Temporal Aggregation Bias and Monetary Policy Transmission*

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Abstract

Temporal aggregation biases estimates of monetary policy effects. We hypothesize that information mismatches between private agents and the econometrician—the source of temporal aggregation bias—are as important as the more studied mismatch between private agents and the central bank (the "Fed information effect") in the study of monetary policy transmission. In impulse responses from both local projections and an unobserved components model, we find that the response of daily inflation to high-frequency monetary shocks confirms theoretical predictions. If there is an adverse-signed response such that inflation increases in response to a contractionary monetary shock, it is much less prominent than previously thought and explained by frequency mismatches of shocks and dependent variables.

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1 Introduction

This paper revisits a fundamental question of monetary economics: What is the transmission of monetary policy to the economy? Empirical work often finds that responses of macroeconomic variables to monetary policy shocks have the opposite sign of what standard theory predicts. Researchers trace these adverse responses to information issues, with existing solutions consisting of either adding more information [Sims (1992)] or emphasizing information mismatches between central banks and private sector agents as a "Fed information effect".[1]

We propose temporal aggregation bias as a new information-based explanation for the adverse transmission of monetary policy. When using the daily CPI from the Billion Prices Project [Cavallo and Rigobon (2016)] as a temporally disaggregated macroeconomic indicator, we find that the adverse response of inflation is short-lived, if it is present at all. We argue that existing work on monetary policy transmission finds an adverse response because of the frequency mismatch between the information sets of the econometrician and private agents. A temporally disaggregated measure of inflation overcomes this mismatch by better aligning the frequencies of shocks and dependent variables.

To understand how one can obtain a sizable adverse response to monetary policy shocks with monthly or quarterly data when only a limited adverse response actually exists, we combine a simple model of temporal aggregation bias with informal and formal empirical evidence. We begin by using Monte Carlo evidence to show how there is no clean identification of monetary policy transmission when time aggregating with local projections. We then use a well-known model from the monetary policy literature consisting of an Euler equation and a monetary policy rule to show how temporal aggregation can exacerbate initial impulse response functions.

Our main finding—the response of inflation is conventionally-signed with only a short-lived adverse response if one is present at all—is obtained from the local projection specification advocated by Nakamura and Steinsson (2018b). The monetary policy shocks are identified via high-frequency variation in asset prices around monetary policy announcements, as is standard in the literature [Kuttner (2001), Gürkaynak et al. (2005), Campbell et al. (2012), Nakamura and Steinsson (2018a), Bu et al. (2021)]. We establish that temporally aggregated high-frequency measures of inflation correlate well with official lower-frequency measures (e.g. monthly CPI) over our sample period (July 2008 to August 2015). Our empirical tests corroborate the claim that the high-frequency measure of inflation is "good at anticipating major *changes* in inflation *trends*," [emphasis added, Cavallo and Rigobon (2016)]. We thus align the frequency of our variable of interest (inflation) more closely to the frequency of variation used to identify shocks. Impulse response functions show the response of inflation to a contractionary monetary policy shock is positive for a few weeks with a 90% credible set covering zero over this time horizon and negative thereafter.

Because the effect of temporal aggregation bias in local projections depends on the timing of high-

[1] Bauer and Swanson (2023), Bu et al. (2021), and Caldara and Herbst (2019) also emphasize adding more information. For a "Fed information effect" see Romer and Romer (2000), Campbell et al. (2012, 2017), Nakamura and Steinsson (2018a), Jarocinski and Karadi (2020), Miranda-Agrippino and Ricco (2021), Lunsford (2020), Hoesch et al. (2021), Cieslak and Schrimpf (2019), Acosta (2022), Sastry (2021), Karnaukh and Vokata (2022), Lewis (2020), Bundick and Smith (2020), Andrade and Ferroni (2021), Golez and Matthies (2021).

frequency shocks, we build an unobserved components model that explicitly incorporates when monetary policy shocks occur within a month. This state space model adds the daily CPI and daily break-even inflation rates as well as possible effects of monetary policy shocks into a model of inflation dynamics along the lines of Stock and Watson (2016) and Nason and Smith (2020). These impulse responses corroborate our local projection results by showing conventionally-signed transmission of monetary policy.

Our contribution of temporal aggregation bias as an explanation for the transmission of monetary policy shocks provides further support for the ongoing claim, dating back to at least Kuttner (2001), that monetary policy needs to be studied in a high-frequency environment. Even though high-frequency economic indicators and temporal aggregation theory have been available for decades, we are the first—to our knowledge—to apply them to the study of monetary policy transmission.[2] By pairing high-frequency shocks with high-frequency response variables, our work follows existing specifications that estimate the transmission of monetary policy shocks to financial indicators.[3] Financial indicators, however, may not be as susceptible to temporal aggregation bias as macroeconomic indicators because the former are observable at high frequencies. By contrast, economic indicators are accumulated over a fixed time interval and published with a lag, resulting in aggregation bias from potentially mismatched information sets between private agents observing high-frequency indicators and an econometrician relying on official releases.[4]

Unlike other studies, where competing methodologies or conditioning on different data serves to obfuscate analysis, a distinct advantage of our approach is the consistency in inference. We condition on the same data and apply the same methodology with the only distinction being the frequency of the data. An increase in the frequency of inflation observations eliminates adverse monetary impulse responses. Because our temporal aggregation results are generic, we argue that the benefits of using high frequency data are neither limited to the study of monetary policy transmission nor prices and will be a key feature of the nascent field of high-frequency macro [Baumeister et al. (2021), Lewis et al. (2021)]. In a macroeconomic environment characterized by fast-moving turning points, such as the Great Financial Crisis or the COVID-19 recession, estimates of policy effects may be sensitive to the sampling frequency of economic response variables. Although high-frequency observables may be susceptible to measurement noise because they are only proxies of their lower frequency official counterparts, frameworks like our state space model allow for measurement error. We thus argue that measurement noise is not necessarily more important than the bias induced by temporal aggregation.

1.1 Connection to Literature

While Campbell et al. (2012) and Nakamura and Steinsson (2018a) find adverse responses when estimating the transmission of high-frequency monetary policy shocks to lower frequency forecasts of macroeconomic aggregates, subsequent work finds that properly account-

[2] Lewis et al. (2020a) discuss how time aggregation affects their estimates of monetary policy transmission to household expectations. See Shapiro et al. (2022), Aruoba et al. (2009), Lewis et al. (2020b) for other high frequency economic indicators.

[3] See Golez and Matthies (2021), Andrade and Ferroni (2021), Nakamura and Steinsson (2018a), Bauer and Swanson (2022), Gürkaynak et al. (2022), and Gürkaynak et al. (2021).

[4] For example, Stock and Watson (2007) note that time series estimates of the CPI are susceptible to temporal aggregation bias.

ing for information delivers results that are either ambiguous or in line with structural predictions.[5]

Closest to our specification of high-frequency inflation indicators responding to high-frequency monetary policy shocks are specifications that rely on high-frequency expected inflation (TIPS) [Nakamura and Steinsson (2018a)] or commodity prices [Velde (2009)]. Relative to these previously used proxies, we argue that the Billion Prices Project daily CPI is a relatively more complete measure of inflation and hence better suited to assess the transmission of monetary policy shocks. Expected and realized inflation may have different sensitivities to monetary policy shocks because the former tends to be anchored while the latter is more prone to fluctuations.[6] Similarly, commodities are known to be more volatile than measures of inflation which may result in different sensitivities to monetary policy shocks.

Rather than following much of the empirical monetary policy transmission literature and focusing on information refinements to possible explanatory variables, we instead follow Bauer and Swanson (2023) and contribute refinements to the less-studied measurement of response variables.[7] Many studies find predictability and or bias in standard high-frequency monetary policy shocks such as those estimated by Nakamura and Steinsson (2018a). These studies mainly focus on the response of GDP and argue that the adverse sign disappears once the shocks are either orthogonalized [Karnaukh and Vokata (2022), Bauer and Swanson (2022)] or conditioned on missing information [Caldara and Herbst (2019), Sastry (2021), Miranda-Agrippino and Ricco (2021), Bauer and Swanson (2023)].

Many studies account for the adverse transmission of high-frequency monetary policy shocks by appealing to Romer and Romer's (2000) "Fed information effect" which argues that central banks have an information advantage over private agents.[8] Private agents thus revise up their forecasts of inflation in response to tighter monetary policy because they perceive a signal that the central bank has relatively optimistic non-public information. However, several recent papers explicitly test for a central bank information advantage and find no evidence [Sastry (2021), Bundick and Smith (2020) and Bauer and Swanson (2023)]. Other papers take the information advantage as given, control for it directly, and find that it either changes the transmission of monetary policy shocks [Lunsford (2020), Bu et al. (2021), Hoesch et al. (2021), Cieslak and Schrimpf (2019), Acosta (2022)] or eliminates the adverse transmission entirely [Miranda-Agrippino and Ricco (2021), Jarocinski and Karadi (2020)].[9] In contrast to existing work, we do not explicitly test or model how the information sets of central banks and private agents affect monetary policy transmission. We instead focus on the less-studied information mismatch between private agents and the econometrician and how this biases estimates.

Decades of work supports our claim that temporal aggregation bias can affect both the direction and

[5] Uribe (2022) takes a contrasting stance and argues that monetary policy shocks may actually be neo-Fisherian.

[6] Common specifications that rely on the change in Blue Chip forecasts may thus be understating the transmission of monetary policy shocks to inflation because they capture changes in expected rather than current inflation. We posit that the different sensitivities of expectations and actual indicators is less of an issue for the transmission of monetary policy shocks to GDP.

[7] Bauer and Swanson's (2023) survey finds that Blue Chip forecasters rarely change their estimates of economic indicators in response to monetary policy announcements which calls for reexamination of the suitability of these forecasts as response variables.

[8] Faust et al. (2004) find that the adverse response of inflation disappears once the Volcker disinflation is excluded from Romer and Romer's (2000) study.

[9] Lewis (2020) and Acosta (2022) specifically identify a Fed information effect shock and find evidence that is either mixed or against adverse transmission of monetary policy shocks.

magnitude of monetary policy transmission. We follow Marcet (1991) in demonstrating how the systematic effect of time aggregation is to bias the first few coefficients of the moving-average representation. Coupled with results in Amemiya and Wu (1972), who show that temporal aggregation of autoregressive processes preserves invertibility, these biases would infiltrate modern approaches to VAR identification. This puts our main result—that the Fed information effect is an artifact of temporal aggregation—on firm theoretical ground. While applications of these ideas in applied macroeconomics are still relatively rare, Foroni and Marcellino (2016) highlight how jointly using data collected at different frequencies can help with the identification of structural VARs with a focus on traditional recursive identification schemes, whereas Foroni and Marcellino (2014) make a similar argument for dynamic equilibrium models. A related, but distinct, literature has developed tools to estimate regression-type models when the left-hand side is sampled at a different frequency than the right hand side (Ghysels et al., 2004).

2 A Few Properties of Temporal Aggregation

We employ stylized models of monetary policy in order to establish properties of temporal aggregation designed to shed light on the empirical results of Section 4. Using simulated data and local projections, we show how a short-lived adverse response (i.e., positive response of inflation to a contractionary monetary policy shock) can seep into lower frequencies due to temporal aggregation bias. We then provide a more theoretical framework to demonstrate *how* temporal aggregation leads to substantial bias in impulse response functions; specifically, in the initial values of moving-average representations. We keep the models sufficiently simple in order to provide clear intuition, acknowledging that these are examples as opposed to theorems. However, we conjecture robustness of our results by appealing to an earlier literature that operates in continuous time, and by discussing necessary conditions of our results in a New Keynesian setup.

2.1 Temporal Aggregation with Local Projections

Consider the data-generating process of inflation,

$$\pi_t = \sum_{j=0}^{59} \Theta_j \varepsilon_{t-j}^{mp} + u_t \tag{1}$$
$$u_t = \rho^u u_{t-1} + \varepsilon_t^u$$

where t is assumed to be daily, and the monetary policy shock $\varepsilon_t^{mp} \sim N(0,1)$ is uncorrelated with the persistent shock $u_t \sim N(0,\sigma_u^2)$. We assume the monetary policy shock occurs only once per month, while u_t occurs every day. We examine three alternative specifications of the timing of the monetary policy shock—a shock that occurs at the beginning (day 1), middle (day 15), and end (day 30) of the month. To approximate population moments, we simulate three million daily observations, taking 30-day averages of shocks and the inflation process (1) to obtain corresponding monthly data. Local projections are used to estimate monthly responses of inflation to the monetary policy shock, controlling for lagged inflation outcomes. We set $\rho_u = 0.99$ and $\sigma_u = 1$ to capture the idea that other shocks are just as important as monetary policy for the evolution of inflation at the daily frequency. The parameters governing the reaction of inflation to monetary policy are given by $\Theta_j = 1$ for $j = 0, \ldots, 9$ and $\Theta_j = -1$ for $j = 10, \ldots, 59$.

Our parameterization accomplishes two tasks: first, it introduces what we refer to as an initial "adverse" policy response of inflation; that is, the first ten daily observations of inflation following a monetary policy shock are inconsistent with standard theory in that a contractionary shock would lead to an increase in inflation. Second, the average effect over the 30-day period is consistent with theory. The remaining two-thirds of the daily observations over the month enter with a negative coefficient, implying a contractionary shock would lead to a fall in inflation. Note also that the magnitudes of the first 10 days and last 20 days are similar. *The implication of our calibration is that one would not expect the adverse inflationary response to materialize in the aggregate (monthly) data.*

	Panel A: Beginning			Panel B: Middle			Panel C: 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	-0.40	0.82		0.29	0.82		0.03	0.82	
Π_t	-0.50		-1.16	0.38		-0.85	-0.06		-0.26
Π_{t+1}	-1.09	0.61		-0.92	0.60		-0.19	0.60	

Table 1: Local Projection Results. Three million observations of daily inflation simulated via (1) and aggregated to monthly (30 day) frequency were estimated using local projections. The panels denote when the monetary policy shock hits the economy, at the beginning (day 1), middle (day 15) or end (day 30) of the month. Dependent variables are in the first column, the other columns display the coefficients of the right-hand-side variable given at the top of each column within a panel. The first row of the results is the response of inflation to the monetary policy shocks from the current and previous months. The second and third row of results are the local projections at time $t = 0$ and $t = 1$, respectively.

Table 1 shows results for three local projection specifications and various timing of the monetary policy shock. In two of the three specifications, the econometrician would find a *positive* initial response of inflation to a monthly monetary policy shock, despite the fact that the time-averaged response is negative. Only when the monetary policy shock hits towards the beginning of the month does the sign of the response of inflation match the temporally aggregated negative value. The lagged shock, ϵ_{t-1}, does enter with a negative sign, so while the initial response could be adverse, the subsequent moves are standard.

The timing of the monetary policy shock is important. Figure 1 (left panel) plots the time-aggregated monthly moving average coefficients (i.e. the accumulated response to a monetary shock) (left, y-axis) against the timing of the monetary policy shock (x-axis).[10] The time-aggregated MA coefficients for any month can be written as $\Psi \equiv \sum_{t=0}^{29-j}(\mathbb{1}_{t\leq 9} - \mathbb{1}_{t>9})$ where $j = 0, \ldots, 29$ is the day of the month when the monetary policy shock occurs. For example, when $j = 29$ so that the shock occurs on the last day of the month, $\Psi = 1$. The aggregated response is thus initially increasing as we decrease $j = 29, \ldots, 21$ (the shock occurs earlier in the month) with the largest positive impact $\Psi = 10$ on day $j = 21$. Thereafter, the negative MA coefficients enter into the monthly aggregation and the largest negative impact $\Psi = -10$ is when the shock occurs on day $j = 0$ at the very beginning of the month. The histogram plotted on the left

[10]Note that this accumulated response is not directly comparable to our estimates reported in table 1 since we assume in our simulations that there is only one monetary shock per month.

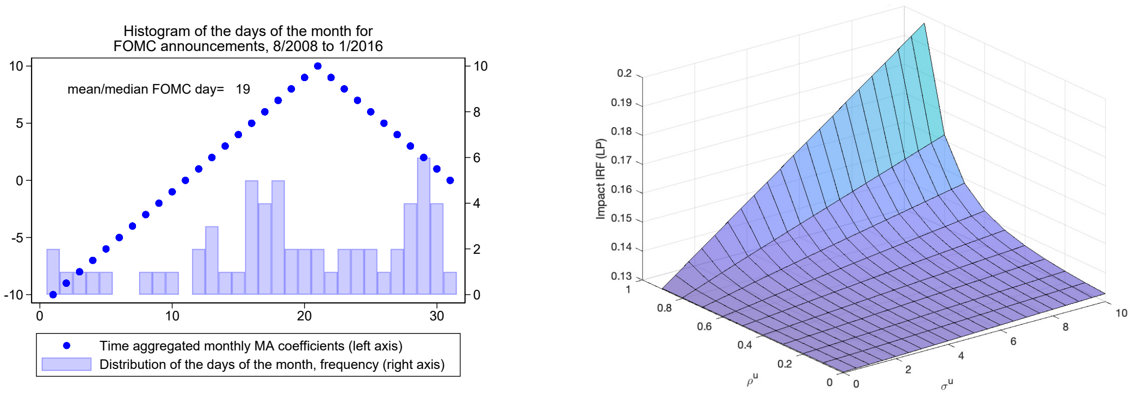


Figure 1: Robustness. Impact IRF estimated via local projections as a function of Autocorrelation (ρ^u) and Standard Deviation (σ^u) (right panel) and accumulated responses as a function of shock timing (left panel).

panel of Figure 1 shows that over our sample period, the timing of FOMC announcements is consistent with the shock hitting during the middle of the month. The mean and median FOMC announcement occurred on the 19th day of the month, and a majority of the announcements occured after the 10th day of the month. This simple example shows how researchers using aggregated data can estimate a positive response of inflation to a contractionary monetary policy shock even though most of the disaggregated response coefficients are negative.

Finally, we note that the results are not contingent on the parameterization of the daily process, u_t. Figure 1 (right panel) plots the initial response using the middle of the month timing as in Panel B of 1 against the serial correlation coefficient and standard deviation. It shows that size of the positive coefficient in the LP regression is increasing in the correlation of the non-monetary policy shock and its standard deviation, but remains substantial (0.13) when these values are close to zero. These results confirm our empirical findings—a short-lived adverse response at daily frequency can be persistent and significant at monthly frequency.

2.2 TEMPORAL AGGREGATION IN A STRUCTURAL MODEL.

We now provide a more theoretical framework to demonstrate *how* temporal aggregation leads to substantial bias in impulse response functions. Consider a nominal bond that costs \$1 at date t and pays off $(1+i_t)$ at date $t+1$. The asset-pricing equation for this bond can be written in log-linearized form as a Fisher equation, $i_t = r + \mathbb{E}[\pi_{t+1}|I_t]$, where the real interest rate is assumed to be constant and $\mathbb{E}[\pi_{t+1}|I_t]$ is the private agents' expectation of next period's $(t+1)$ inflation. Monetary policy follows a Taylor rule, adjusting the nominal interest rate in response to inflation, $i_t = r + \phi[\pi_t|I_t] + x_t$, where the monetary policy shock follows an AR(1) process, $x_t = \rho x_{t-1} + \varepsilon_t$, with $\rho \in (0,1)$ and ε_t distributed as Gaussian with mean zero and variance σ_ε^2. We assume the information set of the monetary authority is consistent with private agents' (I_t) so that we can isolate the effects of the information mismatch between private agents and the econometrician without a confounding "Fed information effect." The unique equilibrium rate of inflation is well known and follows

	$m=1$	$m=2$	$m=5$	$m=10$	$m=20$	$m=30$	$m=40$	$m=50$
ρ^m	0.990	0.980	0.951	0.904	0.818	0.740	0.669	0.605
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
σ_Π^2	1.397	1.389	1.374	1.351	1.307	1.266	1.226	1.186

Table 2: Estimates of the ARMA(1,1) (4) using temporally aggregated observations of (2). Note that for $m=1$ (no temporal aggregation), $\sigma_u^2 = \sigma_w^2$.

from implementing the Taylor principle ($\phi > 1$),

$$\pi_t = -\frac{x_t}{\phi - \rho} = \rho \pi_{t-1} + w_t \tag{2}$$

where $w_t = -\varepsilon_t / (\phi - \rho)$.

We assume the econometrician observes realizations of the equilibrium processes at a frequency that is lower than private agents. Specifically, let $t = mT$ and define the temporally aggregated inflation process as

$$\Pi_T = \left(\frac{1}{m}\right)\left(\sum_{j=0}^{m-1} L^j\right)\pi_{mT} = \left(\frac{1}{m}\right)(\pi_{mT} + \pi_{mT-1} + \cdots + \pi_{mT-m-1}) \qquad T = 1,2,3,\ldots \tag{3}$$

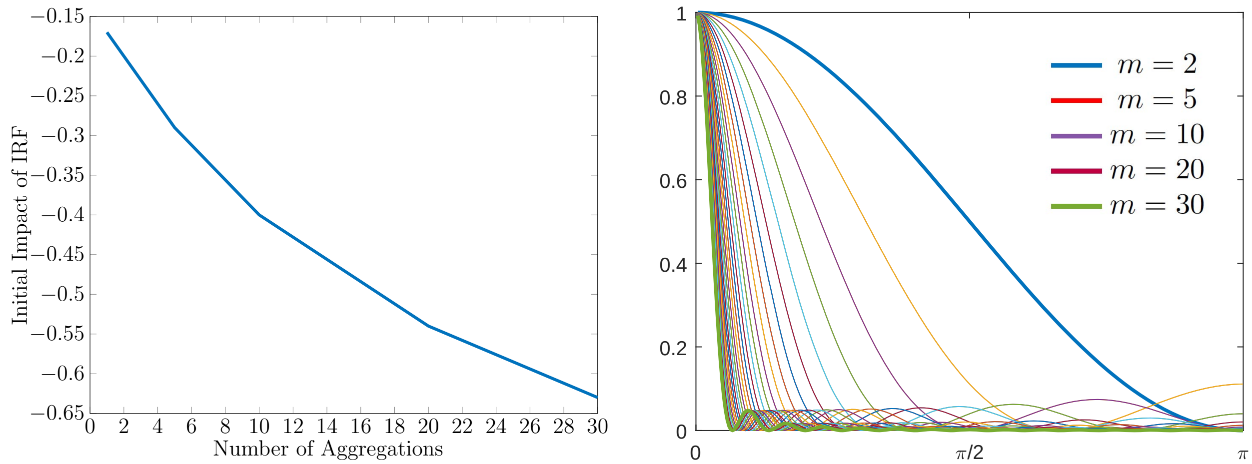
For example, if t is a month and $m = 3$, then T is a quarter. Inflation, π_t, could be interpreted as a monthly year-over-year percentage change, and the three-month non-overlapping arithmetic mean is one possible way of aggregating. Alternatively, we could assume to observe month-over-month inflation and the direct summation yields quarterly inflation. Our analysis below is robust to these alternative aggregation methods.

Appendix C shows that temporally aggregating the AR(1) inflation process given by (2) yields an ARMA(1,1) representation,

$$(1 - \rho^m L)\Pi_T = u_T + \theta u_{T-1} \qquad u_T \sim N(0, \sigma_u^2) \tag{4}$$

where, for lag operator L, the autocorrelation coefficient is raised to the power of m (the number of aggregate components), and the estimated shocks (u_t) will be fundamental for the Π_t process (Amemiya and Wu (1972)). The last fact ensures that an autoregressive (or VAR) representation will accurately estimate the ARMA process. An analytical mapping between the aggregated inflation process and the ARMA(1,1) parameters is not feasible but Table 2 provides estimates of the parameters for various values of m using simulated data. We set $\rho = 0.99$, $\phi = 1.05$, $\sigma_\varepsilon^2 = 0.01$, and use one million disaggregated observations.

The estimates of Table 2 reveal important properties of the mapping between an AR(1) process and its temporally aggregated ARMA(1,1) counterpart: [i.] the autocorrelation coefficient decays exponentially



(a) Impact Response for Various m

(b) Spectrum of MA Filter ($m = 2, ..., 30$)

Figure 2: Initial Impulse Response and Moving-Average Filter for Various m. Panel a shows the decline in the initial impact coefficient as m increases from 1 to 30. Panel b plots the spectrum for $m = 2$ (blue) through $m = 30$ (green), demonstrating why low frequency properties are preserved.

at rate m; [ii.] the variance of the aggregate inflation process,

$$\sigma_{\Pi}^2 = \frac{\sigma_{\pi}^2}{m^2}\left(m + 2[(m-1)\rho + (m-2)\rho^2 + \cdots + \rho^{m-1}]\right) \tag{5}$$

declines multiplicatively in m (see Appendix C for derivation). Taken together, [i] and [ii] imply that the variance of the innovation process σ_u^2 and the moving average parameter θ must compensate for the faster decline in the autocorrelation coefficient, ρ^m. Table 2 shows that the variance of the innovation (σ_u^2) increases 46% for $m = 2$ and by a factor of ten for $m = 20$, and the moving-average parameter also increases with m. The increase in the estimated variance will translate into a more pronounced *initial* impact of the impulse response of inflation to a monetary policy shock. Figure 2a plots the initial impulse response to a one-standard deviation shock (σ_u) for various levels of aggregation. Note that the units of the x-axis correspond to the degree of aggregation m. The disaggregated impulse ($m = 1$) shows an inflation process with an impact response that is substantially mitigated relative to the temporally aggregated responses. Even a slight increase in the degree of aggregation leads to a substantial change in the impact response to a monetary policy shock—temoporally aggregating over six periods more than doubles the initial impact. This dynamic is consistent with our empirical findings in Section 4, see Figures 6 and 7.[11]

Figure 2b plots the moving-average filter $\left(\frac{1}{m}\right)\left(\sum_{j=0}^{m-1} L^j\right)$ in the frequency domain over the range of 0 to π. The figure shows that a MA filter is a low-pass filter, allowing lower frequencies to pass through while attenuating medium and higher frequencies. What is critical for understanding the bias associated with temporal aggregation is *how* the reallocation of the spectrum is distributed across various param-

[11] One distinction between this exercise and our empirics is the normalization of the variance. If one were to normalize the variance for the temporally aggregated series to match the disaggregated value, the correction would come through the moving average term and Figure 2 continues to be relevant.

eters of the estimated ARMA(1,1) process. Lower frequencies are preserved when aggregation occurs despite the decline in the autocorrelation coefficient (from ρ to ρ^m). Amemiya and Wu (1972) show that, for any stationary AR(p) representation, temporal aggregation preserves the order of the autoregressive process (i.e., an AR(p) becomes an ARMA(p,q))[12] with the autoregressive roots all raised to the power m. These seemingly conflicting properties—a decline in the value of the (positive) autocorrelation roots coupled with no subsequent change in the low frequency properties of the time series process—leads to a substantial change in the initial impulse response coefficients through an increase in the variance of the innovation process and appearance of positive moving-average parameters.

2.3 ROBUSTNESS The purpose of this section was to establish how temporal aggregation can substantially alter initial moving-average coeffcients. An econometrician, time-aggregating the data, will attribute a structural interpretation to the significant and potentially adverse initial reaction of inflation to a monetary policy shock, when the lion's share of the response is due to temporal aggregation bias. While we believe this section has established compelling intuition for our results, the models are stylized and so we briefly discuss robustness. First, appealing to Marcet (1991), our primary result is not an artifact of specific assumptions underlying our model but is due to the more generic properties of temporal aggregation. Working in a continuous-time framework and with generic Wold representations, Marcet (1991) finds the "systematic effect of time aggregation is to increase the absolute size of the *first few coefficients* of the MAR (moving-average representation) (emphasis added)." This result, coupled with the fact that temporal aggregation preserves invertibility for autoregressive processes (Amemiya and Wu (1972)), suggests that our results are robust to alternative specifications.

Second, how do we square our results with the ubiquitous price-stickiness frictions now standard in the New Keynesian literature? Our result will continue to go through under the assumption that *some* firms have the ability to adjust prices at a frequency higher than monthly. Building a New Keynesian model with multiple Calvo adjustment frequencies, we can show that temporal aggregation bias will be substantial if only 1/5 of firms change prices at frequencies higher than monthly.[13] Observing data at a monthly or quarterly frequency, the econometrician will be susceptible to temporal aggregation bias.

3 DATA

Our analysis uses the Billion Prices Project Daily CPI (BPP). Several papers have already established the ability of the BPP to improve forecasts of the CPI [Cavallo and Rigobon (2016), Aparicio and Bertolotto (2020) and Harchaoui and Janssen (2018)]. We also refer readers to these papers for a detailed discussion of BPP construction. Our analysis below confirms that the BPP contains *additional* information that helps forecast the CPI over our sample period.

[12]Stram and Wei (1986) show this condition holds as long as the AR roots are distinct from the MA roots.
[13]Results available upon request.

3.1 DAILY INFLATION DATA

We define daily inflation as the 30-day percentage change in the BPP.[14] The BPP is constructed from over five million online prices from 300 retailers in 50 countries webscraped daily. While we provide a brief overview here, a meticulous description of the data is provided in Cavallo and Rigobon (2016). Our data consists of (publicly available) observations from 2008 to 2015. Advantages of the data are [i.] the higher frequency (daily) vis-a-vis the CPI (monthly or bi-monthly) or scanner data (weekly); and [ii.] the number of prices collected far exceeds the CPI (500k vs. 80k). The disadvantages are [i.] prices are only collected from online retailers and therefore the sample is not representative of all consumer prices; specifically, the sample contains no pricing from the services sector.[15] According to Cavallo and Rigobon (2016), the data contain at least 70 percent of the weights in Consumer Price Index (CPI) baskets of roughly 25 countries; [ii.] Because prices are webscraped, the data does not contain information on quantities sold. Thus, online prices must be coupled with weights from consumer expenditure surveys or other sources to yield expenditure-weighted data.[16] Even though prices obtained by physically visiting stores may not necessarily coincide with those observed online, Cavallo (2017) finds a 70 percent match rate.

3.2 CONNECTION TO CPI INFLATION

To alleviate concerns that BPP data may not align well with the US CPI, we now conduct several tests to show that the BPP is effective at anticipating changes in inflation, a fact that we will exploit in our econometric analysis.

Statistic	Release delay (days)
Mean	16.97
Standard error	2.73
Min	13
Max	30

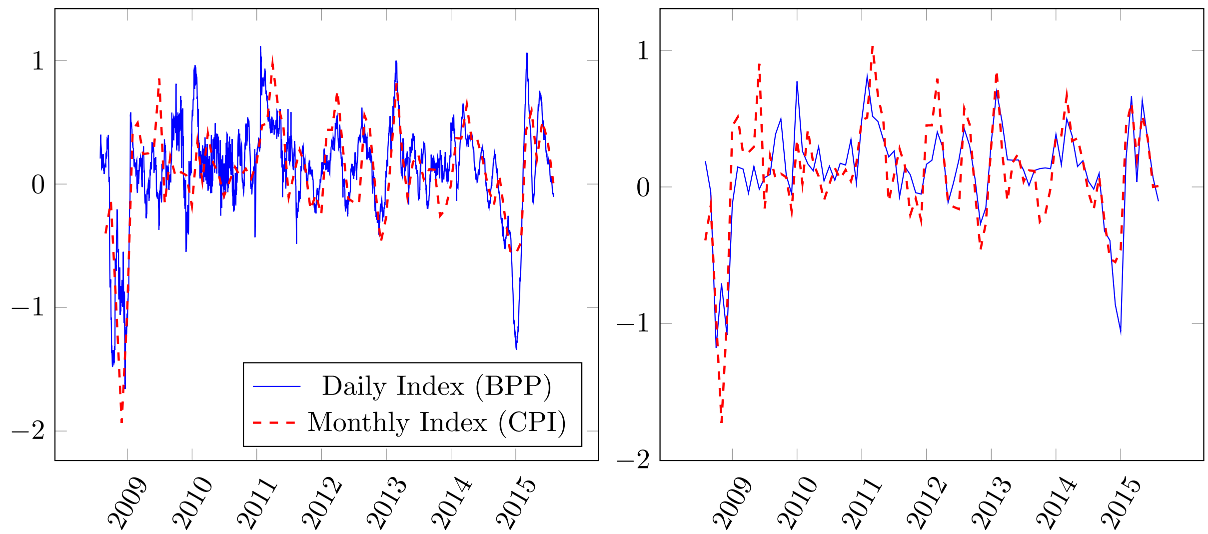
Table 3: Summary statistics on CPI release delays from July 2008 to August 2015.

Panel 3a plots the percentage change of the monthly CPI and the BPP daily index; Panel 3b plots the percentage change of the monthly CPI against the aggregated monthly BPP. While the correlation of the two series plotted in Panel 3b is only 0.64, several studies have shown that the BPP index is particularly adept at picking up turning points in the CPI, which leads to improved forecasts [Cavallo and Rigobon (2016), Aparicio and Bertolotto (2020) and Harchaoui and Janssen (2018)]. To show this result holds over our sample period, we use the monthly aggregated BPP series to conduct a Nowcast of the CPI by estimating, $\Delta CPI_T = \beta_0 + \beta_1 \Delta BPP_T + e_T$. Despite both indices being denoted with subscript T, the CPI at date T is announced with a slight delay as shown by Table 3, which documents the summary statistics of release

[14]In contrast to day-over-day percentage, 30-day percentage change allows for the units of daily inflation to be comparable to those of official inflation which are measured at monthly frequency.

[15]Although comparing the BPP to a version of the CPI with the same coverage of categories would be an ideal exercise, we are limited by data availability. We have instead repeated some of the calculations of this section using sub-categories of the CPI and the results are broadly similar as shown in Appendix A. These sub-categories include the commodity price index, the commodity plus shelter index, the official index less energy, and the official index less medical services.

[16]The BPP only discloses weights pooled across all countries where they collect data. They do not disclose country specific weights. See https://www.pricestats.com/approach/data-composition.



(a) Daily Index (BPP) vs CPI

(b) Monthly Averaged Daily Index (BPP)

Figure 3: Official and daily inflation, monthly and 30-day percentage change. For month T, $\Delta CPI_T = 100 \times (\log CPI_T - \log CPI_{T-1})$ and for day t, $\Delta BPP_t = 100 \times (\log BPP_t - \log BPP_{t-30})$ so that $\Delta BPP_T = \frac{1}{m}\sum_{t=1}^{m} 100 \times (\log BPP_t - \log BPP_{t-30})$ for $t = 1, \ldots, m$ days in month T.

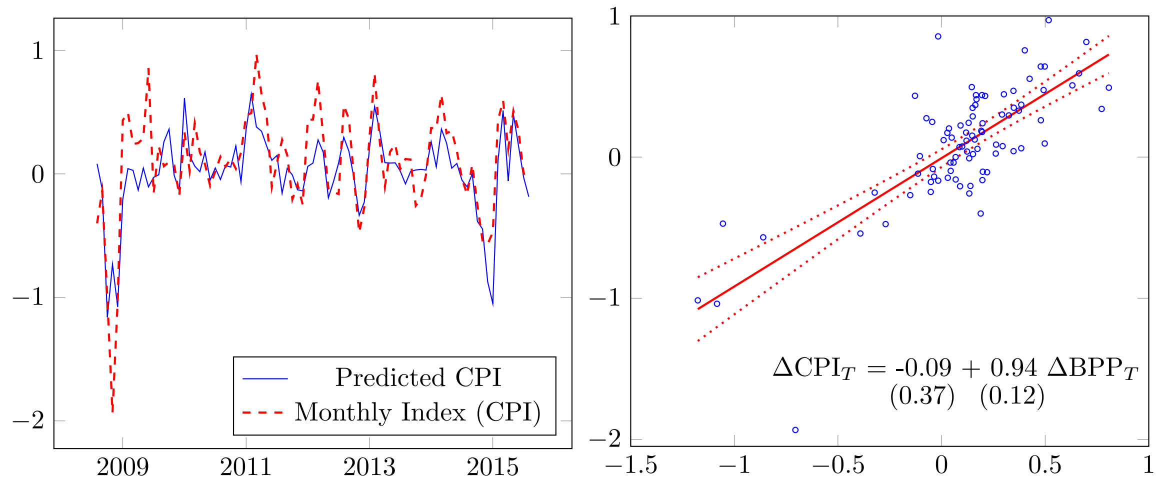
delays in days (e.g., June 2008 CPI was released July 16). Given that our interest lies in high-frequency changes in inflation, the slight difference in timing is relevant as one can use the monthly average of the BPP to predict that month's CPI number. A coefficient equal to unity ($\beta_1 = 1$) suggests the BPP perfectly predicts the CPI. The estimated value is 0.94 with an R-squared of 0.58, implying substantial predictive power, see Panel 4b. Panel 4a plots the in-sample predicted values against the realized values.

Given the persistence of inflation, we address the following question: Is there any *additional* predictive power of the BPP beyond that contained in past values of the CPI? Table 4 compares the Nowcast to an autoregressive representation of the CPI. Column one reports the AR(1) specification results. Columns two and three condition only on past values of the BPP, and show a substantial increase in the R-squared value when conditioning on the contemporaneous BPP, while the lagged BPP has less predictive content than last month's CPI. Columns four and five demonstrate an affirmative answer to the question of additional predictive power of the BPP: The coefficients on the contemporaneous BPP are positive and statistically significant. The R-squared value is twice as high as the autoregressive specification.[17]

4 EMPIRICAL RESULTS

4.1 MEASURES OF HIGH-FREQUENCY MONETARY POLICY SHOCKS Before estimating monetary policy transmission with disaggregated inflation data, we briefly describe our choice of monetary policy shocks and their respective timing and identification. We discuss two such constructions in detail—Nakamura

[17] We conduct several robustness checks in Appendix A which corroborate our findings that the BPP index is effective at predicting changes in inflation. For example, we construct alternative metrics for computing inflation (levels, end-of-month values) and examine different types of seasonality (day-of-the-week).



(a) Predicted vs Actual

(b) Model Fit

Figure 4: Nowcast of CPI using monthly aggregated BPP, monthly percentage change. Standard errors in parentheses on Panel 4b. For month T, $\Delta CPI_T = 100 \times (\log CPI_T - \log CPI_{T-1})$ and for day t and month T, $\Delta BPP_T = \frac{1}{m}\sum_{t=1}^{m} 100 \times (\log BPP_t - \log BPP_{t-30})$ for $t = 1, \ldots, m$ days in month T.

	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	−0.03
			(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	0.6

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

Table 4: Nowcast of BPP vs. autoregressive CPI. For month T, $\Delta CPI_T = 100 \times (\log CPI_T - \log CPI_{T-1})$ and for day t and month T, $\Delta BPP_T = \frac{1}{m}\sum_{t=1}^{m} 100 \times (\log BPP_t - \log BPP_{t-30})$ for $t = 1, \ldots, m$ days in month T.

and Steinsson (2018a) (NS) and Bu et al. (2021) (BRW). We focus on these shocks because they are characterized by a single factor that can be parsimoniously embedded into more complex frameworks like our state space model. Even though the NS shock is widely used, there are known concerns about predictability and bias. For this reason, we also include estimates using the BRW shock as it claims to control for some of these concerns. NS find a substantial adverse transmission of monetary policy shocks, while BRW claim to overcome such dynamics. Our aggregated results replicate these findings.

NS define a "policy news shock" as the first principal component of the change in five interest rates / futures around a 30-minute window of FOMC announcements: the expected federal funds rate at the end of the month of the FOMC announcement, the expected federal funds rate at the end of the month of the next scheduled FOMC announcement, and expected 3-month Eurodollar interest rates at horizons of two, three and four quarters. The last three futures are meant to capture the effects of forward guidance as it impacts expectations beyond the federal funds rate. Our extension of this shock series is constructed from the Chicago Mercantile Exchange futures tick data to assure as close of a match as possible to the original series. BRW use the Fama and MacBeth (1973) two-step procedure to extract unobserved monetary policy shocks from the common component of zero-coupon yields encompassing the full yield curve. The first step in the procedure estimates the sensitivity of yields of different maturity to monetary policy via standard time-series regressions. Filtering out non-monetary policy news is done through the heteroskedasticity-based estimator of Rigobon (2003) and Rigobon and Sack (2004), implemented by employing instrumental variables (IV).

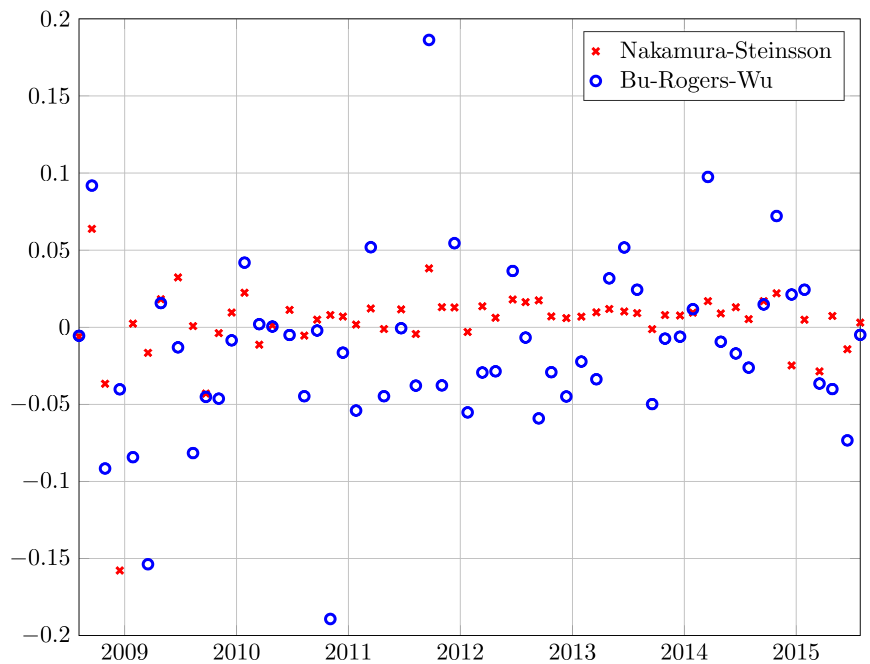
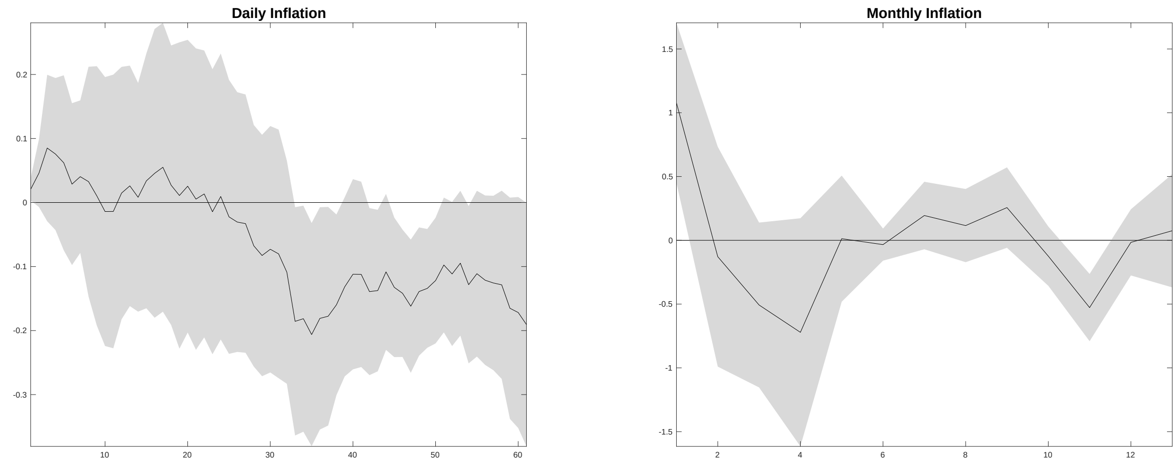


Figure 5: Extracted shock series from Nakamura and Steinsson (2018a) and Bu et al. (2021). The shocks are scaled so that their effects equal unity on nominal Treasury yields of tenures equal to one year (NS) and two years (BRW).

Figure 5 plots the extracted shock series for each approach over our sample period. As noted in BRW, their shock series has “moderately high correlation" with that of NS in addition to those of Swanson (2021) and Jarocinski and Karadi (2020). What is evident from the figure is that the BRW shock series has much more dispersion which is likely attributed to the different frequencies, methods, tenures, and asset prices used in the construction. Despite these differences in dispersion, our empirical analysis confirms that temporal aggregation exacerbates initial impulse responses for both shock series.



(a) Daily inflation

(b) Aggregated (daily to monthly) inflation

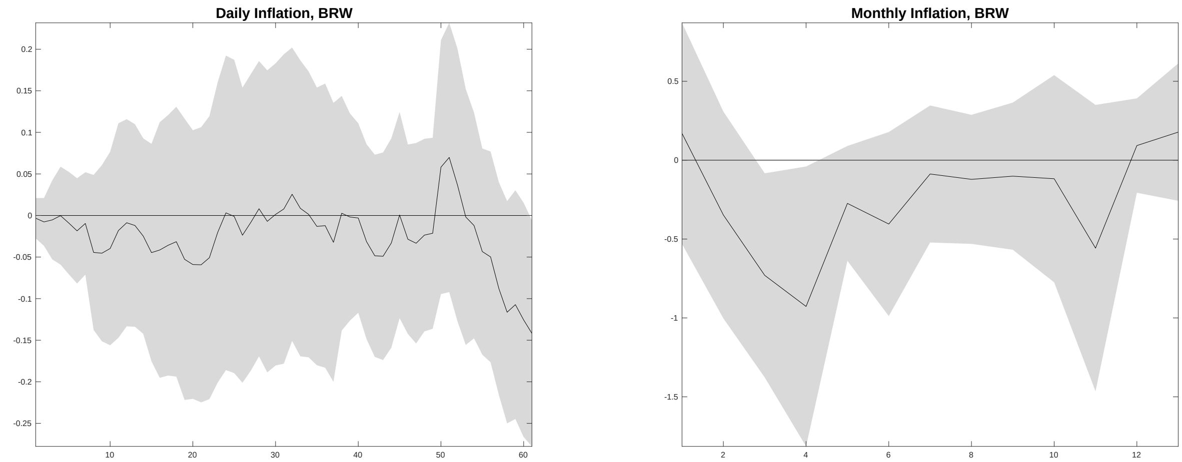
Figure 6: Impulse response of daily inflation (30-day percentage change) to a one standard deviation Nakamura and Steinsson (2018a) shock: aggregated vs disaggregated. For a given month, the aggregated series are the sum of the monetary policy shocks and the average of 30-day annualized percentage change of daily inflation, $BPP_T = \frac{1200}{m}\sum_{t=1}^{m}(\log BPP_t - \log BPP_{t-30})$ for days $t = 1, \ldots, m$ of month T.

4.2 Local Projections We employ local projections using the methodology of Canova and Ferroni (2022) to estimate the impulse responses of disaggregated and aggregated inflation. Let y_{t+h} be the value of daily inflation over the past 30 days at day $t+h$, x_{t-1} be the monetary policy shock, and z_t be the vector of controls which are the 30 lags of daily inflation. Given the model,

$$y_{t+h} = \alpha_{(h)} + \beta_{(h)} x_{t-1} + \Gamma_{(h)} z_t + e_t^{(h)}, \qquad e_t^{(h)} \sim N(0, \sigma_{(h)})$$

estimates are computed via instrumental variables with robust heteroskedasticity and autocorrelation consistent (HAC) standard errors. We report 90% confidence bands and examine the response of inflation observed at various frequencies. We normalize the shock series to have unit variance.

Figure 6 plots the impulse response to a one-time contractionary NS monetary policy shock at both the daily and monthly frequency. Panel 6a shows median disaggregated daily inflation responds positively initially; however, the 90% confidence interval substantially overlaps zero for periods zero through 33. After roughly 30 periods (one month), the inflation response turns negative and is significantly so for the remaining periods shown. By itself this impulse response is merely suggestive. At a daily frequency, the NS shock sequence does not produce a substantial and long-lasting positive response of inflation to a contractionary monetary policy shock. The magnitude of the initial positive response is roughly half that of the negative (and much more persistent) response. Since the NS monetary policy shock is associated with initially adverse responses, feeding in this sequence gives us the best chance of recovering one. At daily frequency, such a response materializes only temporarily.



(a) Daily inflation

(b) Aggregated (daily to monthly) inflation

Figure 7: Impulse response of daily inflation (30-day percentage change) to a one standard deviation Bu et al. (2021) shock: aggregated vs disaggregated. For a given month, the aggregated series are the sum of the monetary policy shocks and the average of 30-day annualized percentage change of daily inflation, $BPP_T = \frac{1200}{m}\sum_{t=1}^{m}(\log BPP_t - \log BPP_{t-30})$ for days $t = 1,\ldots,m$ of month T.

Panel 6b aggregates the daily index to a monthly frequency.[18] The adverse response emerges. When aggregated, the data suggest the initial adverse response is quantitatively large and one of the few components of the impulse response function for which the confidence band does not cover zero. In contrast, the disaggregated initial response of the daily frequency was dominated by the larger and more significant negative response of the later time periods. Figure 6b behooves researchers to provide an explanation for this adverse response when in fact it is not the prominent feature of the data at a slightly higher frequency. Our modeling results in section 2 can reconcile these discrepancies in the estimated adverse response via substantially altered moving-average coefficients due to temporal aggregation bias.

One explanation is that monetary policy announcements contain novel information about economic fundamentals and private agents are reacting to this news.[19] What we refer to as an “adverse" shock or one that runs counter to standard theory could be explained by introducing a discrepancy in information between the Federal Reserve and private agents, Nakamura and Steinsson (2018a). However, testing for this effect requires high frequency data. Previous studies [e.g., Jarocinski and Karadi (2020), Lunsford (2020)] examined the reaction of asset prices, such as stocks and bonds, but we are the first to study the most intriguing economic fundamental—inflation—at high frequency. Figure 6 definitively demonstrates that the adverse response to inflation could be due to an information discrepancy between the econometrician and private agents, and not just the Federal Reserve and private agents.

Figure 7 plots the impulse response of inflation to a contractionary BRW monetary policy shock.

[18]We average the daily shocks for each month and then normalize the resulting shock to have unit variance.

[19]Romer and Romer (2000), Campbell et al. (2012, 2017), Nakamura and Steinsson (2018a), Jarocinski and Karadi (2020), Miranda-Agrippino and Ricco (2021), Lunsford (2020), Hoesch et al. (2021), Cieslak and Schrimpf (2019), Acosta (2022), Lewis (2020), Bundick and Smith (2020), Andrade and Ferroni (2021), Golez and Matthies (2021).

Panel 7a shows that, at daily frequency, the median response of inflation is close to zero or slightly negative until about period 60 (two months) when it becomes more negative and on the margin of the confidence bands. In contrast, when the daily index is aggregated to a monthly frequency, the point estimate of the impact response is positive, albeit zero is well contained in the 90% credible sets. The results using BRW shocks are not surprising given that the “information effect" is not a feature of the shock series. Indeed, the primary takeaway of Bu et al. (2021) is that the long-end of the yield curve is necessary to eliminate the information effect:

> Whereas alternative measures are constructed from only short rates, we use the entire yield curve. This is important because we find that the Fed information effect is essentially nonexistent in maturities of five years and longer.

While we certainly agree that there could be additional information in interest rates of duration longer than two years, it is not clear that this additional data is the sole reason for eliminating the Fed information effect, especially when the methodologies generating the shock sequences are drastically different. From a theoretical perspective, one would have to assume that FOMC announcements contain substantial information about economic fundamentals at horizons longer than two years and that this horizon is most relevant for explaining *impact* impulse responses, which seems highly unlikely. We instead take the same shock sequence and temporally aggregate the same inflation data to construct alternative impulse response functions. The adverse response, often attributed to the “Fed information effect", is absent at higher frequencies because the mismatch between econometrician and private agents is eliminated. Temporal aggregation bias explains this response at lower frequencies, as opposed to an informational discrepancy between policy makers and private agents.

4.3 UNOBSERVED COMPONENTS MODEL

To study the response of high-frequency inflation to a monetary policy shock more systematically, we now introduce an unobserved components model. We employ this methodology for several reasons. First, the permanent-transitory decompositions cast in state space form have proven very useful for inflation at lower frequencies [Stock and Watson (2020)]. Second, there is transparency in modeling assumptions. Relative to the local projections methodology, which relies on IV and HAC errors, the modeling assumptions here are more straightforward. This allows us to take a more definitive stance on our finding of a conventionally-signed transmission of monetary policy, as opposed to disentangling how temporal aggregation might interact with, say, our IV estimation. Third and relatedly, the model specification is parsimonious. Finally and most importantly, the state space / estimation methodologies allow us to more easily handle data observed at different frequencies and with observations missing at different dates—we use daily inflation data, data on break-even inflation rates that is available daily except for holidays and weekends, infrequent monetary policy shocks, and monthly inflation rates. Furthermore, the unobserved components approach allows us to explicitly take into account the exact timing of monetary policy shocks and releases of official inflation releases within a month.

Our model consists of the following state equations: [i.] Unobserved daily CPI inflation, $\pi_t = \tau_t + g_t + e_t^{\pi}$, broken down into a permanent component τ, a transitory component g, and i.i.d. shock e^{π}. The per-

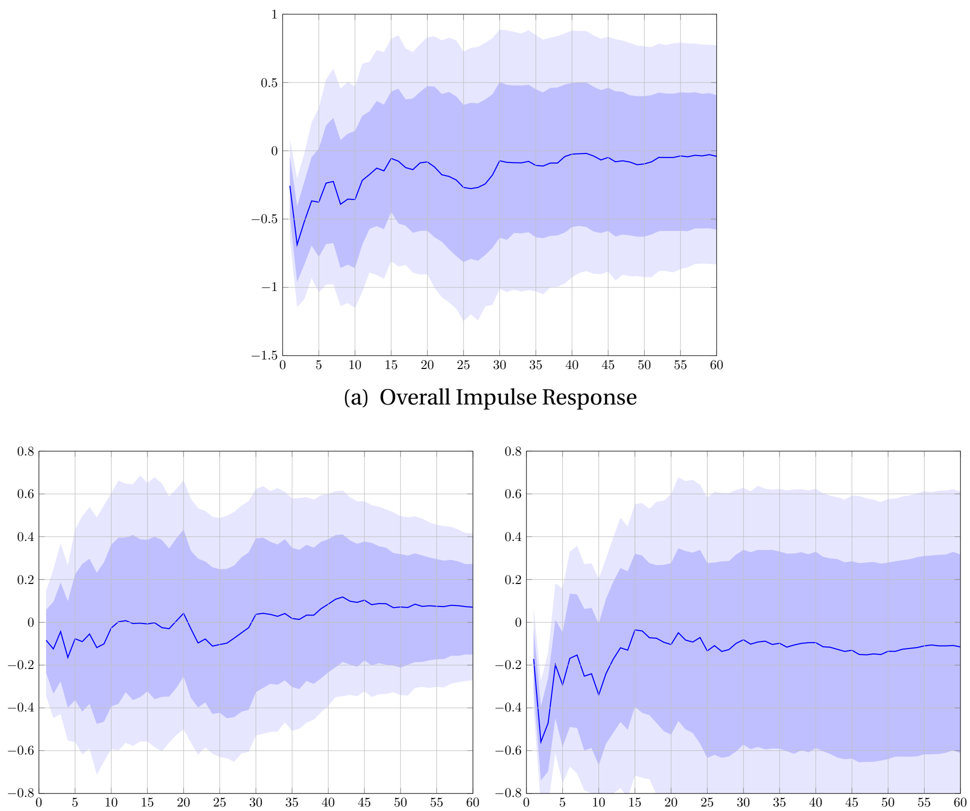
#	Parameter	Prior	Notes
1	σ_π	$\Gamma(1,0.5)$	standard deviation of i.i.d. component of underlying inflation
2	σ_τ	$\Gamma(1,0.5)$	standard deviation of innovation to random walk permanent component
3	ρ_g	$\beta(4,4)$	persistence of stationary part
4	σ_g	$\Gamma(1,0.5)$	standard deviation of innovation to stationary part
5	α^m	$N(0,0.0001^2)$	intercept of measurement equation of monthly CPI inflation
6	$\sigma^{monthly}$	$\Gamma(1,0.5)$	standard deviation of measurement error of monthly CPI inflation
7	α^{daily}	$N(0,5^2)$	intercept of measurement equation of daily (30-day) inflation
8	σ^{daily}	$\Gamma(1,0.5)$	standard deviation of measurement error of daily inflation
9	α^{BE}	$N(0,5^2)$	intercept of measurement equation of daily BE inflation
10	σ^{BE}	$\Gamma(1,0.5)$	standard deviation of measurement error of daily BE inflation
11	θ_0^g	$N(0,0.25^2)$	contemporaneous impact of monetary shock on g
12	θ_0^τ	$N(0,0.25^2)$	contemporaneous impact of monetary shock on τ
13	$\sigma^{m,obs}$	$\Gamma(1,0.5)$	standard deviation of monetary shock
14 ~ 72	$\underset{59\times1}{\theta_i^g}$	$N(0,(0.25*0.95^i)^2)$	vector of effects of 59 days lagged monetary shocks on g
73 ~ 131	$\underset{59\times1}{\theta_i^\tau}$	$N(0,(0.25*0.95^i)^2)$	vector of effects of 59 days lagged monetary shocks on τ

Table 5: Prior Specification

manent and transitory components follow, $\tau_t = \tau_{t-1} + \sum_{k=0}^{K} \theta_k^\tau m_{t-k} + e_t^\tau$ and $g_t = \rho g_{t-1} + \sum_{j=0}^{J} \theta_j m_{t-j} + e_t^g$, respectively.[20] The permanent component of inflation allows for a unit-root specification and a sequence of monetary policy shocks for 60 periods ($K = J = 60$). The transitory component permits autocorrelation and the same number of monetary policy shocks. We assume monetary shock dynamics $m_t = e_t^m$ with all shocks e being i.i.d. and Gaussian. The observation equations are the monthly observation of CPI (real-time vintages): $\pi_t^m = \alpha^m + \pi_{t-p} + e_t^{monthly}$, where p is publication lag mentioned in Section 3 (which can vary over time as shown in Table 3). At higher frequencies, we use the daily measure of monthly (30-day) inflation: $\pi_t^{daily} = \alpha^{daily} + \pi_t + e_t^{daily}$, and the 10-year break-even rates: $\pi_t^{BE,h} = \alpha^{BE} + E_t \pi_{t,t+h} + e_t^{BE}$. We assume that the monetary policy surprise is a noisy measurement of the true monetary policy shock: $m_t^{obs} = m_t + e_t^{m,obs}$, along the lines of Caldara and Herbst (2019). Note that the model implies $E_t \pi_{t+h} = E_t(\tau_{t+h} + g_{t+h}) = \tau_t + \rho^h g_t \approx \tau_t$, where the last approximation is imposed on the estimation procedure (our prior imposes that the daily persistence of the transitory component $|\rho| < 1$, and h represents the 10 year horizon).

The estimation is Bayesian with the likelihood function evaluated using the Kalman filter. To effectively explore the posterior distribution, a sequential Monte Carlo algorithm is implemented [Herbst and Schorfheide (2016)]. We use 15,000 particles with 200 steps to go from the prior to the full posterior and five Metropolis Hastings steps per iteration of the algorithm. Table 5 reports our prior distributions, which are largely uninformative. The one are where we impose somewhat informative priors are the effects of monetary policy shocks on the transitory and permanent components of inflation. We center those priors at 0 to not bias our results for or against finding adverse effects, but we do impose shrinkage

[20] In contrast to previous work using state space models to describe inflation dynamics, we explicitly incorporate a role for monetary policy shocks. We allow these shocks (which are measured with error) to affect both transitory and permanent components of inflation. This is important because movements in inflation that might seem permanent at the daily frequency can correspond to persistent, but non-permanent components at a lower frequency.



(a) Overall Impulse Response

(b) Response of Transitory Component (g_t)

(c) Response of Permanent Component (τ_t)

Figure 8: Impulse responses to a one standard deviation Nakamura and Steinsson (2018a) shock . Error bands are 68 % and 90 % posterior bands centered at the median.

- the further a monetary policy shock is in the past, the more we shrink its effect towards zero. In the Appendix we show that our findings are robust to imposing less shrinkage.

Panel 8a plots the overall impulse response function of inflation to a contractionary NS monetary policy shock, while Panels 8b-8c plot the response of the transitory and permanent components, respectively.[21] Darker shaded error bands are 68th percentiles, while lighter shades are 90th. The initial observation is that inflation—at a daily frequency—does not contain an adverse response. The initial reaction of inflation to a one standard deviation monetary policy shock is negative, even at the 90th percentile, followed by an increase and an error band that contains zero over the remaining horizon. The permanent component response of Panel 8c shows that the standard and theory-consistent response of inflation is present in our daily data. These results further corroborate our findings from the local projections; namely, that the positive reaction of inflation to a monetary policy shock is difficult to detect at the daily frequency. By decomposing into permanent and transitory components, we are able to parse the conventionally signed impulse response as permanent. Most importantly, the transitory response is shown to be quantitatively small relative to trend.[22]

[21] Results are similar for the BRW shock series and are available upon request.

[22] Appendix B shows that our results are robust to less shrinkage of the estimators. In fact, the permanent component shows a more substantial conventionally signed response at longer horizons in that case.

The variance decomposition, plotted in Figure 9, shows that the lion's share of volatility is explained by the permanent component of inflation as opposed to the transitory component. Taken together, these figures suggest that methodologies that de-trend inflation prior to analysis could miss conventionally signed responses. More germane to our argument, the transitory component *when evaluated at daily frequencies* does not display a substantial adverse response despite the fact that the shocks fed into the system generate substantial adverse responses at much lower (monthly) frequencies.

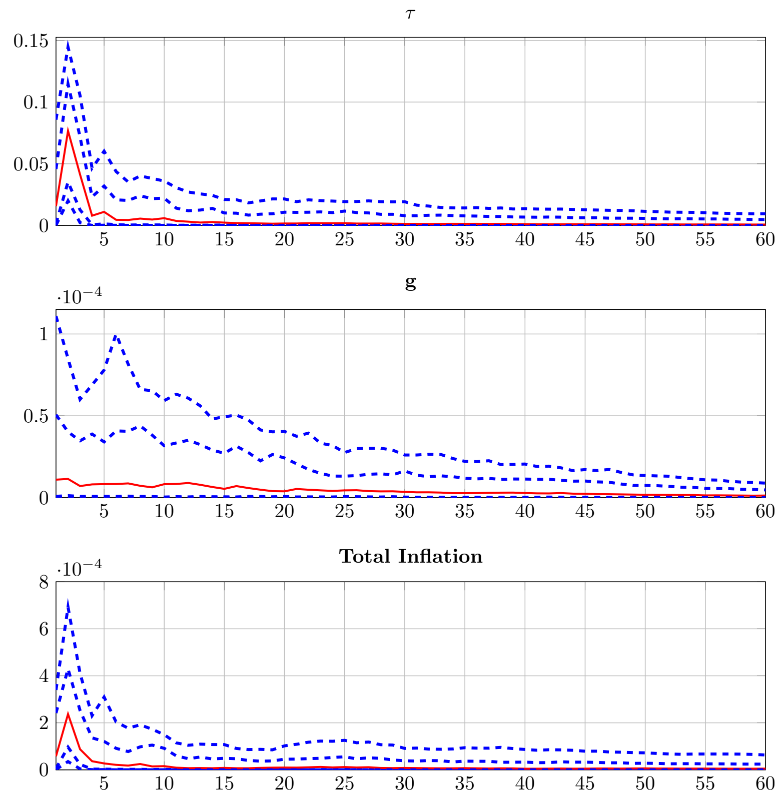


Figure 9: Variance Decomposition associated with Monetary Policy Shock as a fraction of total variance.

5 CONCLUDING THOUGHTS

This paper revisits a fundamental question of monetary economics: What is the transmission of monetary policy to the economy? We introduce temporal aggregation bias as a new information-based explanation for the adverse transmission of monetary policy shocks. When using the daily CPI from the Billion Prices Project as a temporally disaggregated macroeconomic indicator, we find a conventionally-signed response with only a short-lived adverse sign when present at all. To understand how one can obtain a sizable adverse response to monetary policy shocks with monthly or quarterly data when only a limited adverse response actually exists, we combine a simple model of temporal aggregation bias with informal and formal empirical evidence. Because our temporal aggregation results are generic, and macroeconomic indicators are published with a lag, we argue that temporal aggregation bias is not limited to our study of monetary policy transmission and will likely be a key feature of the nascent field of high-frequency macro.

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A Appendix: BPP Robustness Checks

A.1 Alternative constructions of BPP inflation This section shows an alternative version of figure 4.

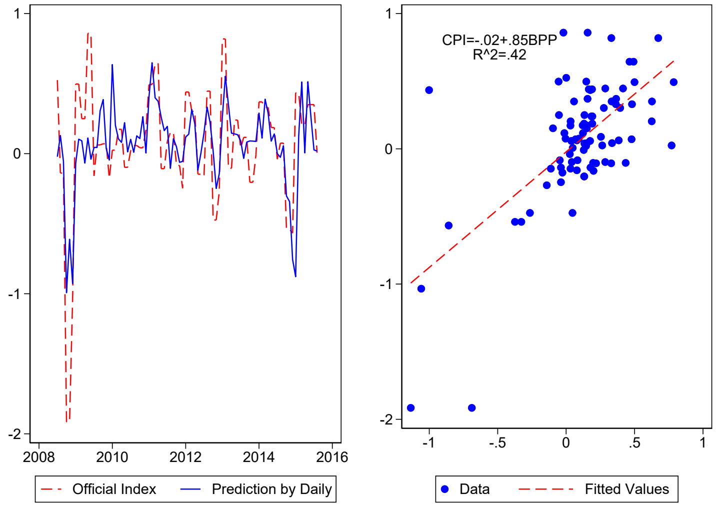

Figure 10: Nowcast of CPI using end of month values of the BPP, monthly and 30-day percentage change. For month T, $\Delta CPI_T = 100 \times (\log CPI_T - \log CPI_{T-1})$ and for day m of of month T, $\Delta BPP_T = 100 \times (\log BPP_m - \log BPP_{m-30})$.

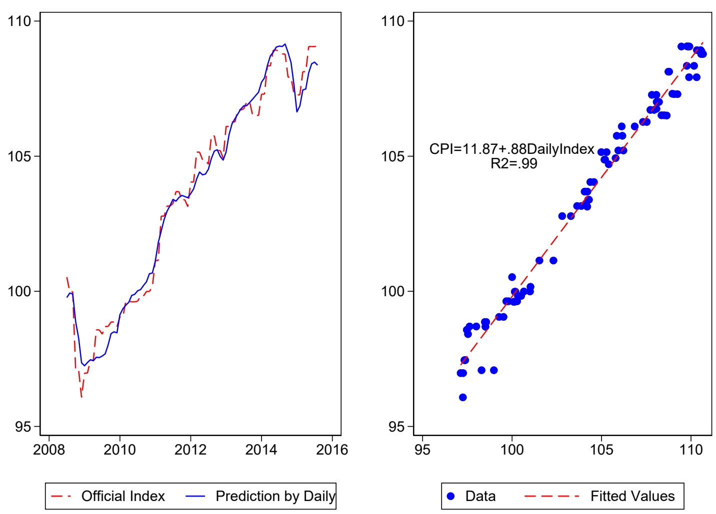

Figure 11: Nowcast of CPI using aggregated monthly values of the BPP, index. For month T, $CPI_T = \log CPI_T$ and for day t of month T, $\Delta BPP_T = \sum_{t=1}^{m} \log BPP_t$ for $t = 1, \ldots m$ days in month T.

A.2 CPI SUB-CATEGORIES

Table 6 shows how the BPP Nowcast of the headline CPI compares to other CPI sub-categories.

	ΔCPI^i_T, various CPI Sub-categories, i				
	(1)	(2)	(3)	(4)	(5)
	Headline	Commodities	Commodities & Shelter	Headline ex energy	Headline ex Medical
ΔBPP_T	0.937***	1.618***	0.53***	0.18***	1.001***
	(0.129)	(0.283)	(0.121)	(0.052)	(0.137)
R^2	0.58	0.48	0.36	0.21	0.59
Adj. R^2	0.58	0.47	0.36	0.2	0.58

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

Table 6: Nowcast of CPI sub-categories using the BPP. For month T and sub-category i, $\Delta CPI^i_T = 100 \times (\log CPI^i_T - \log CPI^i_{T-1})$ and for day t and month T, $\Delta BPP_T = \frac{1}{m}\sum_{t=1}^{m} 100 \times (\log BPP_t - \log BPP_{t-30})$ for $t = 1, \ldots, m$ days in month T.

A.3 SEASONALITY

$$BPP_t = trend_t + \sum_j \alpha_j^{day} \mathbf{1} day\, of\, week + \epsilon_t$$

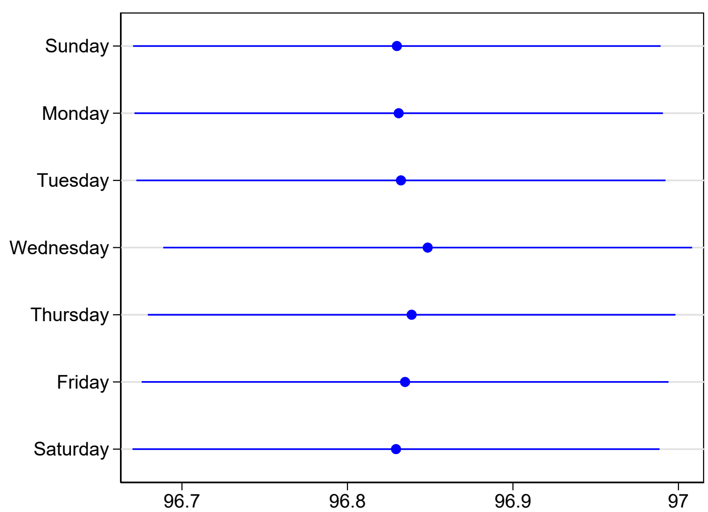

Figure 12: Day of week effects of the Billion Prices Project daily inflation.

B APPENDIX: IMPULSE RESPONSE FUNCTIONS WITH LESS SHRINKAGE

This Appendix shows the impulse responses from the state space model under the assumption of less shrinkage - the prior standard deviation of lagged coefficients is now $0.25 * 0.99^i$, where i is the lag.

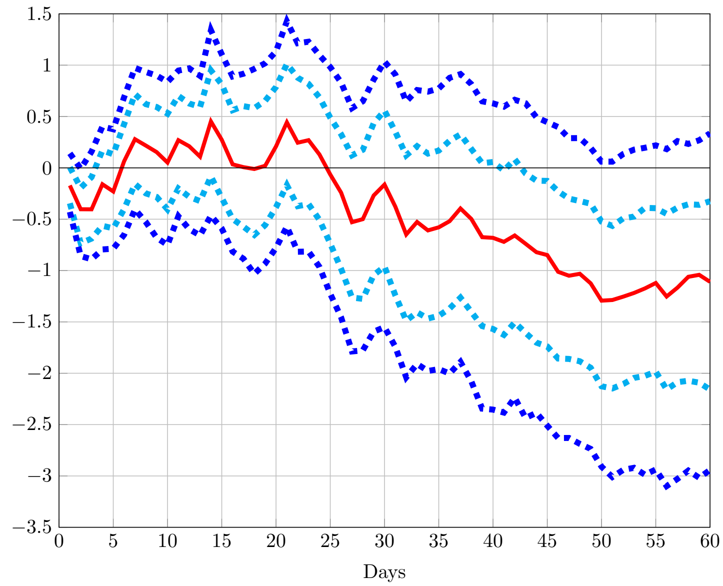

Figure 13: Impulse response of inflation (π_t) to a one standard deviation Nakamura and Steinsson (2018a) monetary policy shock . Error bands are 68 % and 90 % posterior bands centered at the median.

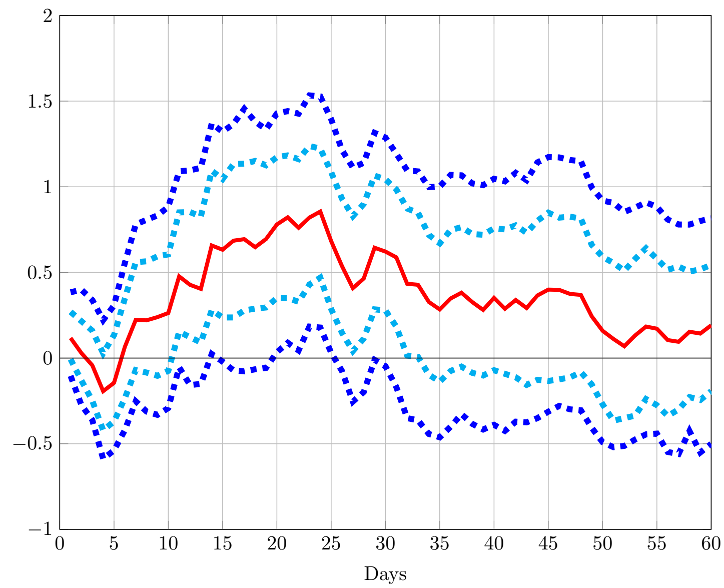

Figure 14: Impulse response of the transitory component of inflation (g_t) to a one standard deviation Nakamura and Steinsson (2018a) monetary policy shock . Error bands are 68 % and 90 % posterior bands centered at the median.

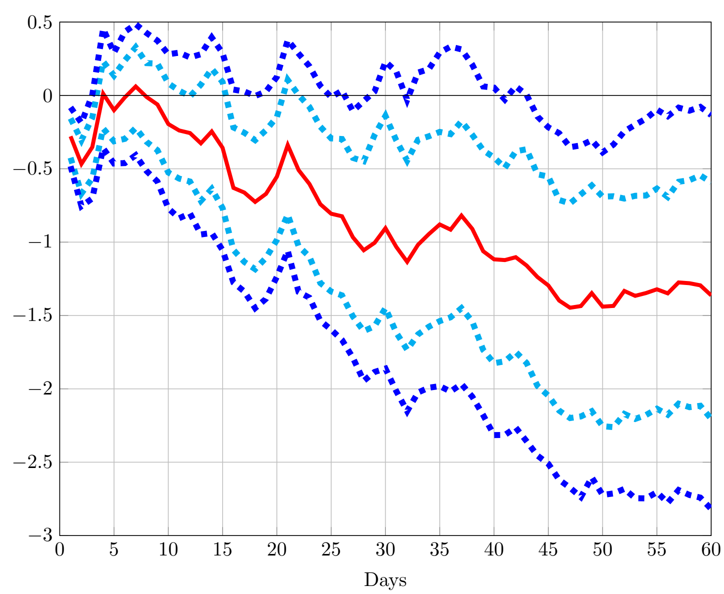

Figure 15: Impulse response of the permanent component of inflation (τ_t) to a one standard deviation Nakamura and Steinsson (2018a) monetary policy shock . Error bands are 68 % and 90 % posterior bands centered at the median.

C Appendix: Temporal Aggregation

Theorem 1. *The temporally aggregated inflation process given by* (3) *and* (2) *satisfies the following two properties:*

1. *The temporally aggregated inflation series, Π_T, follows an ARMA(1,1) process.*

$$(1-\rho^m L)\Pi_T = u_T + \theta u_{T-1} \tag{6}$$

2. *The innovation of the ARMA(1,1) process* (6) *is fundamental for the temporally aggregated inflation sequence, Π_T.*

This theorem is well known and dates back to at least to Amemiya and Wu (1972); thus, we do not offer a complete proof but provide intuition and references. To understand part (1), let $\pi_t = \rho\pi_{t-1} + w_t$, where w_t is Gaussian with mean zero and variance $\sigma_w^2 = \sigma_\varepsilon^2/(\phi-\rho)^2$, and note

$$\gamma(0) = \mathrm{Var}(\Pi_T) = \frac{\sigma_\pi^2}{m^2}\left(m + 2[(m-1)\rho + (m-2)\rho^2 + \cdots + \rho^{m-1}]\right) \tag{7}$$

$$\gamma(s) = \mathrm{Cov}(\Pi_t, \Pi_{t-s}) = \frac{\sigma_\pi^2}{m^2}\rho^{m(|s|-1)+1}(1+\rho+\rho^2+\cdots+\rho^{m-1})^2 \qquad s \neq 0 \tag{8}$$

$$\gamma(s) = \rho^m \gamma(s-1) \qquad |s| \geq 2 \tag{9}$$

where $\sigma_\pi^2 = \sigma_w^2/(1-\rho^2)$, see Wei and Ahsanullah (1984). The intuition of (7)–(8) comes from the correlation structure of an autoregressive process, where all elements are multiplied by $\frac{\sigma_\pi^2}{m_2}$. Thus, there are $(m-1)$ "neighbors", $(m-2)$ elements two periods removed, etc. Given the strength of the autocorrelation of many macro aggregates, the following limits are useful. As $\rho \to 1$, the term in brackets in (7) converges to $m(m-1)/2$ and therefore, $\mathrm{Var}(\Pi_T) \to \sigma_\pi^2$ and $\mathrm{Var}(\Pi_T) \in (0, \sigma_\pi^2)$. Further, the parenthetic term in (8) converges to m as $\rho \to 1$, and $\mathrm{Cov}(\Pi_t, \Pi_{t+s}) \to \sigma_\pi^2$.

	π_t	π_{t-1}	π_{t-2}	$\cdots$	π_{t-m}
π_t	1	ρ	ρ^2	$\cdots$	ρ^{m-1}
π_{t-1}	ρ	1	ρ	$\cdots$	ρ^{m-2}
π_{t-2}	ρ^2	ρ	1	$\cdots$	ρ^{m-3}
$\vdots$					
π_{t-m}	ρ^{m-1}	ρ^{m-2}	ρ^{m-3}	$\cdots$	1

The covariance difference equation (9) identifies the autocorrelation coefficient of the Π_T process as ρ^m. We can then multiply $[(1-\rho^m L)/(1-\rho L)]\sum_{j=0}^{m-1} L^j$ to both sides of π_t to give,

$$\left(\frac{(1-\rho L)(1-\rho^m L)\sum_{j=0}^{m-1} L^j}{1-\rho L}\right)\pi_t = \left(\frac{(1-\rho^m L)\sum_{j=0}^{m-1} L^j}{1-\rho L}\right) w_t$$

$$(1-\rho^m L)\Pi_T = \sum_{j=0}^{m-1} (\rho L)^j w_t = u_T + \theta u_{T-1} \tag{10}$$

where $u_T \sim N(0, \sigma_u^2)$. The errors defined by the the m moving-average terms $\sum_{j=0}^{m-1} (\rho L)^j w_t$ are correlated and therefore cannot be used to obtain the Wold innovations associated with predicting Π_T linearly from its past. Theorem 1 of Amemiya and Wu (1972) proves that with $m \geq 2$, then the moving-average terms are at most of order one, which establishes the final equality.

The proof of Part 2 also relies on arguments in Amemiya and Wu (1972). In order for the process to be fundamental, one must show that the roots of $1 - \theta z$ lie outside of the unit circle (i.e., $|\theta| < 1$). Given that the initial AR(1) process is positive definite ($\rho \in (0, 1)$), then it has a positive spectral density. As shown in Amemiya and Wu (1972), temporal aggregate maintains the positive definite structure and hence the roots of the moving-average representation must lie outside the unit circle.

C.1 MOVING-AVERAGE FILTERS

Suppose we have a stationary stochastic process x_t that is aggregated according to

$$X_T = \left(\frac{1}{m}\right)\left(\sum_{j=0}^{m-1} L^j\right) x_{mT} = \left(\frac{1}{m}\right)(x_{mT} + x_{mT-1} + \cdots + x_{mT-m-1}) \tag{11}$$

Note that $1 + L + L^2 + \cdots + L^{m-1} = (1 - L^m)/(1 - L)$. Thus, the covariance generating function of X_T is related to x_t by

$$g_X(z) = \frac{1}{m^2}\left(\frac{1 - z^m}{1 - z}\right)\left(\frac{1 - z^{-m}}{1 - z^{-1}}\right) g_x(z) \tag{12}$$

In the frequency domain ($z = e^{-i\omega}$),

$$\begin{aligned} g_X(e^{-i\omega}) &= \frac{1}{m^2}\left(\frac{1 - e^{-i\omega m}}{1 - e^{-i\omega}}\right)\left(\frac{1 - e^{i\omega m}}{1 - e^{i\omega}}\right) g_x(e^{-i\omega}) \\ &= \frac{1}{m^2}\left(\frac{1 - \cos(\omega m)}{1 - \cos(\omega)}\right) g_x(e^{-i\omega}) \end{aligned} \tag{13}$$

where $(1 - e^{-i\omega m})(1 - e^{-i\omega m}) = 2 - (e^{i\omega m} + e^{-i\omega m}) = 2 - 2\cos(\omega m) = 2(1 - \cos(\omega m))$ because $e^{i\omega m} = \cos(\omega m) + i \sin(\omega m)$ and $e^{-i\omega m} = \cos(\omega m) - i \sin(\omega m)$. Plotting this function over the range of $[0, \pi]$ gives Figure 2b.

D APPENDIX: DATA

This section lists the source and description of each series used in this paper.

OFFICIAL CPI INDEX Analysis in section 3.2 use the BLS' seasonally adjusted Consumer Price Index (`FRED: CPIAUCSL`) at a monthly frequency. Results in section (4) use the seasonally adjusted (`PCPI`) and not seasonally adjusted (`CPIN`) real-time Consumer Price Index which is accessed via the Real-time Data Research Center at the Federal Reserve Bank of Philadelphia.[23] In each real-time spreadsheet, the columns are the date of the vintage and the rows are the time series for that vintage. We then construct a time series by calculating the monthly percentage change for the last two entries for each vintage.

DAILY CPI The Billion Prices Project publicly available daily inflation index can be obtained via Cavallo and Rigobon (2016) for July 2008 through August 2015.[24] The index is obtained by webscraping prices from multichannel retailers that sell both online and offline.

BREAK-EVEN INFLATION RATES 10-year spot breakeven inflation rates are the daily 10-year treasury yield at constant maturity (`FRED: BC_10YEAR`) less the daily 10-year TIPS at constant maturity (`FRED: TC_10YEAR`). These rates are obtained from the U.S. Treasury Department via FRED.

ZERO-COUPON TREASURY YIELDS Continuously compounded zero-coupon yields (mnemonic: `SVENYXX`) are obtained via the Federal Reserve Board.[25]

NAKAMURA AND STEINSSON (2018A) MONETARY POLICY SHOCK High-frequency monetary policy shocks are originally available from 1995 to 2014.[26] We extend this shock series from 1994 to present using futures tick data accessed via CME Group Inc. DataMine (https://datamine.cmegroup.com/) at the Federal Reserve Board.[27] The construction of the shock series follows that of Gürkaynak et al. (2005) as described in Nakamura and Steinsson (2018a) and relies on the changes in five short-term interest rate futures. Let

[23] We thank Tom Stark for help obtaining these series. https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/real-time-data-set-full-time-series-history

[24] Series `indexCPI` for `country==USA` in spreadsheet `pricestats_bpp_arg_usa.csv` in folder `all_files_in_csv_format.zip` at website https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi%3A10.7910%2FDVN%2F6RQCRS. Alternatively, the data are also available from the `pricestats_bpp_ar_usa.dta` file in the `RAWDATA` folder on the website https://www.openicpsr.org/openicpsr/project/113968/version/V1/view.

[25] See https://www.federalreserve.gov/data/yield-curve-tables/feds200628_1.html or as a csv file.

[26] Series `FFR_shock` from the spreadsheet `PolicyNewsShocksWeb.xlsx` https://eml.berkeley.edu/~jsteinsson/papers/PolicyNewsShocksWeb.xlsx

[27] https://eml.berkeley.edu/~jsteinsson/papers/realratesreplication.zip

t index FOMC announcements and the changes in the five interest rate futures be given as:

$mp1_t$: change in federal fund futures expiring at the end of the month of the FOMC announcement

$mp2_t$: change in federal funds futures expiring at the end of the month of the *next* scheduled FOMC announcement

$ed2_t$: change in eurodollar futures expiring in the next quarter from the FOMC announcement (called 2nd contract)

$ed3_t$: change in eurodollar futures expiring two quarters after the FOMC announcement (called 3rd contract)

$ed4_t$: change in eurodollar futures expiring three quarters after the FOMC announcement (called 4th contract)

The calculations underlying the above series are given below.[28] Let s index the month of the current FOMC announcement and s' index the month of the next FOMC announcement. For example, s = March 2014 and s' = April 2014 for the March 19, 2014 FOMC announcement where s and s' need not be consecutive months. We define t more precisely as 20 minutes *after* the FOMC announcement while $t-\Delta t$ is defined as 10 minutes *before* the FOMC announcement.[29] For the March 19, 2014 FOMC announcement which occurred at 14:00, t = March 19, 2014 14:20 and $t-\Delta t$ = March 19, 2014 13:50. Let q index the quarter of the current FOMC announcement and $q+1$ index the of the next FOMC announcement. For example, q = 2014:Q1, $q+1$ = 2014:Q2, and $q+2$ = 2014:Q3 for the March 19, 2014 FOMC announcement.

$$mp1_t = \frac{D1}{D1-d1}(ff1_{s,t} - ff1_{s,t-\Delta t}) \tag{14}$$

$$mp2_t = \frac{D2}{D2-d2}\left[(ff2_{s',t} - ff2_{s',t-\Delta t}) - \frac{d2}{D2}mp1_t\right] \tag{15}$$

$$ed2_t = ed2_{q+1,t} - ed2_{q+1,t-\Delta t} \tag{16}$$

$$ed3_t = ed3_{q+2,t} - ed3_{q+2,t-\Delta t} \tag{17}$$

$$ed4_t = ed4_{q+3,t} - ed4_{q+3,t-\Delta t} \tag{18}$$

For month s indexing the current FOMC announcement...

[28] Nakamura and Steinsson (2018a) explain that, "A eurodollar futures contract expiring in a particular quarter (say 2nd quarter 2004) is an agreement to exchange, on the second London business day before the third Wednesday of the last month of the quarter (typically a Monday near the 15th of the month), the price of the contract p for 100 minus the then current three-month US dollar BBA LIBOR interest rate."

[29] In practice, the windows are not always this precise and we follow the online Appendix of Nakamura and Steinsson (2018a). For the $t-\Delta t$ contact, we use the contract as close to the 10 minutes before the policy announcement as possible and only consider trades on the day in question. For the t contract, we similarly use the contract as close to the 20 minutes after the announcement as possible and consider trades as late as noon on the following day. If there are no eligible trades to consider, the change is set to zero (i.e., we interpret no trading as no price change). We source the time of the announcements from the Federal Reserve Board and then from Gürkaynak et al. (2005) and Bloomberg News Wire. If there is a conflict in announcement times, we follow this order of priority.

$mp1_t$: monetary policy surprise

$D1$: number of days in month

$d1$: day of month

$ff1_{s,t-\Delta t}$: federal funds futures contract at most 10 minutes before

$ff1_{s,t}$: federal funds futures contract at least 20 minutes after

For month s' indexing the next scheduled FOMC announcement...

$mp2_t$: monetary policy surprise

$D2$: number of days in the month

$d2$: day of month

$ff2_{s',t-\Delta t}$: federal funds futures contract at most 10 min. before

$ff2_{s',t}$: federal funds futures contract at least 20 min. after

For quarter q indexing the current FOMC announcement...

$ed2_{q+1,t-\Delta t}$: 2nd expiring eurodollar futures contract at most 10 minutes before

$ed2_{q+1,t}$: 2nd expiring eurodollar futures contract at least 20 minutes after

$ed3_{q+2,t-\Delta t}$: 3rd expiring eurodollar futures contract at most 10 minutes before

$ed3_{q+2,t}$: 3rd expiring eurodollar futures contract at least 20 minutes after

$ed4_{q+3,t-\Delta t}$: 4th expiring eurodollar futures contract at most 10 minutes before

$ed4_{q+3,t}$: 4th expiring eurodollar futures contract at least 20 minutes after

If the current FOMC announcement occurs in the last 7 days of the month then the scaling is not used as it may be quite large towards the end of the month. Instead, the future's contract for the month following that of the current FOMC announcement is used, $s+1$. For example, the futures contract for February 2015 would be used instead of January 2015 for the January 28, 2015 announcement.

$$mp1_t = (ff1_{s+1,t} - ff1_{s+1,t-\Delta t}) \tag{1.a}$$

And similarly if the next scheduled FOMC announcement occurs in the last 7 days of the month, the following month's futures contract is is used, $s'+1$. For example, the announcement following that on March 18, 2015 is on April 29, 2015 would use the futures contract for May 2015 instead of April 2015.

$$mp2_t = (ff2_{s'+1,t} - ff2_{s'+1,t-\Delta t}) \tag{2.a}$$

The monetary policy shock is then the first principal component of expressions (14)-(18) scaled so that its effect on one-year nominal Treasury yields is equal to one.

BU ET AL. (2021) MONETARY POLICY SHOCK Daily monetary policy shock are available from 1994 to 2020.[30] This shock series is constructed by a Fama and MacBeth (1973) two-step procedure that extracts unobserved monetary policy shocks Δi_t from the common component of the change in zero-coupon yields $\Delta R_{j,t}$.

1. estimate sensitivity of yields with maturity $j = 1, \ldots, 30$ to monetary policy 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 two-year yield $\Delta R_{2,t}$ to allow for normalization
$$\Delta R_{j,t} = \theta_j + \beta_j \Delta R_{2,t} + \underbrace{\epsilon_{j,t} - \beta_j \epsilon_{2,t}}_{\xi_{j,t}}$$
$\text{corr}(\Delta R_{j,t}, \xi_{i,t})$ due to $\beta_j \epsilon_{2,t}$ reconciled with IV or the heteroskedasticity-based estimator of Rigobon (2003).

2. recover aligned monetary policy shock $\Delta i_t^{aligned}$ form cross-sectional regressions of $\Delta R_{j,t}$ on the sensitivity index $\hat{\beta}_j$ for each FOMC announcement t
$$\Delta R_{j,t} = \alpha_j + \Delta i_t^{aligned} \hat{\beta}_j + v_{j,t}, \quad t = 1, \ldots, T$$

3. re-scale the shock. We follow Bu et al. (2021) and use 2-year Treasuries, but our results are robust to scaling by 1-year Treasuries to match the scaling of the NS shocks.

[30]Series `BRW_fomc` of spreadsheet `brw-shock-series.csv` https://www.federalreserve.gov/econres/feds/files/brw-shock-series.csv