

Temporal Aggregation Bias and Monetary Policy Transmission

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June 30, 2023 - Society for Economic Dynamics

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.

Q:What Does Monetary Policy Do To Inflation?

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

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- **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 $i = 0, \dots, 9$
- $\Theta_i = -1$ for $i = 10, \dots, 59$
- $\pi_{\textcolor{red}{0}} = \varepsilon_{\textcolor{red}{0}}^m + u_{\textcolor{red}{0}}$

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Temporal Aggregation Bias Intuition

- Aggregate from daily t to monthly T

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

Temporal Aggregation Bias Intuition

- Aggregate from daily t to monthly T with the monetary shock on day i_T

$$\pi_T = \sum_{t=0}^{29-i_T} \underbrace{(\mathbb{1}_{t \leq 9} - \mathbb{1}_{t > 9})}_{\text{lagged shock}} \varepsilon_{i_T}^m + \sum_{t=0}^{29} u_t$$

Temporal Aggregation Bias Intuition

- Aggregate from daily t to monthly T with the monetary shock on day $i_T = 29$

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

- Timing of shock matters, no clean identification

Temporal Aggregation Bias Intuition

- Aggregate from daily t to monthly T with the monetary shock on day $i_T = 28$

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

- Timing of shock matters, no clean identification

Temporal Aggregation Bias Intuition

- Aggregate from daily t to monthly T with the monetary shock on day $i_T = 20$

$$\pi_T = \sum_{t=0}^{29-20} \underbrace{(\mathbb{1}_{t \leq 9} - \mathbb{1}_{t > 9})}_{=10} \varepsilon_{20}^m + \sum_{t=0}^{29} u_t$$

- Timing of shock matters, no clean identification

Temporal Aggregation Bias Intuition

- Aggregate from daily t to monthly T with the monetary shock on day $i_T = 19$

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

- Timing of shock matters, no clean identification

Temporal Aggregation Bias Intuition

- Aggregate from daily t to monthly T with the monetary shock on day $i_T = 0$

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

- Timing of shock matters, no clean identification

Days of the Month of FOMC Announcements

figures-for-todd/histogram-FOMC-announcement

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	

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

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

Defining the Econometrician's Information Set

$$\Pi_T = \left(\frac{1}{m}\right) \left(\sum_{j=0}^{m-1} L^j\right) \pi_{mT} = \left(\frac{1}{m}\right) (\pi_{mT} + \pi_{mT-1} + \cdots + \pi_{mT-m+1})$$

For example, if t is a day, then $m = 30$ and T is a month so that $t = mT$.

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From AR to ARMA

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

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

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_{Π}^2	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_u^2	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

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► (freq. domain)

Tackling Temporal Aggregation using Daily Inflation Data

- 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)

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Text/ForecastFigure.pdf

Text/RegressionFigure.pdf

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

► (High-frequency shocks)



new_lp_figs/irfs_IV_MP_1_daily_hac.pdf

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

► (High-frequency shocks)

► (12 lags)

► (FOMC cycles)

► (Bu et al. 2021 IRFs)

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Controlling for Timing

Why a State Space Model?

- Decompositions into permanent and transitory components have proven useful for inflation (Stock & Watson)
- Transparent modeling assumptions
- 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
- Johansen & Mertens (2020) find adverse response at a quarterly frequency

State Dynamics

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

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3. **Transitory component:** $g_t = \rho g_{t-1} + \sum_{j=0}^J \theta_j m_{t-j} + e_t^g$

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3. **Transitory component:** $g_t = \rho g_{t-1} + \sum_{j=0}^J \theta_j m_{t-j} + e_t^g$
4. **Monetary shock dynamics:** $m_t = e_t^m$

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

Observation Equations

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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

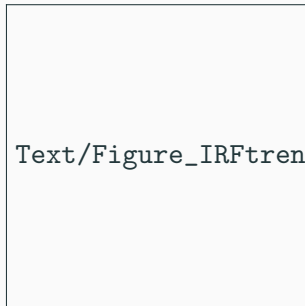
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Impulse response of τ and g_t to a one standard deviation monetary policy shock

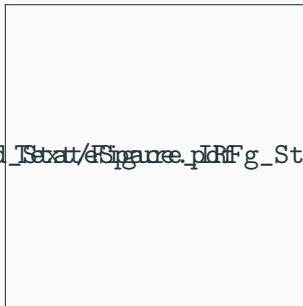
▸ (less shrinkage)

▸ (Bu et al. 2021 shock)

▸ (variance decomposition)



Permanent component



Transitory component

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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

figures-for-todd/LP_IRFs_MC.pdf

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



Text/MA_Filter.pdf



	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

- Official: Monthly percentage change, month T

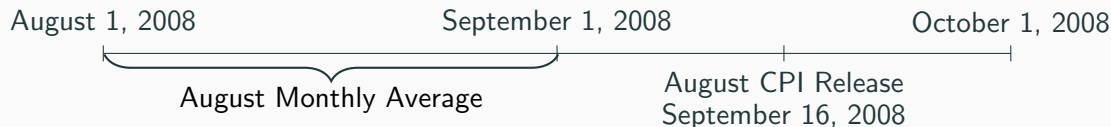
$$\Delta CPI_T = 100 \times (\log CPI_T - \log CPI_{T-1})$$

- 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*** (0.143)				0.178 (0.107)
ΔBPP_T		0.937*** (0.129)		0.878*** (0.097)	0.828*** (0.106)
ΔBPP_{T-1}			0.591** (0.248)	0.109 (0.193)	-0.030 (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

month_mean_scatter_combine.pdf

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

◀ (monthly average)

mom_ann_index_scatter_combine_monthly.pdf

`weeklyseasonality.pdf`

monthlyseasonality.pdf

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:

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

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

Combining and re-arranging:

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

Construction of Nakamura & Steinsson (2018) Shocks

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

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

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 $\Delta i_t^{\text{aligned}}$ from the common component of zero-coupon yields $\Delta R_{j,t}$

1. estimate sensitivity of yields with maturity $j = 1, \dots, 30$ 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

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

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

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

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

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

	ΔCPI_T^i , 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*** (0.129)	1.618*** (0.283)	0.530*** (0.121)	0.180*** (0.052)	1.001*** (0.137)	0.497*** (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. * ($p < .10$), ** ($p < .05$), *** ($p < .01$)

month_mean_scatter_combine.pdf

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*** (0.136)				0.138 (0.111)
ΔBPP_t		0.646*** (0.121)		0.497*** (0.104)	0.461*** (0.111)
ΔBPP_{t-1}			0.609*** (0.155)	0.437*** (0.115)	0.360*** (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*** (0.00895)				0.803*** (0.0460)
BPP_t		0.879*** (0.0138)		1.137*** (0.173)	0.696*** (0.0875)
BPP_{t-1}			0.880*** (0.0178)	-0.257 (0.170)	-0.522*** (0.0842)
(R^2)	0.994	0.985	0.975	0.986	0.997

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

- 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

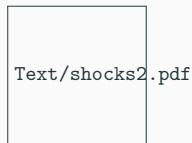


Figure 1: Nakamura & Steinsson (2018) and Bu et al. (2021) monetary policy shocks. The sample is from July 2008 to January 2015 which is when the daily CPI index is publicly available.

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

new_lp_figs/irfs_IV_MP_1_monthly_12_lag_HAC.pdf

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

new_lp_figs/Figure_IRF_Aggregated2_BRW.pdf

- 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

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

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

figures-for-todd/less_shrinkage/Fig3_less_shrinkage.pdf

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



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



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



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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

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`figures-for-todd/maggie-figures/FOMC-inflation-median.pdf`

`figures-for-todd/maggie-figures/FOMC-inflation-exGFC.pdf`

`figures-for-todd/maggie-figures/FOMC-inflation-45.pdf`

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