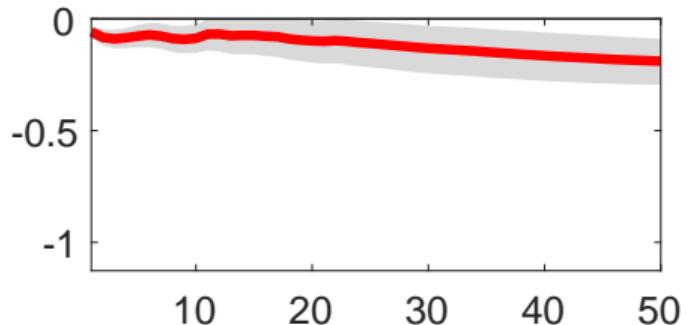
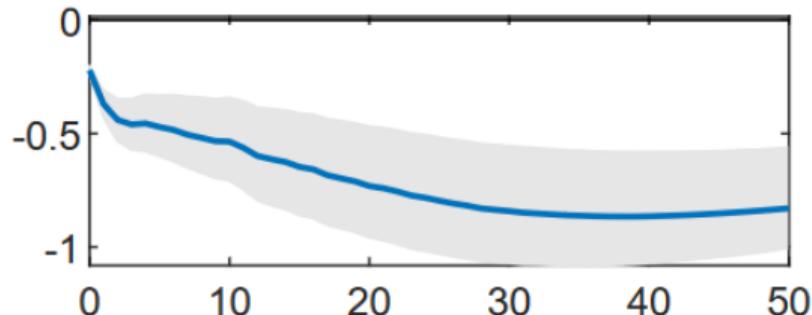
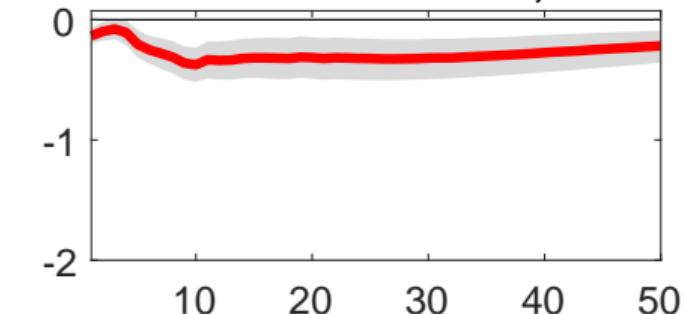
Bauer & Swanson IRFs, 25 bps Monetary Shock



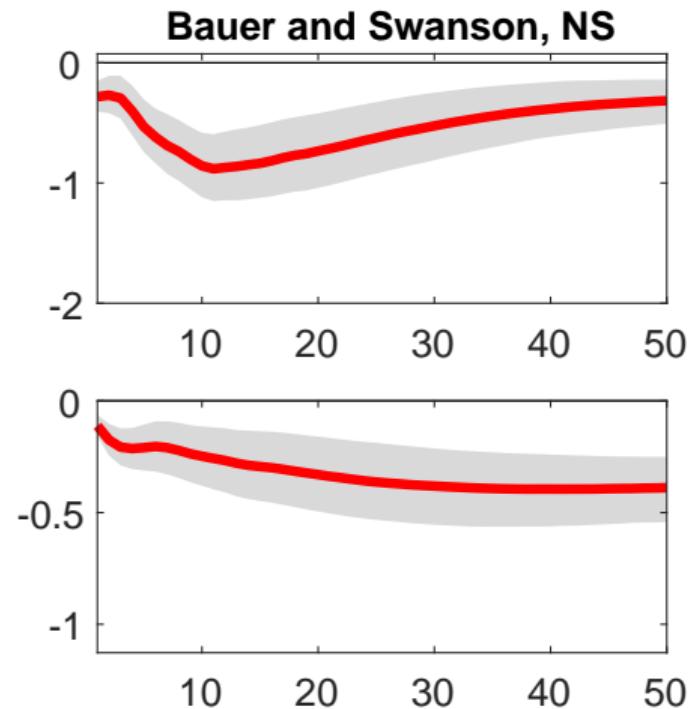
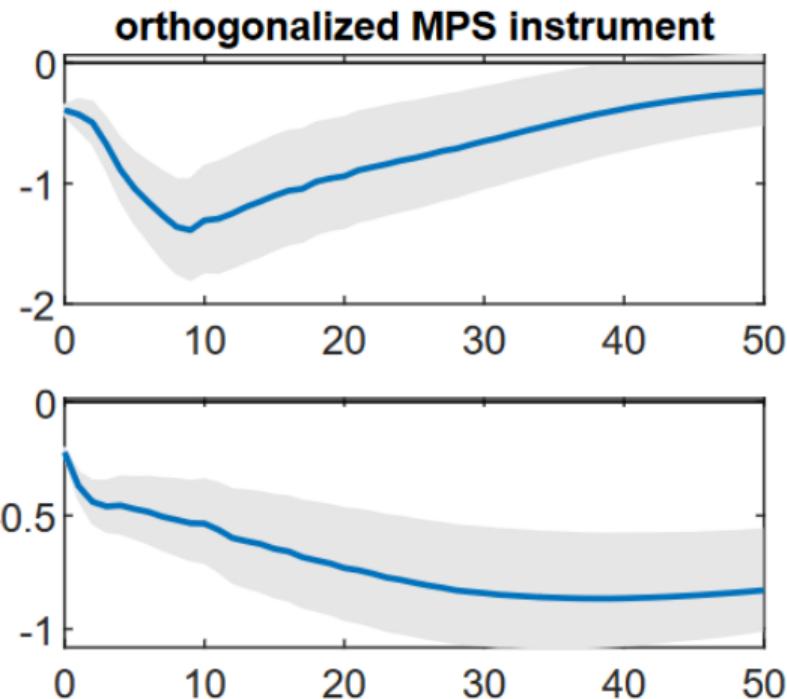
orthogonalized MPS instrument



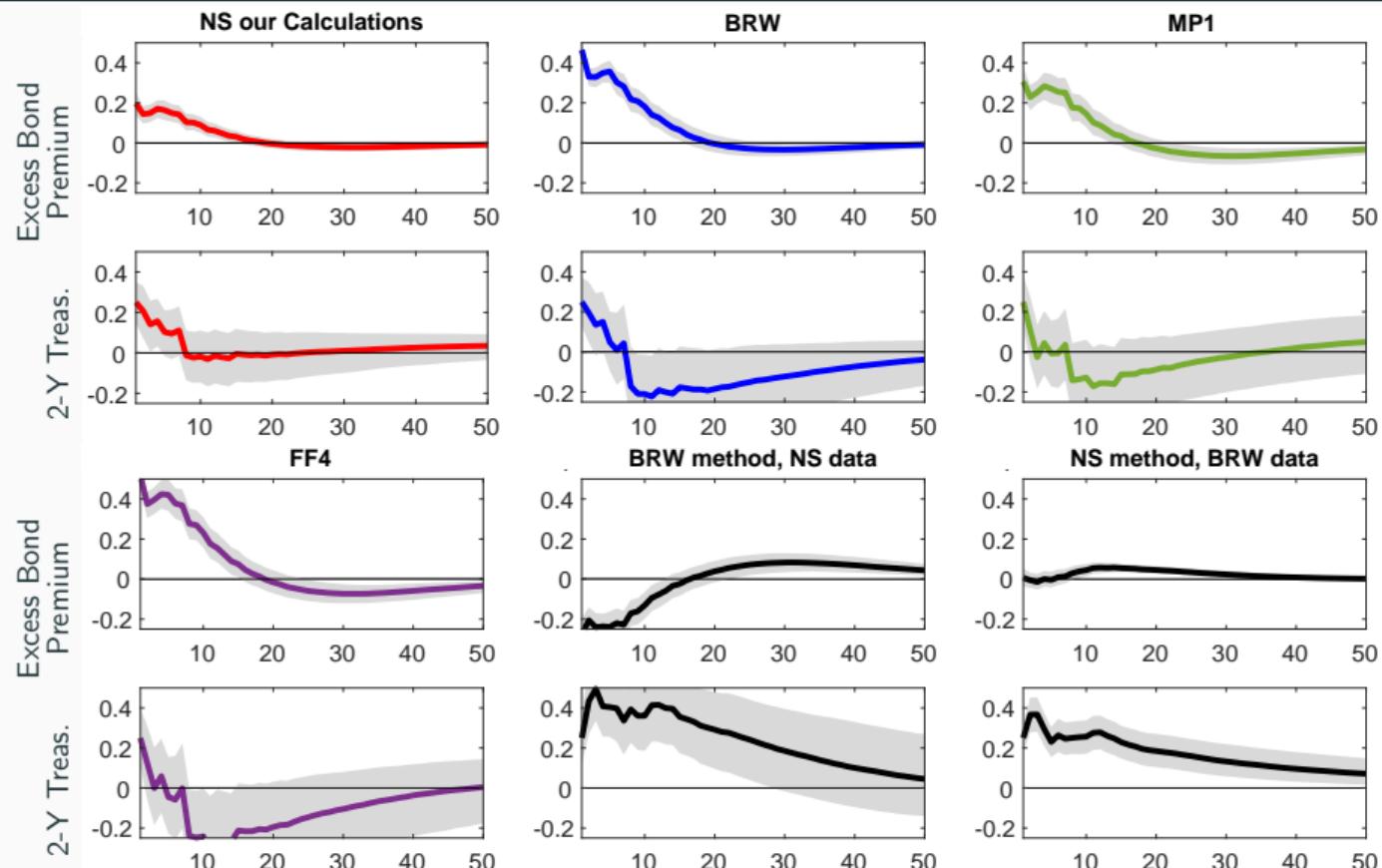
Bauer and Swanson, NS



Bauer & Swanson IRFs, 25 bps Monetary Shock, 1995 start, 8 lags



VAR IRFs, 25 bps Monetary Shock



Recursive vs. Full Sample

	NS Shock	NS Shock (Recursive)	BRW Shock	BRW Shock (Recursive)
Mean	-0.004	-0.002	-0.004	-0.005
Median	0.002	0.003	-0.005	-0.006
SD	0.037	0.034	0.054	0.0678

$$\text{Corr}[\text{NS Shock}, \text{NS Shock (Recursive)}] = 0.9946$$

$$\text{Corr}[\text{BRW Shock}, \text{BRW Shock (Recursive)}] = 0.9874$$