Temporal Aggregation Bias and Monetary Policy Transmission

Margaret M. Jacobson (**Federal Reserve Board**)
Christian Matthes (**Indiana University**)
Todd Walker (**Indiana University**)

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New Challenges in Monetary Economics and Macro Finance

Revisiting an Age-Old Question

Q:What Does Monetary Policy Do To Inflation?

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- **New Keynesian answer: Contractionary monetary shock $\Rightarrow$ inflation $\downarrow$**

Revisiting an Age-Old Question

Time series evidence - Two guises of the same issue?

- **Price puzzle (Sims 1992)**: Standard VAR identification schemes can lead to **increases** in inflation after a contractionary monetary shock. Partial solution: Add more **information**/variables.

Revisiting an Age-Old Question

Time series evidence - Two guises of the same issue?

- **Price puzzle (Sims 1992)**: Standard VAR identification schemes can lead to **increases** in inflation after a contractionary monetary shock. Partial solution: Add more **information**/variables.
- **Fed information effect**: Increases in prices using high-frequency identification due to **information** mismatch between private sector and Fed. (Campbell et al 2012, Nakamura & Steinsson 2018). Possible resolution: Information effect might disappear after controlling for all available information (Bauer & Swanson 2023)

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  - adversely-signed when aggregated, conventionally-signed when not
  - estimates affected by timing of the shocks
- State space model
  - confirms conventionally-signed transmission

What Are We Doing?

- Existing transmission literature refines monetary policy shocks (RHS)
    - Miranda-Agrippino & Ricco (2021), Cieslak & Schrimpf (2019), Andrade & Ferroni (2021), Bu et al. (2021), Hoesch et al. (2023), Sastry (2022), Karnaukh & Vokata (2022), Caldara & Herbst (2019), Lunsford (2020), Lewis (2020), Bundick & Smith (2020), Acosta (2023)
- We refine response variables (LHS)
    - via a daily measure of inflation based on the Billion Price Project
- Temporal aggregation results are generic and will be a key feature of the nascent field of high-frequency macro (Baumeister et al. 2021, Lewis et al. 2021, and Buda et al. 2023)

Temporal Aggregation with Local Projections

Some Monte Carlo Evidence - Setup

The data-generating process

- DGP: $\pi_t = \Theta(L) \underbrace{\varepsilon_t^m}_{\text{monetary policy shock}} + u_t$
- $u_t = \rho^u u_{t-1} + \varepsilon_t^u$, $\varepsilon_t^u \sim N(0,1)$, $\rho^u = 0.99$
- $\varepsilon_t^m \sim N(0,1)$, one shock every 30 days
- $\Theta(L) = \sum_{i=0}^{59} \Theta_i L^i$

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Impulse response coefficients

- $\Theta_i = 1$ for $i = 0, ..., 9$
- $\Theta_i = -1$ for $i = 10, ..., 59$
- $\pi_0 = \varepsilon_0^m + u_0$

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- $\pi_1 = \varepsilon_0^m + u_1$

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- $\pi_9 = \varepsilon_0^m + u_9$

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Impulse response coefficients

- $\Theta_i = 1$ for $i = 0, ..., 9$
- $\Theta_i = -1$ for $i = 10, ..., 59$
- $\pi_{10} = -\varepsilon_0^m + u_{10}$

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- $\Theta_i = -1$ for $i = 10, ..., 59$
- $\pi_{59} = -\varepsilon_0^m + u_{59}$

Temporal Aggregation Bias Intuition

Aggregate from daily t to monthly T

- Timing of shock matters, no clean identification

$$\Pi_T = \sum_{t=0}^{29} \pi_t$$

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- Monetary shock on day i_T

$$\Pi_T = \sum_{t=0}^{29-i_T} \left(\mathbb{1}_{t\leq 9} - \mathbb{1}_{t>9}\right) \varepsilon_{i_T}^{m} + \sum_{t=0}^{29} u_t$$

Temporal Aggregation Bias Intuition

Aggregate from daily t to monthly T

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- Monetary shock on day $i_T = 29$

$$\Pi_T = \sum_{t=0}^{29-29} \underbrace{\left(\mathbb{1}_{t\leq 9} - \mathbb{1}_{t>9}\right)}_{=1} \varepsilon_{29}^{m} + \sum_{t=0}^{29} u_t$$

Temporal Aggregation Bias Intuition

Aggregate from daily t to monthly T

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- Monetary shock on day $i_T = 28$

$$\Pi_T = \sum_{t=0}^{29-28} \underbrace{\left(\mathbb{1}_{t\leq 9} - \mathbb{1}_{t>9}\right)}_{=2} \varepsilon_{28}^{m} + \sum_{t=0}^{29} u_t$$

Temporal Aggregation Bias Intuition

Aggregate from daily t to monthly T

- Timing of shock matters, no clean identification
- Monetary shock on day $i_T = 20$

$$\Pi_T = \sum_{t=0}^{29-20} \underbrace{\left(\mathbb{1}_{t\leq 9} - \mathbb{1}_{t>9}\right)}_{=10} \varepsilon^m_{20} + \sum_{t=0}^{29} u_t$$

Temporal Aggregation Bias Intuition

Aggregate from daily t to monthly T

- Timing of shock matters, no clean identification
- Monetary shock on day $i_T = 19$

$$\Pi_T = \sum_{t=0}^{29-19} \underbrace{\left(\mathbb{1}_{t\leq 9} - \mathbb{1}_{t>9}\right)}_{=9} \varepsilon_{19}^{m} + \sum_{t=0}^{29} u_t$$

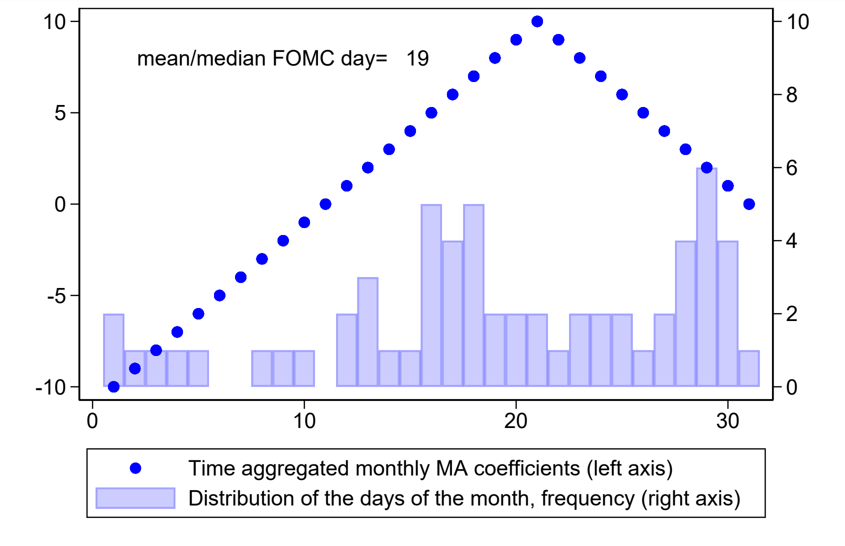
Temporal Aggregation Bias Intuition

Aggregate from daily t to monthly T

- Timing of shock matters, no clean identification
- Monetary shock on day $i_T = 0$

$$\Pi_T = \sum_{t=0}^{29-0} \underbrace{\left(\mathbb{1}_{t\leq 9} - \mathbb{1}_{t>9}\right)}_{=-10} \varepsilon_0^m + \sum_{t=0}^{29} u_t$$

Days of the Month of FOMC Announcements



(Varying the u_t process)

Some Monte Carlo Evidence - Three Population Regressions

- Take 30-day averages of inflation
- Aggregated data can show a positive response on impact despite the majority of MA coefficients being negative
- Largest negative effect at the beginning, positive effect in the middle of the month

Shock	at Beginning			in Middle			at End		
	ϵ_T	Π_{T-1}	ϵ_{T-1}	ϵ_T	Π_{T-1}	ϵ_{T-1}	ϵ_T	Π_{T-1}	ϵ_{T-1}
Π_T	-0.50		-1.16	0.38		-0.85	-0.06		-0.26
LP at T=0	-0.40	0.82		0.29	0.82		0.03	0.82	
LP at T=1	-1.10	0.61		-0.92	0.60		-0.19	0.60	

A Simple Laboratory

Three Ingredients

1. Fisher equation: $i_t = r + E_t[\pi_{t+1}|I_t]$
2. Monetary policy rule: $i_t = r + \phi\pi_t + x_t$
3. Autocorrelated monetary shock: $x_t = \rho x_{t-1} + \epsilon_t$

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Equilibrium Dynamics

$$\pi_t = -\frac{x_t}{\phi - \rho} = \rho\pi_{t-1} + \frac{-\epsilon_t}{(\phi - \rho)}$$

From AR to ARMA

Temporally aggregating AR(1) inflation yields an ARMA(1,1) representation:

$$(1 - \rho^m L)\Pi_T = u_T + \theta u_{T-1}, \quad u_T \sim N(0, \sigma_u^2), \quad t = mT$$

Temporally Aggregated Inflation

	$m=1$	$m=2$	$m=5$	$m=10$	$m=20$	$m=30$	$m=40$	$m=50$
ρ^m	0.990	0.980	0.951	0.904	0.818	0.740	0.669	0.605
σ^2_Π	1.397	1.389	1.374	1.351	1.307	1.266	1.226	1.186
θ	0.000	0.171	0.250	0.264	0.265	0.266	0.266	0.267
σ^2_u	0.028	0.041	0.085	0.160	0.288	0.391	0.476	0.542

Table 1: Estimates of the ARMA(1,1) using temporally aggregated observations. We match moments of the aggregated inflation series to the ARMA(1,1) process.

- ρ^m decays exponentially

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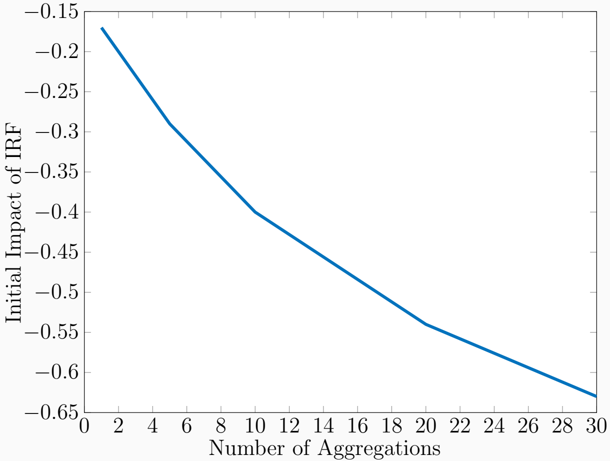
- ρ^m decays exponentially
- σ_Π^2 decays multiplicatively
- θ and σ_u^2 compensate resulting in a more pronounced *initial* impact

Result 1: Temporal Aggregation can Exacerbate Initial Impulse Responses

The “true” IRF ($m = 1$) is mitigated relative to the temporally agg. responses



(freq. domain)

Tackling Temporal Aggregation using Daily Inflation Data

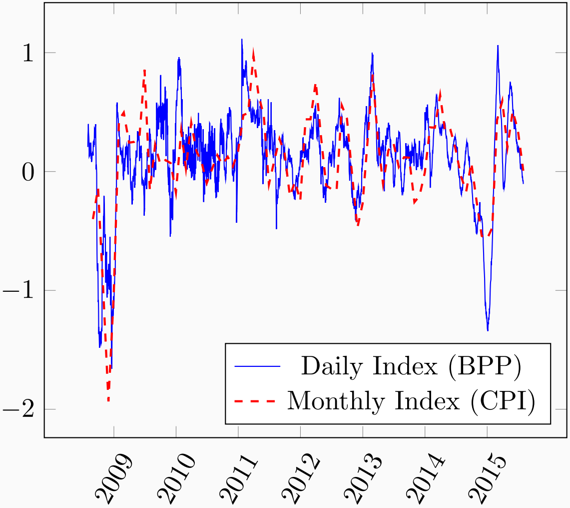
How Do We Measure Daily Inflation?

(comparison of sources)

- Billion Prices Project (BPP): daily CPI for select countries
  - 5 million online prices webscraped daily, 300 retailers in 50 countries
- U.S. index publicly available from 2008 to 2015 via Cavallo & Rigobon (2016)
- Pros: Higher frequency than both monthly official CPI or weekly scanner data
  - 0.5 million prices daily compared to 80,000 per month
- Cons: Not as comprehensive as official CPI
  - smaller subset of retailers and products than official CPI
  - no services, relies on official weights
- Cavallo (2017): 70 percent of online prices identical to those obtained by physically visiting stores
- BPP predicts the CPI, especially with mixed-frequencies
  - Aparicio & Bertolotto (2020), Harchaoui & Janssen (2018)

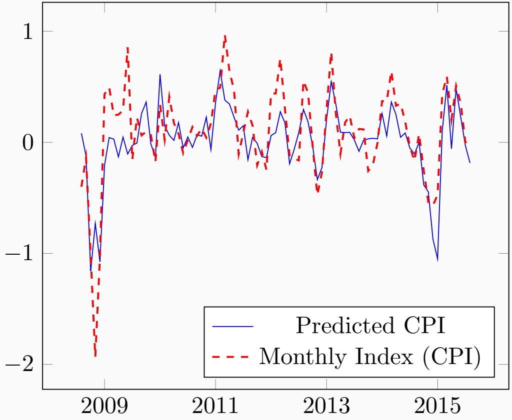
Official and Daily Inflation, Monthly and 30-day Percentage Change

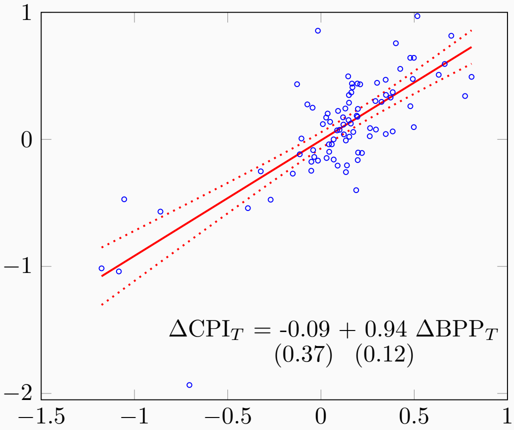
(seasonality)



Predicting the Official CPI

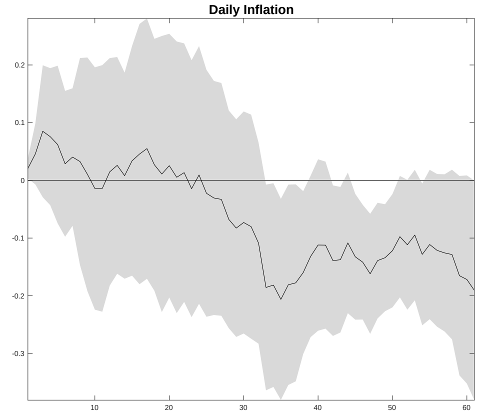
▸ (nowcast) ▸ (table) ▸ (end of month) ▸ (levels) ▸ (other CPI)





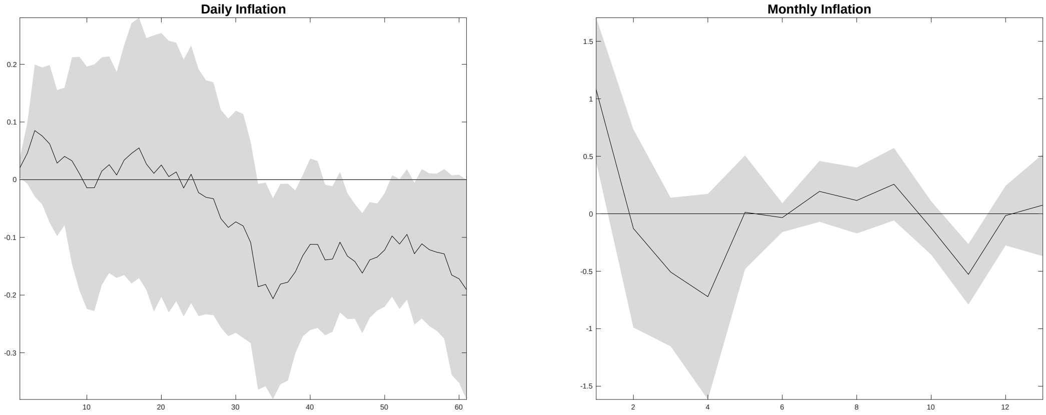
IRF of π_t to a Nakamura & Steinsson (2018) Monetary Shock - LP-IV

▸ (high-frequency shocks



IRF of π_t to a Nakamura & Steinsson (2018) Monetary Shock - LP-IV

(12 lags) (FOMC cycles) (Bu et al. 2021 IRFs) (high-frequency shocks



Controlling for Timing

Why a State Space Model?

- Handles data observed at different frequencies, can control for both the irregular intervals of monetary shocks and official inflation data releases
- Allows for measurement error
- Results: confirms conventionally-signed response of inflation to monetary shocks
- Johannsen & Mertens (2020) find adverse response at a quarterly frequency

Our Model

State Dynamics

1. **Unobserved daily CPI inflation:** $\pi_t = \tau_t + g_t + e_t^{\pi}$

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4. **Monetary shock dynamics:** $m_t = e_t^{m}$

All e shocks are iid Gaussian, $K = J = 60$

Our Model

Observation Equations

1. **Monthly observation of CPI (real-time vintages):** $\pi_t^m = \pi_{t-p} + e_t^{monthly}$, p is publication lag (which can vary over time)

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4. **10-year break-even rates:** $\pi_t^{BE,h} = \alpha^{BE} + E_t \pi_{t,t+h} + e_t^{BE}$

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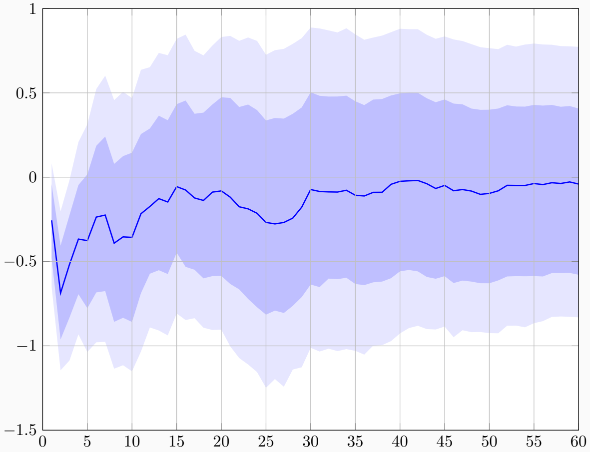
4. **10-year break-even rates:** $\pi_t^{BE,h} = \alpha^{BE} + E_t\pi_{t,t+h} + e_t^{BE}$
    - $E_t\pi_{t+h} = E_t(\tau_{t+h} + g_{t+h}) = \tau_t + \rho^h g_t \approx \tau_t$

All e shocks are iid Gaussian

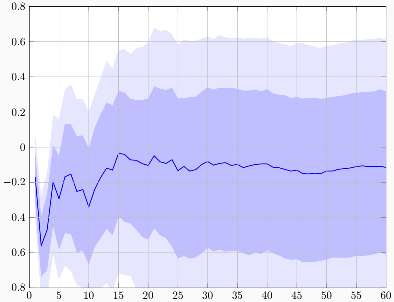
(estimation details

Impulse response of π_t to a one standard deviation monetary policy shock

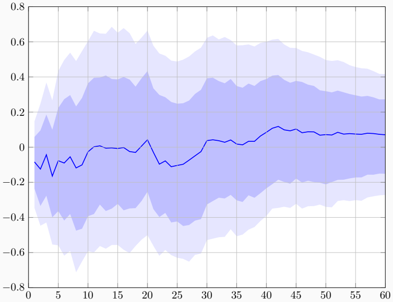


Impulse response of τ and g_t to a one standard deviation monetary policy shock

▸ (less shrinkage) ▸ (Bu et al. 2021 shock) ▸ (variance decomposition)



Permanent component



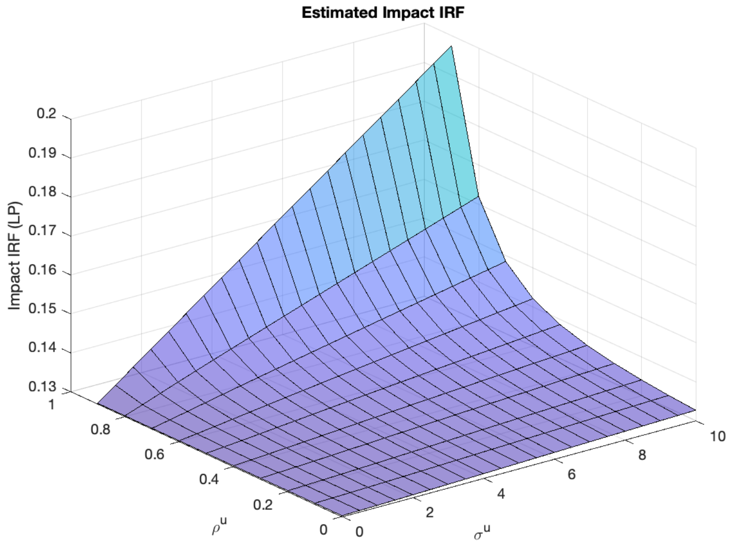
Transitory component

Conclusion

- Propose temporal aggregation bias as a new information-based explanation for the adverse transmission of monetary shocks
- Conventionally-signed transmission at a high-frequency, but adverse when aggregated
- Temporal aggregation bias is generic and will be key for high-frequency macro

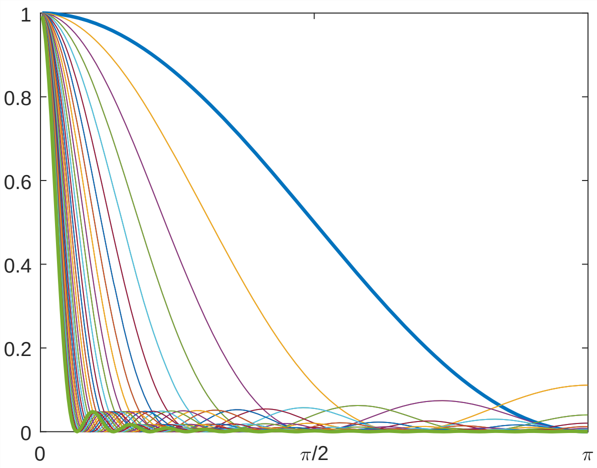
Appendix

Robust to Varying the u_t Process



Result 1: Temporal Aggregation can Exacerbate Initial Impulse Responses

Lower frequencies are preserved even though $\rho > \rho^m$, $\uparrow \sigma_u^2$ and $\theta > 0$ compensate



Alternative Micro-Price Data Sources Cavallo (2015)

	Online data	Scanner data	CPI data
Cost per observation	Low	Medium	High
Data frequency	Daily	Weekly	Monthly
All products in retailer (Census)	Yes	No*	No
Uncensored price spells	Yes	Yes	No
Countries with research data	~ 60	< 10	~ 20
Comparable across countries	Yes	Limited	Limited
Real-time availability	Yes	No	No
Product categories covered	Few	Few	Many
Retailers covered	Few	Few	Many
Quantities or expenditure weights	No	Yes	Yes

*Some scanner data do offer data for all products

Predicting the Official CPI

- Official: Monthly percentage change, month T

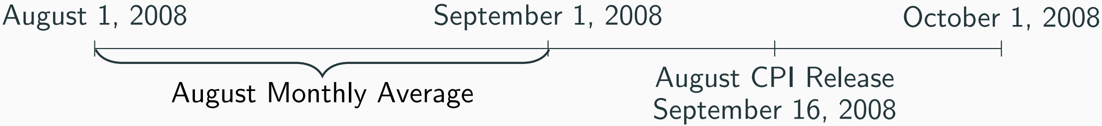
$$\Delta CPI_T = 100 \times (\log CPI_T - \log CPI_{T-1})$$

- BPP: Monthly average of the 30-day percentage change, day t of month T

$$\Delta BPP_T = \frac{1}{T}\sum_{t=1}^{T} 100 \times (\log BPP_t - \log BPP_{t-30})$$

- Nowcast using the aggregated daily CPI

$$\log \Delta CPI_T = \beta_0 + \beta_1 \log \Delta BPP_T$$

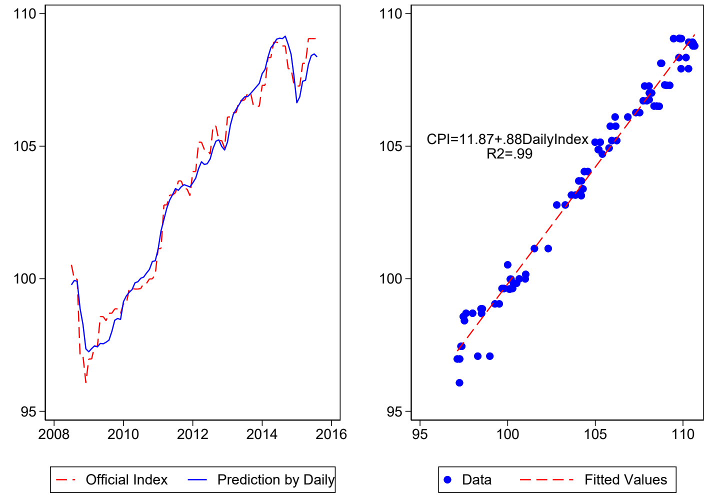


- Day 17 is the mean release day

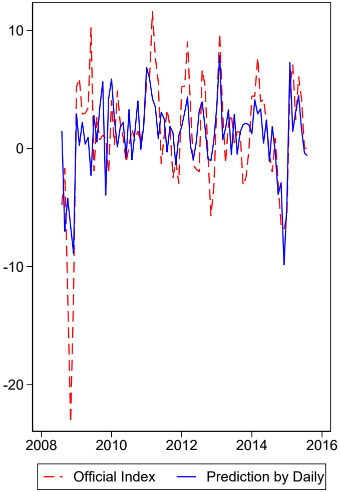
	ΔCPI_T				
	(1)	(2)	(3)	(4)	(5)
ΔCPI_{T-1}	0.558***				0.178
	(0.143)				(0.107)
ΔBPP_T		0.937***		0.878***	0.828***
		(0.129)		(0.097)	(0.106)
ΔBPP_{T-1}			0.591**	0.109	−0.030
			(0.248)	(0.193)	(0.222)
R^2	0.32	0.58	0.23	0.59	0.61
Adj. R^2	0.31	0.58	0.22	0.58	0.60

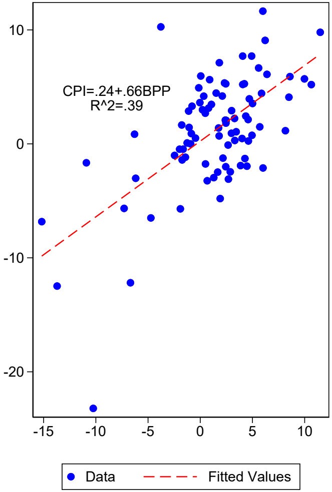
Standard errors in parentheses. $^{*}(p < .10)$, $^{**}(p < .05)$, $^{***}(p < .01)$

Predicting the Official CPI with the Monthly Average of the Daily Index, July 2008=100

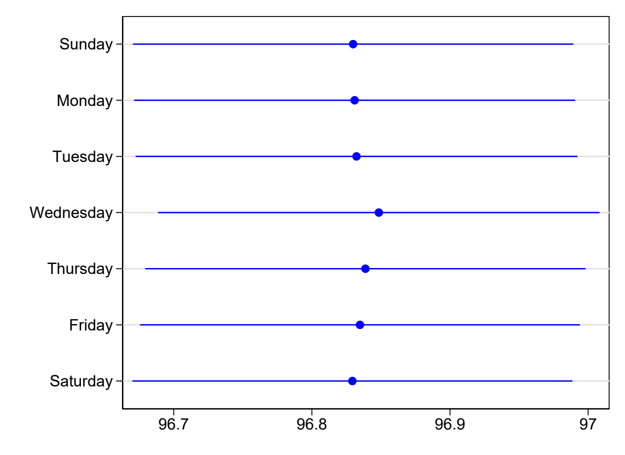


Predicting the Official CPI with the End of Month Obs. of the 30-day Annualized Percentage Change (monthly average)

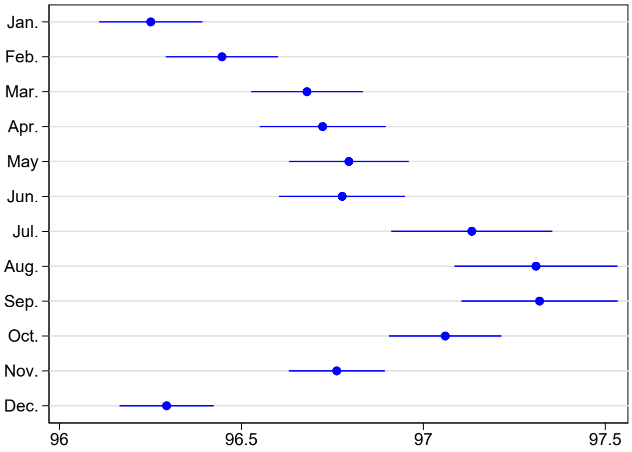




Day of Week Effects?



Month of Year Effects?



Construction of Nakamura & Steinsson (2018) Shocks

Change in five interest rates 10 min. before and 20 min. after the FOMC event

1. expected ffr (r_0) for the month, adjusted for the days of the month already elapsed (d_0) out of total days of the month (m_0) of the FOMC meeting.

For the current month:

$$\underbrace{f^1_{t-\Delta t}}_{\substack{\text{ffr future prior to}\\\text{FOMC meeting}}} = \underbrace{\frac{d_0}{m_0} r_{-1}}_{\substack{\text{actual ffr prior to}\\\text{FOMC meeting}}} + \underbrace{\frac{m_0 - d_0}{m_0} \mathbb{E}_{t-\Delta t} r_0}_{\substack{\text{ffr future prior to}\\\text{FOMC meeting}}}$$

$$\underbrace{f^1_{t}}_{\substack{\text{ffr future}\\\text{after FOMC meeting}}} = \underbrace{\frac{d_0}{m_0} r_{-1}}_{\substack{\text{actual ffr prior to}\\\text{FOMC meeting}}} + \underbrace{\frac{m_0 - d_0}{m_0} \mathbb{E}_{t} r_0}_{\substack{\text{ffr future}\\\text{after FOMC meeting}}}$$

Combining and re-arranging:

$$\underbrace{\mathbb{E}_t r_0 - \mathbb{E}_{t-\Delta t} r_0}_{\text{expected change in ffr}} = \frac{m_0}{m_0 - d_0} \left(f^1_t - f^1_{t-\Delta t} \right)$$

Construction of Nakamura & Steinsson (2018) Shocks

2. expected ffr r_1 for the remainder of the month of the next FOMC meeting

$$\underbrace{\mathbb{E}_t r_1 - \mathbb{E}_{t-\Delta t} r_1}_{\substack{\text{expected change in ffr} \\ \text{in month of next FOMC}}} = \frac{m_1}{m_1 - d_1}\left[\underbrace{(f_t^n - f_{t-\Delta t}^n)}_{\substack{\text{change in ffr future} \\ \text{for next FOMC meeting}}} - \underbrace{\frac{d_1}{m_1}(\mathbb{E}_t r_0 - \mathbb{E}_{t-\Delta t} r_0)}_{\substack{\text{scaled expected change} \\ \text{in current month}}} \right]$$

3. change in expected three-month eurodollar fut. two, three, & four quarters ahead

- Compute first principal component of the changes in the previously described five interest rates
- Rescale the first principal component so that its effect on one-year nominal Treasury yields is equal to one
- Note: when the FOMC event occurs with seven days or less remaining in the month, the change in the price of next month's fed funds futures contract f_t^n is used instead to avoid unreasonably large scaling factors $\frac{m_0}{m_0-d_0}$ or $\frac{m_1}{m_1-d-1}$

Construction of Bu et al. (2021) Shocks

Fama and MacBeth (1973) two-step procedure extracts unobserved monetary policy shocks $\Delta i_t^{aligned}$ from the common component of zero-coupon yields $\Delta R_{j,t}$

1. estimate sensitivity of yields with maturity $j = 1, ..., 30$ via time-series regressions

$$\Delta R_{j,t} = \alpha_j + \beta_j \Delta i_t + \epsilon_{j,t}$$

   assume Δi_t is one-to-one with 2-year yield $\Delta R_{2,t}$ for normalization and estimate

$$\Delta R_{j,t} = \theta_j + \beta_j \Delta R_{2,t} + \underbrace{\epsilon_{j,t} - \beta_j \epsilon_{2,t}}_{\xi_{j,t}}$$

   corr($\Delta R_{j,t}$, $\xi_{i,t}$) due to $\beta_j \epsilon_{2,t}$ reconciled w/ IV or Rigobon (2003) het. estimator

2. recover aligned monetary policy shock $\Delta i_t^{aligned}$ form cross-sectional regressions of $\Delta R_{j,t}$ on the sensitivity index $\widehat{\beta}_j$ for each FOMC announcement t

$$\Delta R_{j,t} = \alpha_j + \Delta i_t^{aligned} \widehat{\beta}_j + v_{j,t}, \quad t = 1, ..., T$$

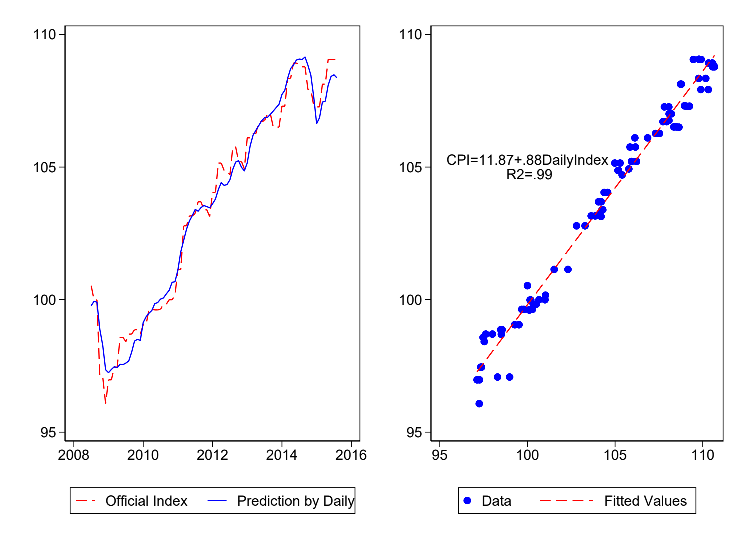
3. Re-scale to $\Delta R_{2,t}$. Note scaling variable used in both step 1 and step 3.

Predicting the Official CPI Categories via Aggregated Daily CPI

	ΔCPI^i_T, sub-categories i					ΔPCE_T
	(1)	(2)	(3)	(4)	(5)	(6)
	Headline	Commodities	Commodities & Shelter	Headline ex energy	Headline ex Medical	Headline PCE
ΔBPP_T	0.937***	1.618***	0.530***	0.180***	1.001***	0.497***
	(0.129)	(0.283)	(0.121)	(0.052)	(0.137)	(0.081)
R^2	0.58	0.48	0.36	0.21	0.59	0.52
Adj. R^2	0.58	0.47	0.36	0.20	0.58	0.52

Standard errors in parentheses. $^{*}(p < .10)$, $^{**}(p < .05)$, $^{***}(p < .01)$

Predicting the Official CPI Index, July 2008=100



Predicting the Official CPI Index using the End of Month Obs. of the Annualized 30-day Percentage Change (monthly average)

	ΔCPI_t				
	(1)	(2)	(3)	(4)	(5)
ΔCPI_{t-1}	0.547***				0.138
	(0.136)				(0.111)
ΔBPP_t		0.646***		0.497***	0.461***
		(0.121)		(0.104)	(0.111)
ΔBPP_{t-1}			0.609***	0.437***	0.360***
			(0.155)	(0.115)	(0.114)
(R^2)	0.304	0.388	0.350	0.555	0.566

Standard errors in parentheses. $^{*}(p < .10)$, $^{**}(p < .05)$, $^{***}(p < .01)$

Predicting the Official CPI (in Levels) with the Monthly Average of the Daily Index

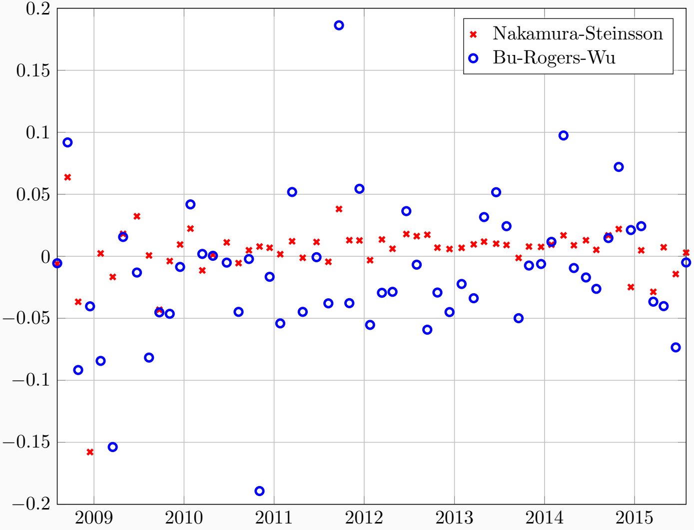
	CPI_t				
	(1)	(2)	(3)	(4)	(5)
CPI_{t-1}	1.000***				0.803***
	(0.00895)				(0.0460)
BPP_t		0.879***		1.137***	0.696***
		(0.0138)		(0.173)	(0.0875)
BPP_{t-1}			0.880***	−0.257	−0.522***
			(0.0178)	(0.170)	(0.0842)
(R^2)	0.994	0.985	0.975	0.986	0.997

Standard errors in parentheses. $^{*}(p < .10)$, $^{**}(p < .05)$, $^{***}(p < .01)$

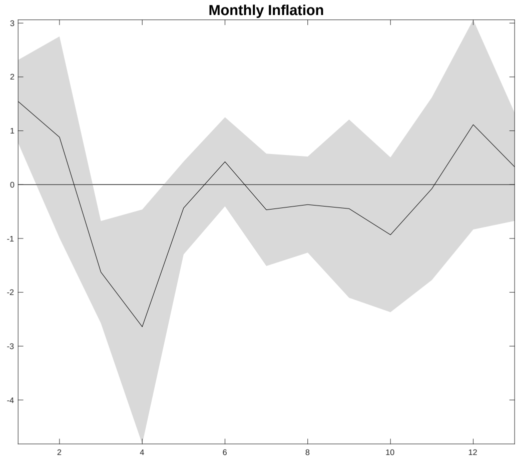
Measures of High Frequency Monetary Policy Shocks

- Nakamura & Steinsson (2018) details
    - first principal component of the change in five short-term interest rate futures
    - 30-minute window surrounding FOMC announcement
- Bu et al. (2021) details
    - Fama and MacBeth (1973) regression on all maturities of bond yields
    - one day window surrounding FOMC announcement

Instruments

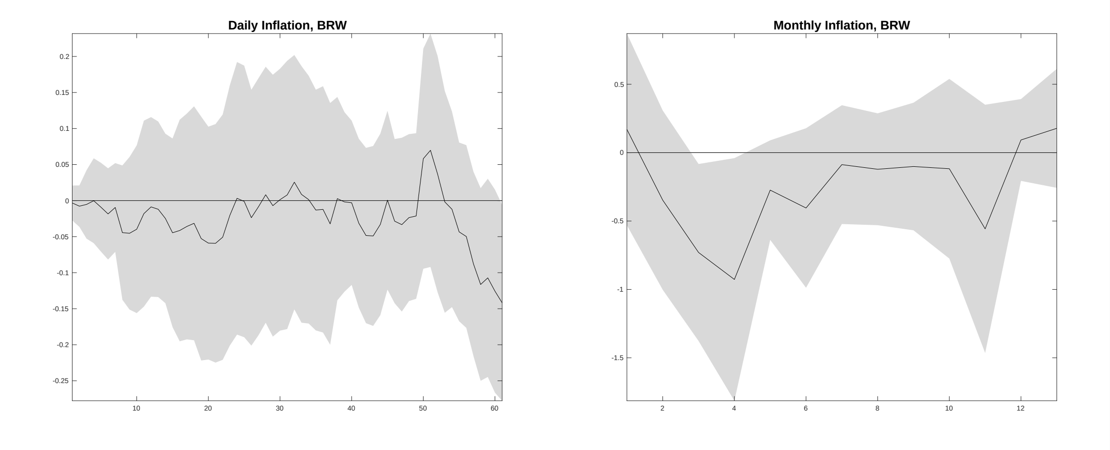


Impulse response of monthly aggregated π_t^{daily} to a Nakamura & Steinsson (2018) monetary shock LP-IV, 12 lags

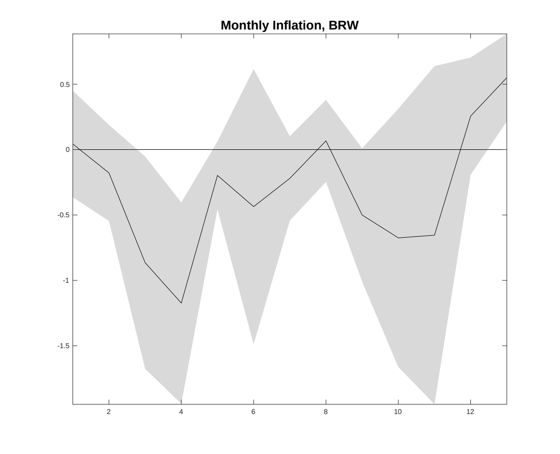


Impulse response of π_t^{daily} to a Bu et al. (2021) monetary shock - LP-IV ▸ (12 lags)

◂



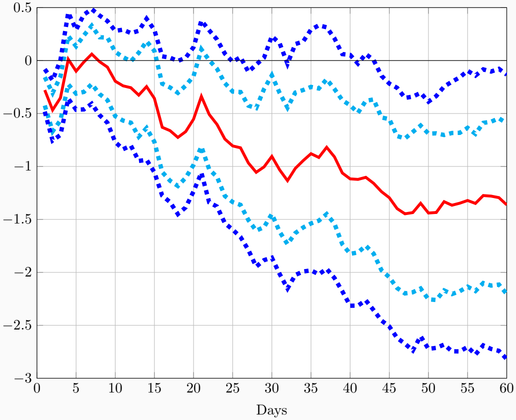
Impulse response of monthly aggregated π_t^{daily} to a Bu et al. (2021) monetary shock - LP-IV, 12 lags



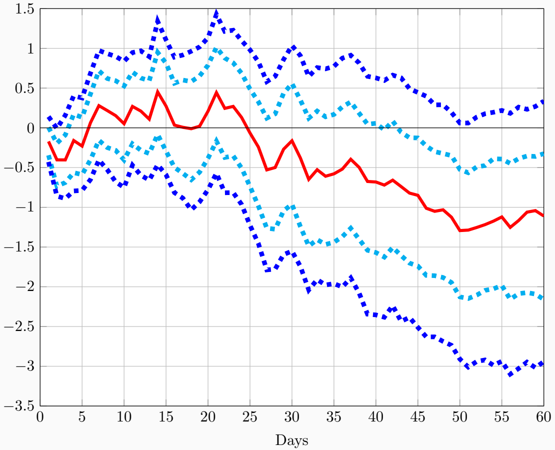
Estimation

- Bayesian estimation (sequential Monte Carlo)
- Likelihood evaluation via Kalman filter
- State space model with time-varying matrices
- 2557 daily observations - July 2008 to July 2015
- 57 monetary policy shock observations
- Priors largely uninformative
- $\theta_j \sim N(0, scaling^j \times 0.25)$, $\theta_j^\tau \sim N(0, scaling^j \times 0.25)$
- $scaling = 0.95$ or $scaling = 0.99$

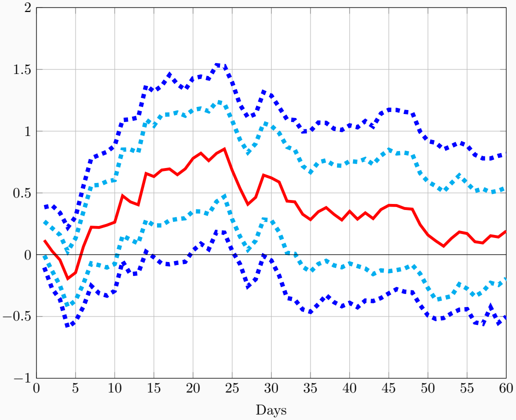
Impulse response of τ_t to a one standard deviation monetary policy shock - less shrinkage



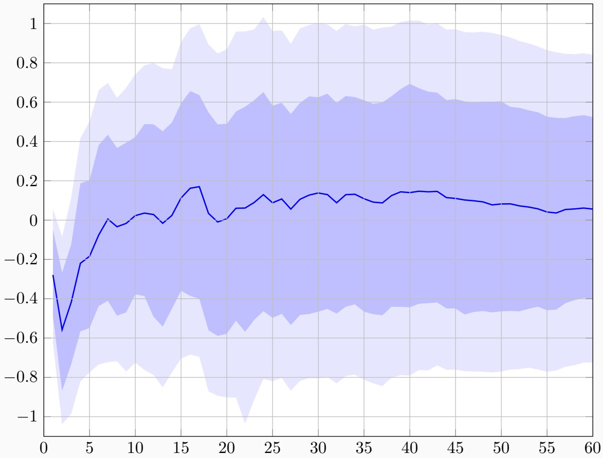
Impulse response of π_t to a one standard deviation monetary policy shock - less shrinkage



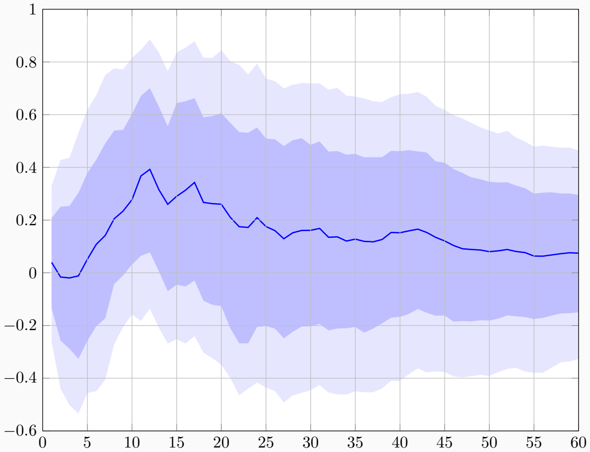
Impulse response of g_t to a one standard deviation monetary policy shock - less shrinkage



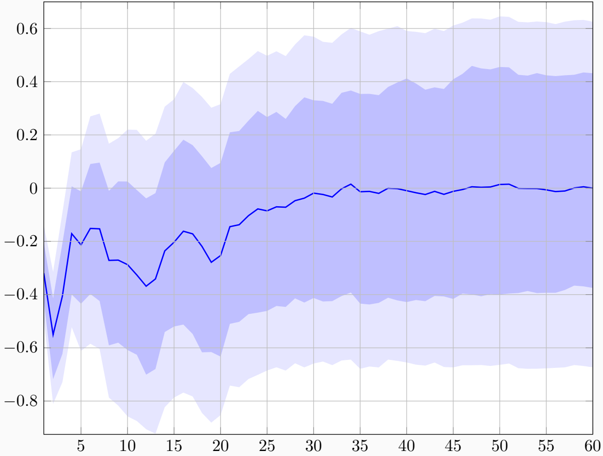
Impulse response of π_t to a one standard deviation monetary policy shock, Bu et al. (2021)



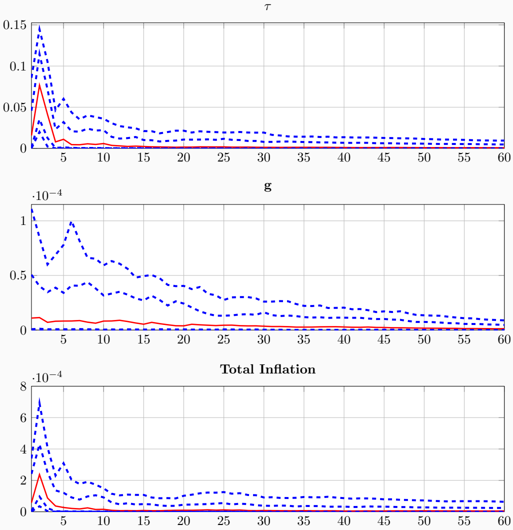
Impulse response of g_t to a one standard deviation monetary policy shock, Bu et al. (2021)



Impulse response of τ_t to a one standard deviation monetary policy shock, Bu et al. (2021)



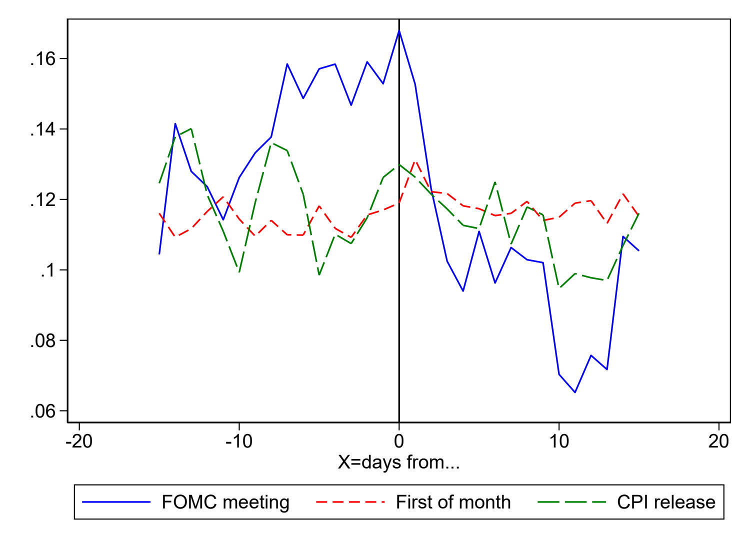
Variance Decomposition



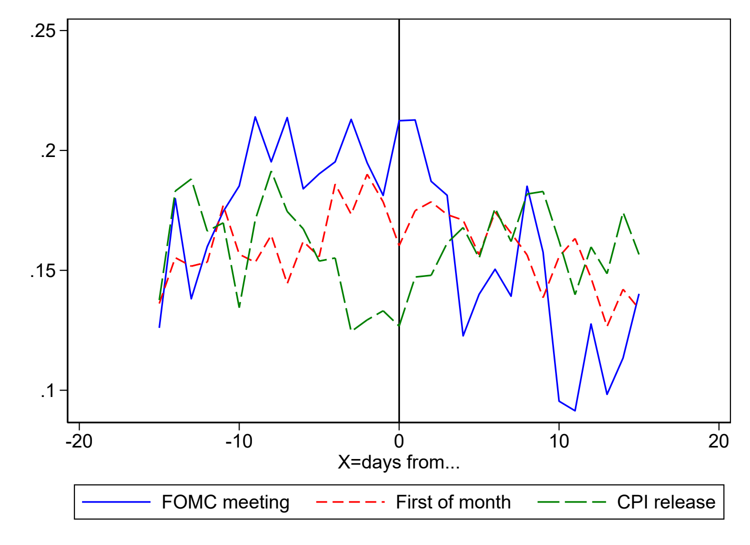
Does inflation respond to FOMC announcements at a daily frequency?

- Line up all FOMC meetings at x-value 0 and take average of BPP inflation across meetings
- Placebo I: x-value 0 instead equals the first of month, CPI release, etc.
- Placebo II: 45-day percentage change ($\approx$ FOMC cycle), etc.
- Result: daily inflation rises then drops, on average, after an FOMC announcement
- Lewis et. al (2019): direct and immediate transmission of monetary policy to daily measure of household confidence

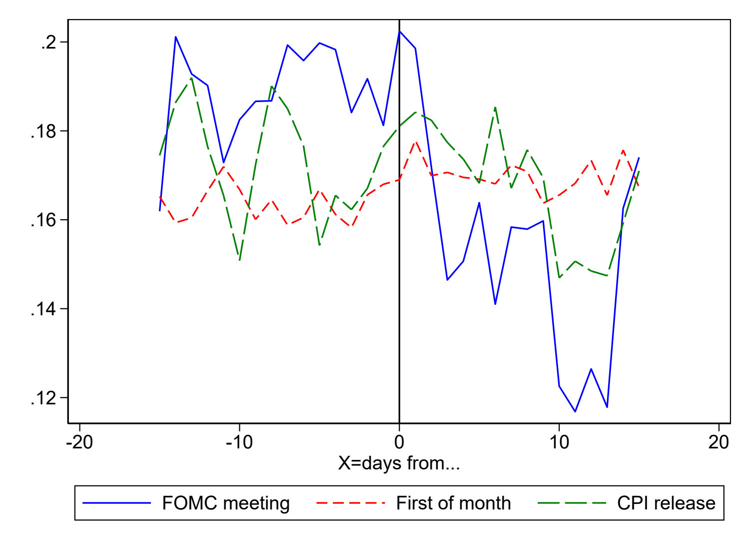
Average Daily CPI, 30-day percentage change



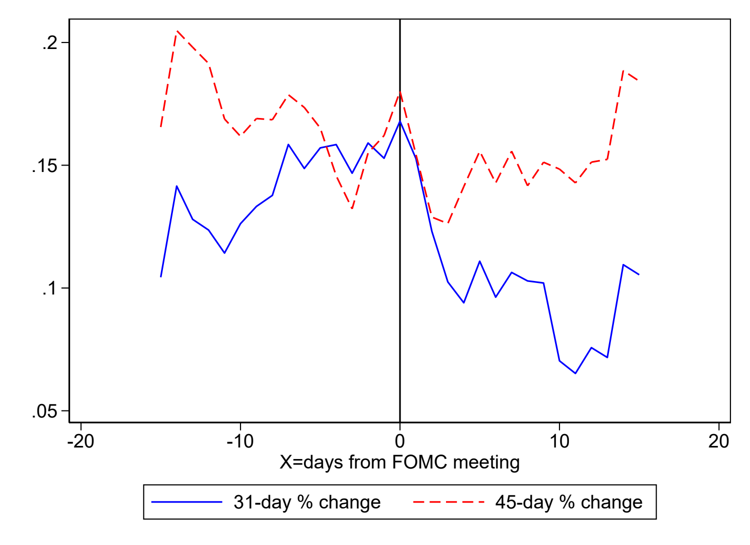
Median Daily CPI, 30-day percentage change



Average Daily CPI, 30-day percentage change



Average Daily CPI, percentage change



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