# Temporal Aggregation Bias and Monetary Policy Transmission*

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**Abstract**

Temporal aggregation can bias estimates of monetary policy transmission. Using impulse responses from both local projections and an unobserved components model, we find that the response of daily inflation to several high-frequency monetary policy shocks can confirm standard theoretical predictions. If there is an adversely-signed response such that inflation increases in response to a contractionary monetary policy shock, it is much more prominent when the dependent variables are aggregated to a lower frequency. We confirm these empirical findings in two data-generating processes that show how short-lived adversely-signed responses can be magnified when aggregating data to a lower frequency.

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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 adversely-signed responses to information issues, with existing solutions consisting of either adding more variables [Sims (1992)] or emphasizing information mismatches between central banks and private sector agents as a "Fed information effect".[1]

We propose temporal aggregation bias—the information mismatch between the econometrician and private agents—as a new information-based explanation for the adversely-signed transmission of monetary policy. We define temporal aggregation bias as the discrepancy arising from the order in which estimation and temporal aggregation are performed. More specifically, our estimates of monetary policy transmission vary considerably whether we estimate at a daily frequency and then aggregate these estimates to a monthly frequency or first aggregate daily data to a monthly frequency and then estimate. This divergence in estimates often occurs because private agents react to information at a finer temporal scale (e.g., daily or weekly), while an econometrician using data aggregated to a lower frequency (e.g., monthly) might be working with a conditional information set that has become stale or obscures these higher-frequency dynamics.

When using the daily CPI from the Billion Prices Project [Cavallo and Rigobon (2016)] as a temporally disaggregated macroeconomic indicator, we find that the adversely-signed response of inflation is short-lived, if it is present at all. A temporally disaggregated measure of inflation controls for temporal aggregation bias by aligning the frequencies of shocks and dependent variables and hence the information sets of the econometrician and private agents. We show that the frequency mismatches can account for the adversely-signed estimates of monetary policy transmission often found in existing work. In fact, we confirm that the shocks of Bu et al. (2021) that are not associated with a Fed information effect, always emit a conventionally-signed response, but those of Nakamura and Steinsson (2018a), which are often associated with the Fed information effect, can emit an adversely-signed response, but with the caveat that the sign of the response depends on the frequency of response data.

To understand how shocks like those of Nakamura and Steinsson (2018a) can estimate a sizable adversely-signed response with monthly inflation data, but only a limited adversely-signed response with high-frequency inflation data, we combine informal and formal empirical evidence with a simple model of temporal aggregation bias. We first 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)].

[1] Bauer and Swanson (2023a), Bu et al. (2021), and Caldara and Herbst (2019) also emphasize adding more information. For evidence and discussions of 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. (2023), Cieslak and Schrimpf (2019), Acosta (2023), Sastry (2022), Karnaukh and Vokata (2022), Lewis (2020), Bundick and Smith (2020), Andrade and Ferroni (2021), Golez and Matthies (2025), Nunes et al. (2023), Zhu (2023).

Our main finding—the response of inflation is conventionally-signed with only a short-lived adversely-signed 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 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 that although the response of inflation to a contractionary monetary policy shock is initially ambiguously positive for a few weeks, it is negative thereafter with 90% credible sets also below zero. By contrast, when inflation is time aggregated to a monthly frequency, impulse response functions show a significant impulse response that is positive. Aggregating daily estimates to a monthly frequency quantifies the distortion from temporal aggregation bias and shows that it is both quantitatively large and can lead to qualitative misinterpretations.

Furthermore, because the effect of temporal aggregation bias in local projections depends on the timing of information, 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 breakeven 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.

Section 4 appeals to the theoretical implications of temporal aggregation to shed light on our empirical findings. Through a Monte Carlo simulation, we first show how the timing of a monetary policy shock can alter the qualitative nature of the inflationary response. Assuming a monetary policy shock occurs only once a month, the simulation demonstrates that the aggregated monthly inflation impulse response is dictated by the shock occurring in the beginning, middle or end of the month. Given that the mean and median FOMC announcement has occurred on the 19th day of the month, and a majority of the announcements have occurred after the 10th day of the month, our 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. Second, we 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. We derive restrictions on a temporally aggregated AR(1) process that conveys the sensitivity of the bias as a function of the degree of aggregation, with slight increases in aggregation leading to significant changes in impulse response functions.

Our contribution of temporal aggregation bias as an explanation for the adversely-signed 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

[2] Lewis et al. (2020a) discuss how time aggregation affects their estimates of monetary policy transmission to household

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 can 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 adversely-signed 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 adversely-signed responses when estimating the transmission of high-frequency monetary policy shocks to lower frequency forecasts of macroeconomic aggregates, subsequent work finds that properly accounting for information delivers results that are either ambiguous or in line with structural predictions. Uribe (2022) takes a contrasting stance and argues that monetary policy shocks may actually be neo-Fisherian.

Closest to our specification of high-frequency inflation indicators responding to high-frequency monetary policy shocks are specifications that rely on commodity prices [Velde (2009)] or high-frequency expected inflation (TIPS) [Nakamura and Steinsson (2018a)]. 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. Commodities are known to be more volatile than measures of inflation which may result in different sensitivities to monetary policy shocks. Similarly, the responses of expected and realized inflation to monetary policy shocks may differ

expectations. See Shapiro et al. (2022), Aruoba et al. (2009), Lewis et al. (2020b) for other high frequency economic indicators. Relatedly, Lee and Sekhposyan (2024) and Kilian (2024) find that the aggregation of high-frequency shocks to lower frequencies can affect the sign and magnitude of VAR estimates.

[3] See Golez and Matthies (2025), Andrade and Ferroni (2021), Nakamura and Steinsson (2018a), Bauer and Swanson (2023b), 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.

because the former tends to be anchored while the latter is more prone to fluctuations. Common specifications that rely on the change in Blue Chip forecasts may understate the transmission of monetary policy shocks to inflation because they capture changes in expected rather than current inflation. By contrast, 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 or other real indicators.

Although Buda et al. (2023) also estimate the response of high-frequency economic indicators to high-frequency monetary policy shocks, they focus on transmission lags rather than the effects of frequency mismatches. Using high-frequency data on Spanish consumption, sales, and unemployment along with monetary policy shocks from European Central Bank announcements, they similarly find conventionally-signed impulse responses without prominent adverse signs. The consistency of our findings with theirs is striking given the differences in indicators (prices vs. quantities) and economies (US vs. EU). Furthermore, our theoretical and Monte-Carlo based analysis highlights how temporal aggregation can emerge as an important source of bias when estimating the effects of monetary policy and can account for the responses of both papers.[5]

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 (2023a) and contribute refinements to the less-studied measurement of response variables. Because Bauer and Swanson's (2023a) survey finds that Blue Chip forecasters rarely change their estimates of economic indicators in response to monetary policy announcements, alternative response variables such as high-frequency indicators may prove useful. The literature's focus on explanatory variables stems from several studies finding predictability and or bias in standard high-frequency monetary policy shocks such as those constructed 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 (2023b)] or conditioned on missing information [Caldara and Herbst (2019), Sastry (2022), Miranda-Agrippino and Ricco (2021), Bauer and Swanson (2023a)].

Many studies—including Nakamura and Steinsson (2018a)—account for the adversely-signed 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.[6] For example, in response to tighter monetary policy private agents revise up their forecasts of inflation because they perceive a signal that the central bank has relatively optimistic non-public information. Other papers find that controlling for central bank information advantages affects estimates of monetary policy transmission [Lunsford (2020), Bu et al. (2021), Hoesch et al. (2023), Cieslak and Schrimpf (2019), Nunes et al. (2023), Zhu (2023)] or eliminates adversely-signed responses entirely [Miranda-Agrippino and Ricco (2021), Jarocinski and Karadi (2020)]. In fact, Acosta (2023) and Lewis (2020) identify Fed information shocks and find evidence that is either mixed or against adversely-signed monetary policy

[5]Grigoli and Sandri (2022) relatedly explore the transmission of high-frequency ECB monetary policy shocks to high-frequency German credit card data and corroborate conventionally-signed responses.

[6]Faust et al. (2004) find that the adversely-signed response of inflation disappears once the Volcker disinflation is excluded from Romer and Romer's (2000) study. Similarly, Sastry (2022), Bundick and Smith (2020) and Bauer and Swanson (2023a) explicitly test for a central bank information advantage and find no evidence.

transmission.

In contrast to these existing studies, we do not explicitly test or model how the information sets of central banks and private agents account for our conventionally-signed estimates of monetary policy transmission. We instead focus on the less-studied but complementary information mismatch between private agents and the econometrician to account for conventionally-signed estimates of monetary policy transmission with high-frequency data, but adversely-signed estimates with time-aggregated data.

Decades of work support our claim that temporal aggregation bias can affect both the direction and magnitude of estimates of monetary policy transmission. We follow Marcet (1991) in demonstrating how the systematic effect of time aggregation can 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.[7] This puts our main result—that adversely-signed estimates of monetary policy transmission can be explained by temporal aggregation bias—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. Christiano and Eichenbaum (1987) highlight the impact temporal aggregation can have using two examples in macroeconomics. 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). This mixed-data sampling (MIDAS) approach can, under some regularity conditions, recover the true coefficient of interest, but is less efficient than directly estimating the relationship of interest using high frequency data, as we are able to do in our setting.[8] Our findings also complement those of Snudden (2024) who documents substantial information loss when aggregating from daily-to-monthly frequencies and notes that most studies of temporal aggregation instead focus on monthly-to-quarterly frequencies.

## 2 HIGHER-FREQUENCY OBSERVATIONS AND INFLATION DYNAMICS

We first demonstrate that a high-frequency inflation proxy can contain information obfuscated by the publication lags of official series. Our analysis uses the Billion Prices Project Daily Price Index (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 is obfuscated by the official CPI's publication lags over our sample period.[9]

[7] For further theoretical results on temporal aggregation, see Tiao and Wei (1976); Breitung and Swanson (2002).

[8] As such, the trade-off between our method and MIDAS-based methods is not necessarily related to any temporal aggregation bias, which we define in Section 3.3.

[9] See Appendix E for specific details on the series used including seasonal adjustment.

2.1 DAILY INFLATION DATA We define daily inflation as the 30-day percentage change in the BPP, which allows for the units of daily inflation to be comparable to those of official inflation which are measured at a monthly frequency. 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.[10] 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.[11] Even though prices obtained by physically visiting stores may not necessarily coincide with those observed online, Cavallo (2017) finds a 70 percent match rate.

2.2 CONNECTION TO THE CPI To alleviate concerns that BPP data may not align well with the US CPI, we now conduct several tests to show that the BPP can contain additional information obfuscated by the official CPI's publication lags, a fact that we will exploit in our econometric analysis.

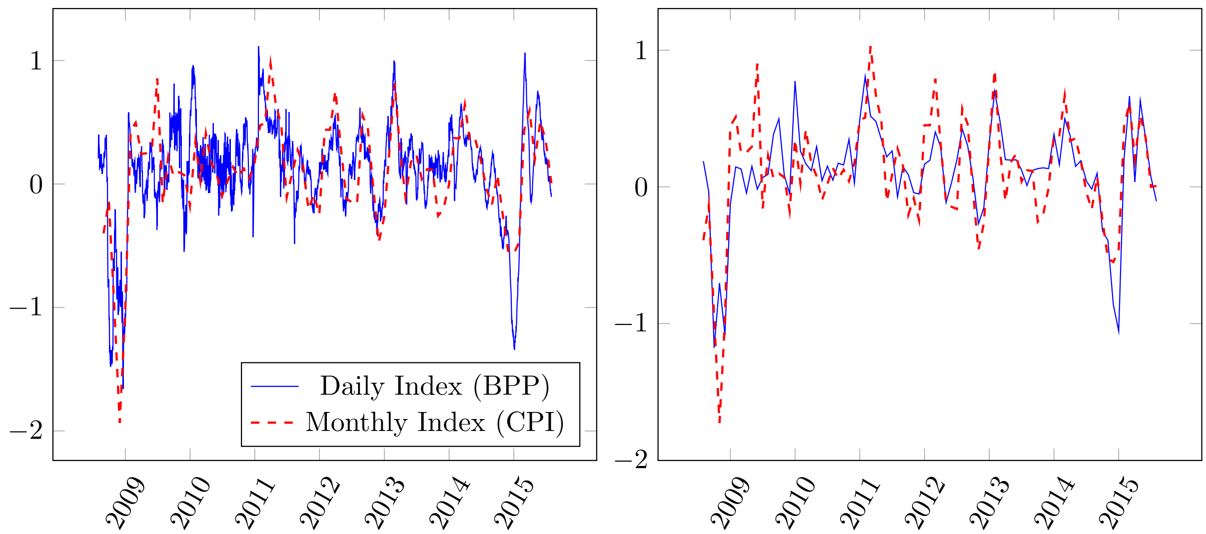
| Statistic | $\Delta BPP_t$ | $\Delta CPI_T$ | CPI Release delay (days) |
|---|---|---|---|
| Mean | 1.33 | 1.14 | 16.97 |
| Standard error | 4.66 | 5.10 | 2.73 |
| Min | −19.39 | −23.21 | 13 |
| Max | 12.75 | 11.64 | 30 |

Table 1: Summary statistics of official and daily inflation, monthly and 30-day percentage change, respectively. from July 2008 to August 2015, including CPI release delays. For day $t$, $\Delta BPP_t = 100 \times (\log BPP_t - \log BPP_{t-30})$ and for month $T$, $\Delta CPI_T = 100 \times (\log CPI_T - \log CPI_{T-1})$.

Panel 1a plots the percentage change of the monthly CPI and the BPP daily index; panel 1b plots the percentage change of the monthly CPI against the aggregated monthly BPP. While the correlation of the two series plotted in panel 1b is only 0.63, 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

[10] 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. Although we focus on comparing the BPP to the CPI because the former is constructed from the weights of the latter, we also compare the BPP to the PCE index. In fact table 6 shows that the BPP's Nowcast of the PCE has an $R^2$ that is similar to that of the CPI. The reported Nowcast coefficient of the PCE specification is much lower than its CPI counterpart which likely can be attributed to the different weights used in construction.

[11] 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

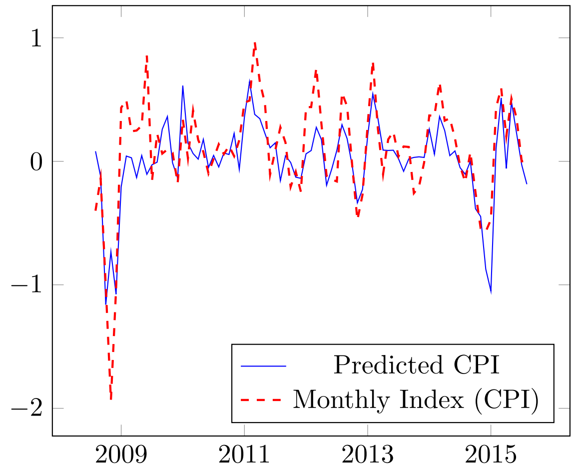
(b) Monthly Averaged Daily Index (BPP)

Figure 1: Official and daily inflation, monthly and 30-day percentage change, respectively. 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 $t = 1, \dots, m$ days in month $T$.

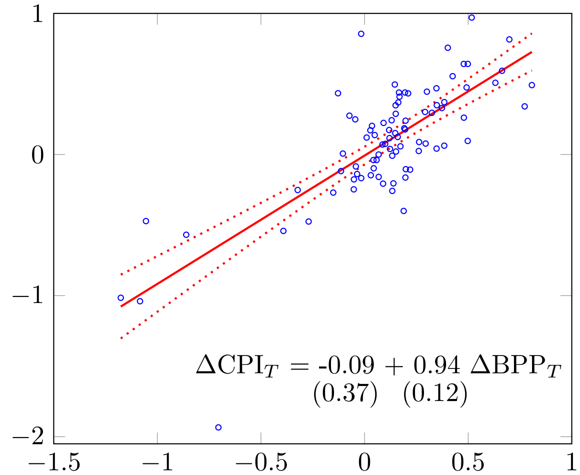
(2016), Aparicio and Bertolotto (2020) and Harchaoui and Janssen (2018)]. To show this result holds over our sample period, we use the monthly aggregated BPP series to conduct a Nowcast of the CPI by estimating, $\Delta CPI_T = \beta_0 + \beta_1 \Delta BPP_T + e_T$. Despite both indices being denoted with subscript $T$, the CPI at date $T$ is announced with a slight delay as shown by Table 1, which documents the summary statistics of release 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. The estimated value is 0.94 with an R-squared of 0.58, implying substantial predictive power as shown in panel 2b. Panel 2a plots the in-sample predicted values against the realized values. Table 1 further confirms the usefulness of the BPP by documenting that its mean, standard deviation, and extreme values are quite similar to those of the official CPI.

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 2 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.[12]

[12]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 2: Nowcast of CPI using monthly aggregated BPP, monthly percentage change. Standard errors in parentheses on panel 2b. 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 $T$.

| | $\Delta CPI_T$ | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| $\Delta CPI_{T-1}$ | 0.558$^{***}$ | | | | 0.178 |
| | (0.143) | | | | (0.107) |
| $\Delta BPP_T$ | | 0.937$^{***}$ | | 0.878$^{***}$ | 0.828$^{***}$ |
| | | (0.129) | | (0.097) | (0.106) |
| $\Delta BPP_{T-1}$ | | | 0.591$^{**}$ | 0.109 | −0.030 |
| | | | (0.248) | (0.193) | (0.222) |
| $R^2$ | 0.32 | 0.58 | 0.23 | 0.59 | 0.61 |
| Adj. $R^2$ | 0.31 | 0.58 | 0.22 | 0.58 | 0.60 |

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

Table 2: 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 $T$.

## 3 Empirical Results

Given that the BPP index can contain information obfuscated by the official CPI's publication lags, the next phase of the analysis asks how the index responds to monetary policy and whether this response is different at a daily or monthly frequency. High-frequency identification methods that exploit variation in asset prices around monetary policy announcements have become the standard in the literature [e.g., Kuttner (2001), Gürkaynak et al. (2005), Campbell et al. (2012), Nakamura and Steinsson (2018a), Bu et al. (2021)]. High-frequency inflation data allows us to align the dependent variable with the independent variables, and to the best of our knowledge, we are one of the first to do so to study monetary policy transmission to the macroeconomy. Our expectation here is *not* that inflation jumps immediately (within the day) in response to surprise changes in interest rates, but that prices could substantially change by the time the CPI is made publicly available.

**3.1 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 three such constructions in detail—Nakamura and Steinsson (2018a) (NS), Bu et al. (2021) (BRW), and Gürkaynak et al. (2005) (target). We focus on the first two shocks because they are each characterized by a single factor that can be parsimoniously embedded into more complex frameworks like our state space model. Additionally, they differ in whether or not they are associated with the Fed information effect—NS shock is known for information contamination, while the BRW shock is not. The third shock is the first of two principal components and can be interpreted as surprise effect of the federal funds rate independent of forward guidance. We construct shocks for all scheduled FOMC announcements as well as one unscheduled announcement on October 8, 2008 included in our July 2008 to August 2015 sample.

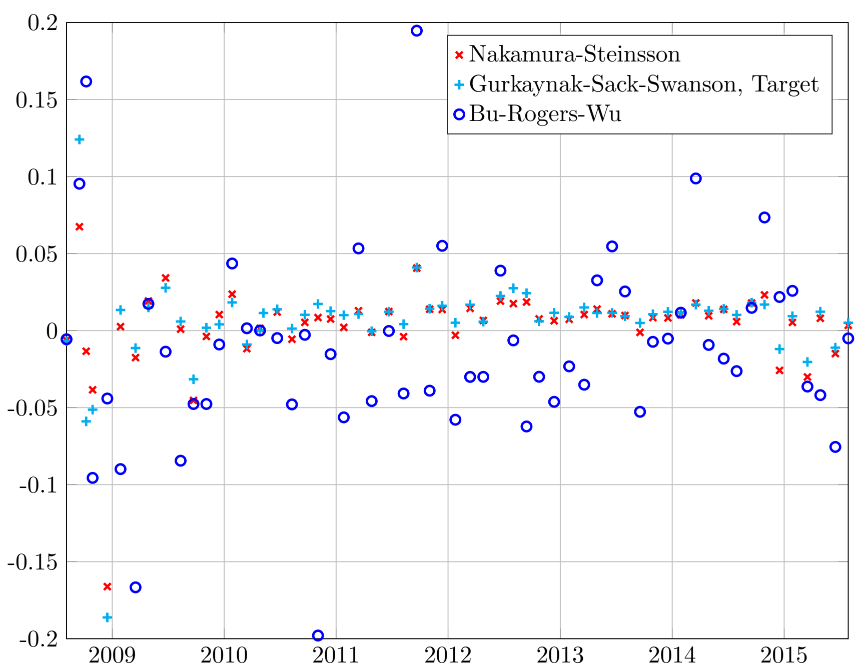



Figure 3: Monetary policy shock series from Nakamura and Steinsson (2018a), Gürkaynak et al. (2005) and Bu et al. (2021). Authors' construction.

Even though the NS shock is widely used, there are known concerns about its predictability by existing economic news and contamination by central bank signals about the underlying state of the economy. Many papers have proposed add-on techniques to purge monetary policy shocks from these undesirable features. Examples include Miranda-Agrippino and Ricco's (2021) projection of shocks onto Green Book forecasts and its own lags, Jarocinski and Karadi's (2020) exploitation of the co-movement of stock prices and interest rates, and Bauer and Swanson's (2023b) orthognalization relative to economic and financial series that are predated and correlated with the shock. Fortunately, the BRW shock does not exhibit the predictability and information contamination found in the NS shocks as noted by Bu et al. (2021) and confirmed by Brennan et al. (2024). Including the BRW shock estimates along with those of the NS shock can therefore address the concerns about the NS shock raised by the aforementioned papers. The third shock—the target shock of Gürkaynak et al. (2005)—is closely related to that of NS, but identifies the effect of the federal funds rate independent of forward guidance. By contrast, the NS shock is essentially a linear combination over surprises in the federal funds rate and forward guidance. Appendix B.2 shows the estimates of monetary policy transmission for the path shock of Gürkaynak et al. (2005), which can be interpreted as the effect of forward guidance independent of the federal funds rate.

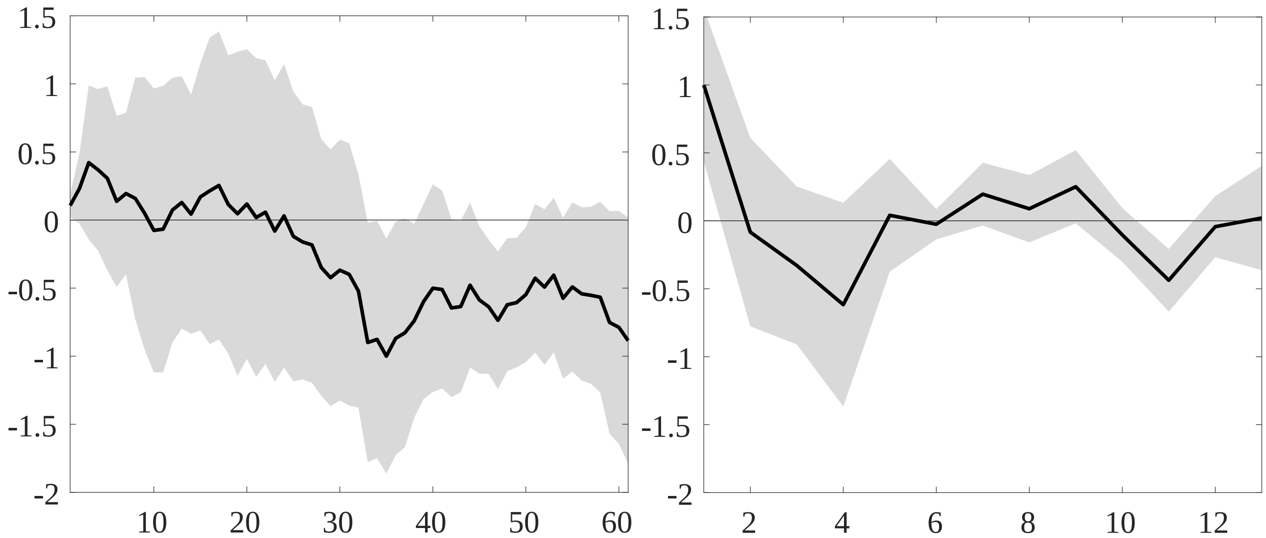
NS define a "policy news shock" as the first principal component of the change in five interest rate futures around a 30-minute window of FOMC announcements. These futures span the first year of the term structure and include the expected federal funds rate at the end of the month of the FOMC announcement, 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. Together, these futures capture the effects of surprise changes in the federal funds rate and forward guidance. Our extension of this shock series is constructed from the Chicago Mercantile Exchange Datamine futures tick data to assure as close of a match as possible to the original series.

BRW use a Fama and MacBeth (1973) two-step regression to extract unobserved monetary policy shocks from the common component of zero-coupon yields encompassing the full yield curve. The first step estimates the responsiveness of yields of different maturities 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).

Finally, the target shock is constructed from the same instrument set as the NS shock, but independently identifies the effect of the federal funds from that of forward guidance. This is achieved by finding suitable rotations for the first and second principal components so that the second principal component has no effect on the current federal funds rate. The resulting rotated first principal component—the target shock—can thus be interpreted as identified exogenous variation in the federal funds rate.

We construct these shock series ourselves using underlying asset pricing data and more details can be found in appendix E as well as Brennan et al. (2024).

Figure 3 plots monetary policy shock for each series over our sample period. While the NS and target shocks are similar, the BRW shock is more different. 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 because it better captures the expansive 21st century monetary policy toolkit as explained in Brennan et al. (2024) and Bu et al. (2021). While the dispersion of the NS and target shocks depend on whether or not the federal funds rate is at the effective lower bound (ELB), the dispersion of the BRW shock is similar in both non-ELB and ELB periods. Although our 2008 to 2015 sample for the Billion Prices Project is dominated by monetary




(a) Daily inflation response to a NS shock

(b) Aggregated (daily to monthly) inflation response

Figure 4: Impulse response of daily inflation (30-day percentage change) to a 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 percentage change of daily inflation, $BPP_T = \frac{100}{m}\sum_{t=1}^{m}(\log BPP_t - \log BPP_{t-30})$ for days $t = 1, \ldots, m$ of month $T$. 90% error bands.

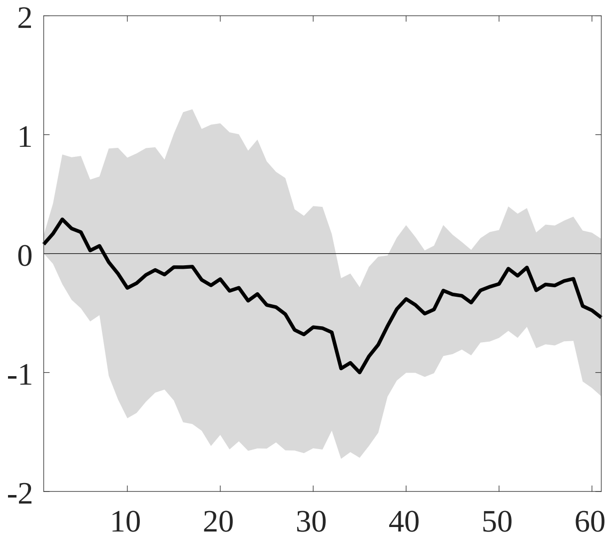
policy tools other than the federal funds rate, the success of the BRW shock at capturing the effects of the expansive policy toolkit should address some of this concern.

### 3.2 Local Projections

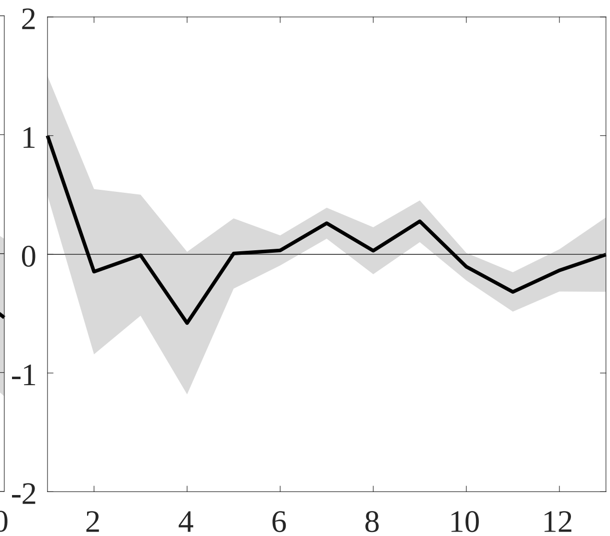
We use local projections (Jorda, 2005) to estimate the impulse responses of inflation to monetary policy shocks at both daily and monthly frequencies. For the daily specification, let $y_{t+h}$ be the value of daily inflation over the past 30 days at day $t+h$, $z_t$ be the high-frequency shock series proxying for exogenous variation in monetary policy—set to zero on days without an FOMC announcement and left unstandardized—, and $x_{t-1}$ be the vector of controls, which are 30 lags of daily inflation. We estimate

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

with robust heteroskedasticity and autocorrelation consistent (HAC) standard errors. We normalize impulse responses so that the largest absolute effect of the point estimate is 1. We use either the aforementioned series from Nakamura and Steinsson (2018a), Gürkaynak et al. (2005), or Bu et al. (2021). The model specification at monthly frequency simply aggregates daily data via an arithmetic average and includes one lag of monthly data as controls to be comparable to the daily specification. The shocks are aggregated via summation as in Brennan et al. (2024). Because there is only one unscheduled meeting in our sample, there is only one month where the daily shocks differ from their monthly counterparts. Appendix B.3 shows that there is little material difference in impulse responses with and without the unscheduled meeting. Appendix B.1 shows a 365 day impulse response horizon for panels (4a)-(6a) instead of a 60 day impulse response horizon.




(a) Daily inflation response to a target shock

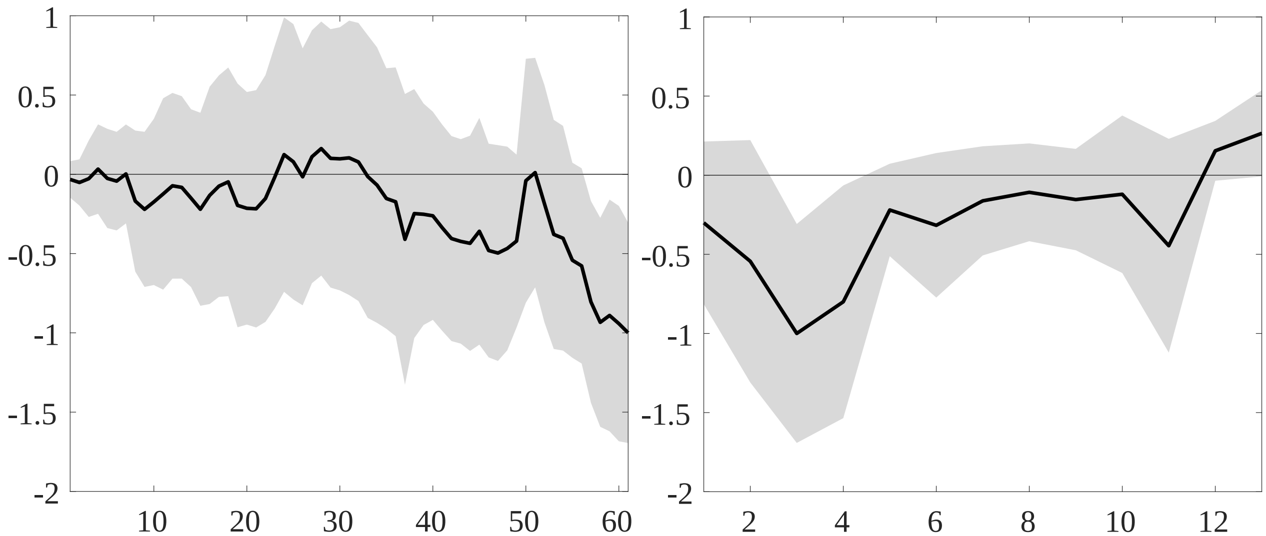



(b) Aggregated (daily to monthly) inflation response

Figure 5: Impulse response of daily inflation (30-day percentage change) to a target 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 percentage change of daily inflation, $BPP_T = \frac{100}{m}\sum_{t=1}^{m}(\log BPP_t - \log BPP_{t-30})$ for days $t = 1, \ldots, m$ of month $T$. 90% error bands.

Figure 4 plots the impulse response to a one-time contractionary NS monetary policy shock at both the daily and monthly frequency. Panel 4a shows 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 days shown. 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. Panel 4b aggregates the daily index to a monthly frequency and re-estimates the local projection conditioning on monthly data. When inflation is aggregated to a monthly frequency, the initial positive response is quantitatively large and one of the few components of the impulse response function for which the confidence band does not cover zero. Although a prominent positive response is often found in the literature, it contrasts with our findings of a negative and significant response using disaggregated daily inflation.

Figure 5 shows the impulse response to a one-time contractionary Gürkaynak et al. (2005) target shock at both the daily and monthly frequency. The impulse responses are broadly similar to those of the NS shock shown in figure 4 such that the impulse response is conventionally-signed at a daily frequency for all but about 10 days and then adversely-signed at a monthly frequency. Furthermore, Appendix B.2 shows that the impulse response of daily inflation are adversely-signed to the Gürkaynak et al. (2005) forward guidance path shock. If the NS shock can be interpreted as the linear combination of the target and path shocks, we find that the impulse responses to the distinct components are exactly as one would expect. That is, the response to the shock related to the federal funds rate is conventionally-signed and its counterpart response to forward guidance—the component more likely to have an information effect—




(a) Daily inflation response to a BRW shock (b) Aggregated (daily to monthly) inflation response

Figure 6: Impulse response of daily inflation (30-day percentage change) to a 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 percentage change of daily inflation, $BPP_T = \frac{100}{m}\sum_{t=1}^{m}(\log BPP_t - \log BPP_{t-30})$ for days $t = 1,\ldots,m$ of month $T$. 90% error bands.

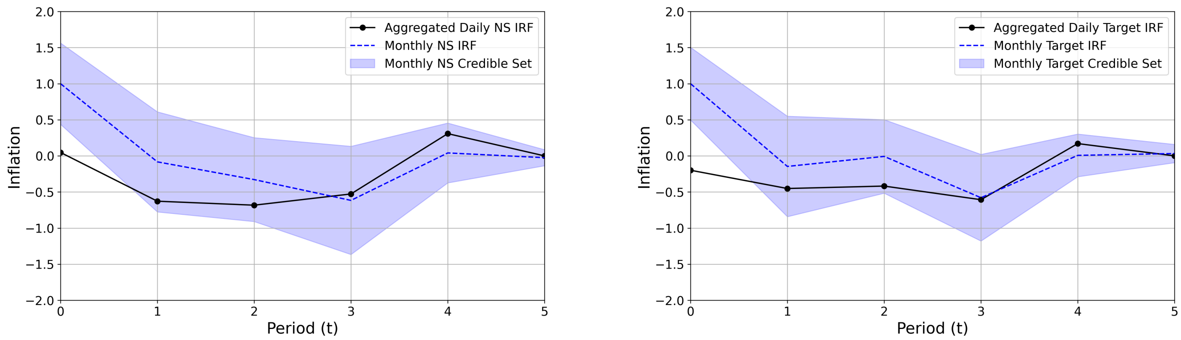
is adversely-signed.

Figure 6 plots the impulse response of inflation to a contractionary BRW monetary policy shock. Panel 6a 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 negative, albeit zero is well contained in the 90% credible sets. Given that the Fed information effect and its associated adversely-signed responses are not detected in the BRW shock, the results plotted in figure 6 are not surprising.

Given that estimates of monetary policy transmission using shocks with a known Fed information effect are conventionally-signed when using inflation data at a daily frequency, but adversely-signed when the same data is aggregated to a monthly frequency, we next calculate the distortion introduced by estimating IRFs on temporally aggregated data. We additionally note that comparing the impulse response of the same shock at different frequencies of response variables may shed more light on how information contamination can bias estimates relative to comparing estimates across shocks. After all, comparing impulse responses across shocks can be problematic when shocks are constructed from different data and methods. By contrast, comparing impulse responses within shocks maintains the data and only changes the frequency of the response variable.

### 3.3 TEMPORAL AGGREGATION BIAS

Figure 7 illustrates the impact of temporal aggregation by comparing two types of monthly impulse response functions (IRFs). First, we reproduce the estimated monthly IRFs from panel (b) of Figures 4 and 5 (dashed blue lines), shown with 90% credible intervals. We then




(a) NS Shock (b) Target Shock

Figure 7: Aggregated daily impulse response and monthly estimated inflation response of Figure 4

overlay the IRFs obtained by aggregating the daily IRFs from panel (a) of the same figures up to monthly frequency (solid black lines). This aggregation is performed by computing the arithmetic average of the daily responses within each month. Both sets of IRFs are constructed using the same underlying dataset. The only difference between them lies in how the temporal aggregation is handled: the dashed blue lines represent IRFs estimated directly from monthly data, while the solid black lines are derived from estimates conditional on daily data that have been aggregated to the monthly level.

The comparison reveals substantial differences, particularly on impact. In both the NS and target shock specifications, the initial value of the aggregated IRF (solid line) lies *outside* the 90% credible interval of the directly estimated monthly IRF. This suggests a significant distortion introduced by estimating IRFs on temporally aggregated data. If the true data-generating process is daily, then the solid line provides the correct approximation of the underlying response. The distance between the solid and dashed lines thus represents a temporal aggregation *bias*. Importantly, this bias is not only quantitatively large but can also lead to qualitative misinterpretations—such as a reversal in the sign of the impact response, as seen in the case of the target shock. These findings are complemented by those of Snudden (2024) who documents substantial information loss when aggregating from daily-to-monthly frequencies and those of Tiao and Wei (1976) who show information loss in parameter estimation.

One explanation for what we refer to as an adversely-signed response is the Fed information effect or the notion that private agents react to the novel information revealed in monetary policy announcements.[13] Thus, an impulse response that runs counter to standard theory could be explained by introducing a discrepancy in information between the Federal Reserve and private agents, as advocated by Nakamura and Steinsson (2018a).[14] 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,

[13] 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. (2023), Cieslak and Schrimpf (2019), Acosta (2023), Lewis (2020), Bundick and Smith (2020), Andrade and Ferroni (2021), Golez and Matthies (2025).

[14] Moreover, in Brennan et al. (2024) we show that a conventionally-signed impulse response of daily inflation is robust to other monetary policy shock series—like those of Kuttner (2001) and Jarocinski and Karadi (2020)—in addition to those of Nakamura and Steinsson (2018a) and Bu et al. (2021) shown here.

such as stocks and bonds, but we are the first to study inflation at high frequency. Figures 4-5 demonstrate that the adversely-signed response to inflation could be due to an information discrepancy between the econometrician and private agents, and not policy makers and private agents.

More specifically, consider the conditional expectation of inflation given a sequence of monetary policy shocks, denoted $\mathbb{E}[\pi_t \mid \varepsilon_t, \varepsilon_{t-1}, \ldots]$, where $t$ indexes daily observations. Both private agents and policy makers form expectations based on the full history of fundamental structural shocks $\{\varepsilon_{t-j}\}_{j=0}^{\infty}$. Suppose the equilibrium inflation process admits a Wold representation: $\pi_t = B(L)\varepsilon_t = (B_0 + B_1 L + B_2 L^2 + \cdots)\varepsilon_t$, where $L$ is the lag operator and the $B_j$ are impulse response coefficients. An econometrician who has access to daily data and aggregates the impulse responses over $m$ periods—forming $\sum_{j=0}^{m-1} B_j L^j$—constructs an IRF that is conditional on the original structural shocks $\varepsilon_t$. In this case, the aggregation is applied to the coefficients, not the data, and so the structural interpretation is preserved. In contrast, an econometrician who only observes temporally aggregated data—such as $\sum_{j=0}^{m-1} \pi_{t-j}$—and estimates a VAR or local projection at the aggregated frequency does not condition on the same underlying structural shocks. Temporal aggregation alters the statistical properties of the stochastic process: the aggregated inflation series no longer adheres to the same Wold representation, and the structural shocks $\varepsilon_t$ are no longer recoverable in a one-to-one manner from the aggregated data. This fundamental disconnect is a source of temporal aggregation bias, which we explore more formally in Section 4. Before turning to theory, we first corroborate our local projection results showing conventionally-signed transmission of monetary policy with estimates from a state space model.

### 3.4 UNOBSERVED COMPONENTS MODEL

An unobserved components model allows us to study the response of high-frequency inflation to a monetary policy shock more systematically by taking into account both the exact timing of monetary policy shocks and official inflation releases within a month as well as explicitly modeling the link between data observed at different frequencies (this will be clear below when we describe the measurement equation for monthly inflation). 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, the modeling assumptions here are more straightforward. This allows us to take a more definitive stance on our finding of a conventionally-signed estimate of monetary policy transmission, 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 breakeven inflation rates that are available daily except for holidays and weekends, infrequent monetary policy shocks, and monthly inflation rates.

| # | Parameter | Prior | Notes |
|---|---|---|---|
| 1 | $\sigma_\pi$ | $\Gamma(1,0.5)$ | standard deviation of i.i.d. component of underlying inflation |
| 2 | $\sigma_\tau$ | $\Gamma(1,0.5)$ | standard deviation of innovation to random walk permanent component |
| 3 | $\rho_g$ | $\beta(4,4)$ | persistence of stationary part |
| 4 | $\sigma_g$ | $\Gamma(1,0.5)$ | standard deviation of innovation to stationary part |
| 5 | $\alpha^m$ | $N(0,0.0001^2)$ | 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 | $\alpha^{daily}$ | $N(0,5^2)$ | intercept of measurement equation of daily (30-day) inflation |
| 8 | $\sigma^{daily}$ | $\Gamma(1,0.5)$ | standard deviation of measurement error of daily inflation |
| 9 | $\alpha^{BE}$ | $N(0,5^2)$ | intercept of measurement equation of daily BE inflation |
| 10 | $\sigma^{BE}$ | $\Gamma(1,0.5)$ | standard deviation of measurement error of daily BE inflation |
| 11 | $\theta_0^g$ | $N(0,0.25^2)$ | contemporaneous impact of monetary policy shock on g |
| 12 | $\theta_0^\tau$ | $N(0,0.25^2)$ | contemporaneous impact of monetary policy shock on $\tau$ |
| 13 | $\sigma^{m,obs}$ | $\Gamma(1,0.5)$ | standard deviation of monetary policy shock |
| 14 ~ 72 | $\underset{59\times 1}{\theta_i^g}$ | $N(0,(0.25*0.95^i)^2)$ | vector of effects of 59 days lagged monetary policy shocks on g |
| 73 ~ 131 | $\underset{59\times 1}{\theta_i^\tau}$ | $N(0,(0.25*0.95^i)^2)$ | vector of effects of 59 days lagged monetary policy shocks on $\tau$ |

Table 3: Prior Specification

Our model consists of the following state equations:

$$\pi_t = \tau_t + g_t + e_t^\pi \qquad \text{Unobserved daily CPI inflation}$$

$$\tau_t = \tau_{t-1} + \sum_{k=0}^{K} \theta_k^\tau m_{t-k} + e_t^\tau \qquad \text{Permanent component}$$

$$g_t = \rho g_{t-1} + \sum_{j=0}^{J} \theta_j m_{t-j} + e_t^g \qquad \text{Transitory component}$$

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 auto-correlation and the same number of monetary policy shocks. Lags of the monetary shocks are directly included in our specification to allow for richer dynamics at the daily frequency. The $\theta$ coefficients cannot, however, be directly interpreted as impulse response coefficients because they encapsulate the marginal effects of a monetary shock conditional on past trend or cyclical components.[15] We assume monetary policy shock dynamics $m_t = e_t^m$ with all shocks $e$ being i.i.d. and Gaussian.[16] Our data for monetary policy shocks are the externally calculated high-frequency shocks discussed in section 3. We assume that monetary shocks are possibly non-zero on days when there is a FOMC announcement. The FOMC meeting schedule is typically set years in advance to have a meeting roughly once every 60 days. Although unscheduled FOMC announcements do occur, they are quite rare and there is only one such announcement in our

[15] We compute impulse responses by stacking all equations for the state variables in a large autoregressive system, as is standard in state space models.

[16] 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.

sample.[17]

The observation equations are:

$$\pi_t^m = \alpha^m + \pi_{t-p} + e_t^{monthly} \qquad \text{Monthly observation of CPI}$$
$$\pi_t^{daily} = \alpha^{daily} + \pi_t + e_t^{daily} \qquad \text{Daily measure of 30-day inflation}$$
$$\pi_t^{BE,h} = \alpha^{BE} + E_t\pi_{t,t+h} + e_t^{BE} \qquad \text{10-year breakeven rates}$$

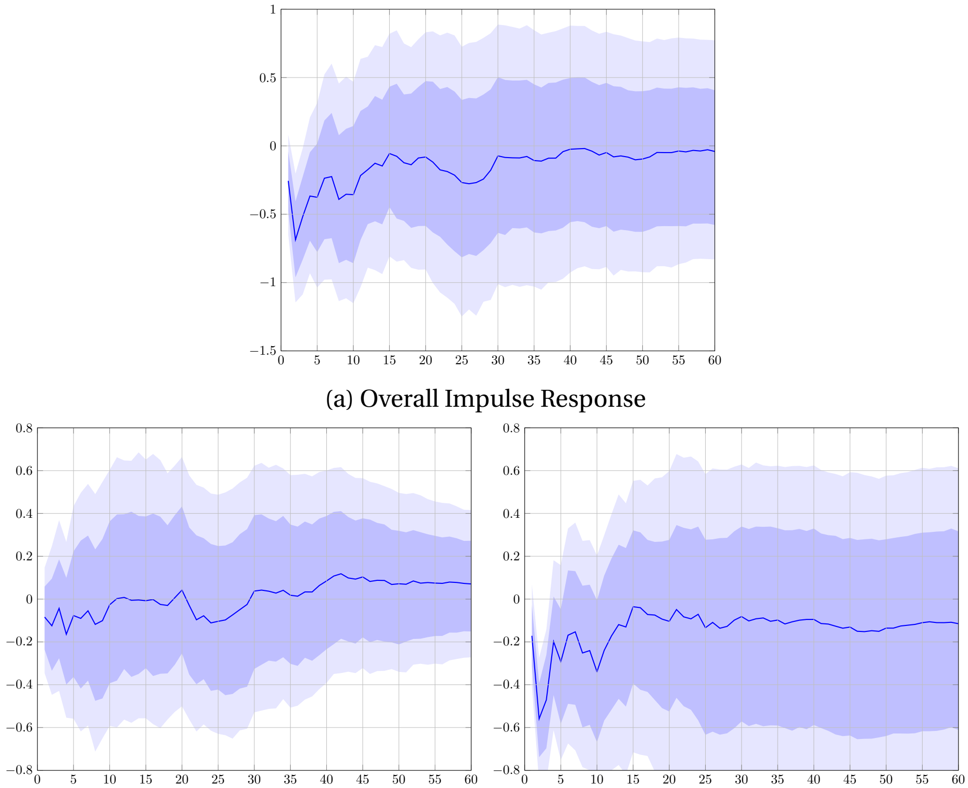
where $p$ is the publication lag mentioned in Section 2 (which can vary over time as shown in Table 1). We assume that high-frequency monetary policy shock series are a noisy measurement of the true exogenous variation in monetary policy: $m_t^{obs} = m_t + e_t^{m,obs}$, along the lines of Caldara and 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). $\pi_t^{daily}$ is measured as the change in the log price level over the past 30 days. $\pi_t^m$ is the month to month difference in log CPI. Not all measurement equations are used for every day $t$. For example, we observe monthly inflation $\pi_t^m$ only once a month. On the publication date $t$ we observe a possibly noisy and biased measurement of the monthly inflation rate $p$ days prior where the lag structure is due to publication lags. Similarly, on days when financial markets are not open, we cannot observe breakeven rates. We assume that the monetary policy shock is only non-zero on days when the instrument for the shock is not equal to zero, i.e. on FOMC announcement days.

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 3 reports our prior distributions, which are largely uninformative. We do impose somewhat informative priors on 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 adversely-signed responses, but we do impose shrinkage—the further a monetary policy shock is in the past, the more we shrink its effect toward zero. These findings are robust to imposing less shrinkage as shown in Appendix C.

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.[18] Darker shaded error bands are 68th percentiles, while lighter shades are 90th. Panel 8a shows that inflation—at a daily frequency—does not contain an adversely-signed response. The initial reaction of inflation to a monetary policy shock is negative, even at the 90th percentile, followed by an increase

[17] Because we use monetary policy shocks that encompass both fundamentals about interest rate decisions and forward guidance about the future path of monetary policy, we cannot simply add on events that are purely forward guidance such as speeches by Federal Reserve officials as described by Swanson and Jayawickrema (2024). More specifically, monetary news delivered via speeches could have an effect on inflation that is distinct from that estimated via shocks that encompass both forward guidance *and* fundamentals. As a result, including speeches would necessarily expand monetary shock dynamics from $m_t = e_t^m$ to $m_t = e_t^m + e_t^{fg}$ so that $e_t^{fg}$ can occur on any day outside of the pre-set FOMC meeting schedule.

[18] Results are similar for the BRW and target shocks and are available upon request.




(a) Overall Impulse Response

(b) Response of Transitory Component ($g_t$) (c) Response of Permanent Component ($\tau_t$)

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

and an error band that contains zero over the remaining horizon. These results further corroborate our findings from the local projections shown in section 3.2; namely, that the adversely-signed response of inflation to a monetary policy shock is difficult to detect when controlling for the information sets of the econometrician and private agents.

By decomposing into permanent and transitory components, we are able to parse the conventionally-signed impulse response as permanent. Panel 8c shows a conventionally-signed impulse response in the permanent component of daily inflation. The less-persistent transitory response is shown to be quantitatively small relative to trend as shown in panel 8b. The variance decomposition, shown 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 adversely-signed response despite the fact that the shocks fed into the system are known to generate adversely-signed responses at much lower (monthly) frequencies.

### 3.5 DISCUSSION

To summarize, our empirical findings suggest that temporal aggregation, going from daily observations of inflation to monthly, can generate impulse response functions that are qualitatively

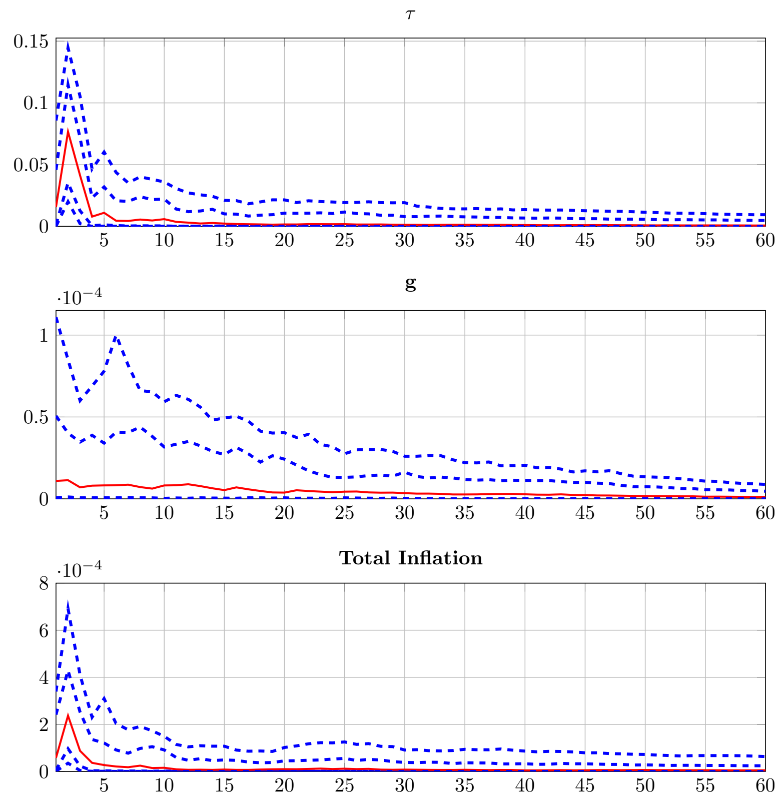



Figure 9: Variance decomposition associated with monetary policy shock as a fraction of total variance.

different. Using the Nakamura and Steinsson (2018a) and target shock series, we find a positive response of inflation to contractionary monetary policy shocks at the monthly frequency, yet no such positive response emerges at daily frequency. We verify these findings by estimating a flexible unobserved components model that allows for permanent and transitory components. At daily frequency, the transitory response is negligible, while the permanent component reacts in a manner consistent with theory (inflation falls in response to a contractionary shock). We now turn to theory to address how such outcomes are possible.

## 4 UNDERSTANDING TEMPORAL AGGREGATION

Figure 7 shows that temporal aggregation can lead to biased estimates of impulse response functions. By aggregating to a lower frequency and then estimating, econometric estimates can deviate substantially from aggregated impulse response coefficients, especially on impact. We now demonstrate *how* this can happen by studying temporal aggregation in stylized settings.

**4.1 AGGREGATING A STRUCTURAL MODEL** 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, $i_t = r + \phi\pi_t + x_t$, where the monetary policy shock follows an AR(1) process, $x_t = \rho x_{t-1} + \varepsilon_t$, with $\rho \in (0,1)$ and $\varepsilon_t$ distributed as Gaussian with mean zero and variance $\sigma_\varepsilon^2$. 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. The unique equilibrium rate of inflation is well known and follows from implementing the Taylor principle $(\phi > 1)$,

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

where $w_t = -\varepsilon_t/(\phi-\rho)$. A one-standard-deviation monetary policy shock at $t = 0$, results in the following impulse response for inflation $\pi_t$: $-(\sigma_\varepsilon\rho^t)/(\phi-\rho)$, $t \geq 0$. For example, with $\sigma_\varepsilon = 0.01$, $\rho = 0.99$ and $\phi = 1.05$, we have $\pi_0 = -0.01/(1.05-0.99) = -0.166$ and $\pi_j = \{-0.165, -0.163, -0.162, -0.160, -0.158\}$ for $j = 1, \ldots, 5$.

Suppose $t$ is daily frequency, an econometrician aggregating these impulse response coefficients to monthly values using an arithmetic average would yield

$$\Pi_0^{\text{true}} = \frac{1}{m}\sum_{j=0}^{m-1}\pi_j = -\frac{\sigma_\varepsilon}{m(\phi-\rho)}\sum_{j=0}^{m-1}\rho^j = -\frac{\sigma_\varepsilon(1-\rho^m)}{m(\phi-\rho)(1-\rho)} \tag{2}$$

where $m = 30$. We obtain: $\Pi_0^{\text{true}} \approx -0.144$, and $\Pi_j^{\text{true}} = \{-0.107, -0.079, -0.059, -0.043, -0.032\}$ for $j = 1, \ldots, 5$. The difference between these estimates (e.g., $-0.166$ vs. $-0.144$) is due to averaging (with weights $1/m$) an exponentially decaying sequence. The degree of decay $\rho^j$ comes directly from the structural model and therefore this temporal aggregation *accurately* depicts the aggregated response of inflation to a monetary policy shock. The gap between the daily and monthly IRF reflects attenuation due to temporal aggregation of a decaying process. This attenuation is not a bias, but a transformation consistent with the model's structure. The theoretical construct of equation (2) is consistent with the solid lines of Figure 7, if the econometrician could temporally aggregate impulse response coefficients. We label this aggregated impulse response as the true dynamic response of aggregated inflation to a monetary policy shock, $\Pi_T^{\text{true}}$. Our definition of aggregation bias is the discrepancy between this true response and the response inferred from an econometric model estimated on that aggregated data.

Now assume the econometrician observes realizations of the equilibrium processes at monthly frequency.[19] Instead of being able to aggregate impulse response coefficients directly, the econometrician must estimate the impulse response from the temporally aggregated data. This is consistent dashed line or "monthly IRF" estimate of Figure 7. Appendix D shows that temporally aggregating the AR(1) inflation

[19] Inflation 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.

| | $m=1$ | $m=2$ | $m=5$ | $m=10$ | $m=20$ | $m=30$ | $m=40$ | $m=50$ |
|---|---|---|---|---|---|---|---|---|
| $\rho$ | 0.990 | 0.980 | 0.951 | 0.904 | 0.818 | 0.740 | 0.669 | 0.605 |
| $\theta$ | 0.000 | 0.171 | 0.250 | 0.264 | 0.265 | 0.266 | 0.266 | 0.267 |
| $\sigma_u^2$ | 0.028 | 0.041 | 0.085 | 0.160 | 0.288 | 0.391 | 0.476 | 0.542 |
| $\sigma_\Pi^2$ | 1.407 | 1.378 | 1.383 | 1.366 | 1.306 | 1.269 | 1.230 | 1.188 |

Table 4: Estimates of the ARMA(1,1) equation (3) using temporally aggregated observations of equation (1). Note that for $m=1$ (no temporal aggregation), $\sigma_u^2 = \sigma_w^2$.

process given by (1) yields an ARMA(1,1) representation,

$$(1-\rho^m L)\Pi_T = u_T + \theta u_{T-1} \qquad\qquad u_T \sim N(0,\sigma_u^2) \tag{3}$$

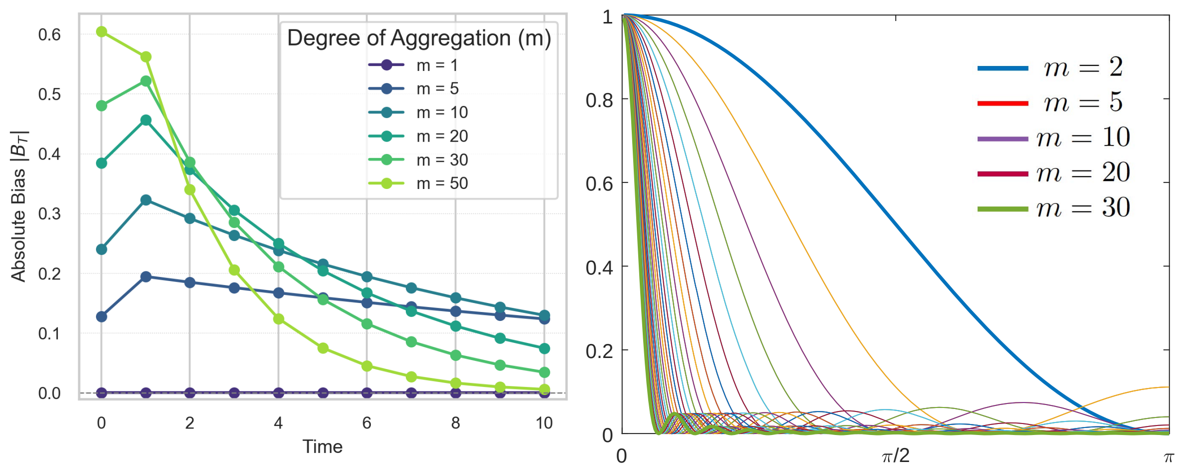
where, for lag operator $L$, the autocorrelation coefficient is raised to the power of $m$ (the number of aggregated components), and the estimated shocks ($u_t$) are fundamental for the $\Pi_t$ process (Amemiya and Wu (1972)). The last fact ensures that innovations from an autoregressive (or VAR) representation will span the shocks given by the sequence $\{u_t\}$. An analytical mapping between the aggregated inflation process and the ARMA(1,1) parameters is not feasible but Table 4 provides estimates of the parameters for various values of $m$ using simulated data. We set $\rho = 0.99$, $\phi = 1.05$, $\sigma_\varepsilon = 0.01$, and use one million observations for each simulation.

Figure 10a illustrates the *temporal aggregation bias*, which quantifies the discrepancy between the true dynamic response of aggregated inflation to a monetary policy shock ($\Pi_T^{\text{true}}$) and the response inferred from an econometric model estimated on that aggregated data. This bias, $B_T$, at each aggregated horizon $T$, is defined as the difference between two impulse responses:

1. $\text{IRF}_{\Pi,T}^{\text{ARMA}}$: The impulse response derived from the ARMA(1,1) model (equation (3)) estimated on the temporally aggregated inflation series $\Pi_T$. Its parameters—the AR coefficient $\rho^m$ (denoted as $\rho$ in the table for the corresponding $m$), the MA coefficient $\theta$, and the innovation variance $\sigma_u^2$—are taken from Table 4.

2. $\Pi_T^{\text{true}}$: The true aggregated impulse response. This is obtained by first calculating the daily inflation response $\pi_t$ to the one-standard-deviation structural monetary policy shock using equation (1), and then averaging these daily responses over $m$ periods, consistent with equation (2) for $T=0$.

The figure plots the absolute value of this bias, $|B_T| = |\text{IRF}_{\Pi,T}^{\text{ARMA}} - \Pi_T^{\text{true}}|$, for various levels of aggregation $m$. It is crucial to emphasize that these calculations reflect *population* biases, not merely discrepancies arising from sampling variation in parameter estimation. As $m$ increases, the bias becomes substantial. For $m=30$, the absolute bias at impact ($T=0$) is approximately 0.481. This occurs because the magnitude of the ARMA-derived response ($|\text{IRF}_{\Pi,0}^{\text{ARMA}}| \approx 0.625$) substantially overstates the magnitude of the true aggregated response ($|\Pi_0^{\text{true}}| \approx 0.145$) by approximately 332% (253% for $m=20$ and 459% for $m=50$). Significant biases, as depicted in Figure 10a, also persist across several subsequent aggregated horizons. Such divergence arises because while the ARMA(1,1) model captures the stochastic process of




(a) Aggregation Bias for Various $m$

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

Figure 10: Temporal Aggregation Bias and Moving-Average Filter for various $m$. Panel a (left-side) shows the absolute value of aggregation bias as $m$ increases from 1 to 50 for monthly observations ($x$-axis time in months). Panel b (right-side) plots the spectrum for $m = 2$ (blue) through $m = 30$ (green), demonstrating why low frequency properties are preserved and higher frequencies are altered.

the aggregated data, its parameters—notably the innovation variance $\sigma_u^2$ and the MA coefficient $\theta$—are fundamentally altered by the aggregation process itself, leading its inferred dynamic response to a standardized shock to differ markedly from the true aggregated structural impulse response. These discrepancies are on par with empirical estimates of Figure 7.

The temporal aggregation mapping into the ARMA parameters reveals the source of the temporal aggregation bias. Estimates in Table 4 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 at rate $m$, $\rho^m$; [ii.] the variance of the aggregate inflation process declines multiplicatively in $m$ (see Appendix D for derivation):

$$\sigma_\Pi^2 = \frac{\sigma_\pi^2}{m^2}\left(m + 2[(m-1)\rho + (m-2)\rho^2 + \cdots + \rho^{m-1}]\right) \tag{4}$$

Taken together, [i] and [ii] imply that the variance of the innovation process $\sigma_u^2$ and the moving average parameter $\theta$ must compensate for the faster decline in the autocorrelation coefficient, $\rho^m$. Table 4 shows that the variance of the innovation ($\sigma_u^2$) 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 one standard deviation shock. Panel 10a plots the initial impulse response to a one-standard deviation shock ($\sigma_u$) 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 shock—temporally aggregating over six periods more than doubles the initial impact.[20]

Panel 10b 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 $\pi$. The panel 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 parameters of the estimated ARMA(1,1) process. Lower frequencies are preserved when aggregation occurs despite the decline in the autocorrelation coefficient (from $\rho$ to $\rho^m$). Even though $\rho^m < \rho$, the moving average component $\theta$ and increased innovation variance $\sigma_u^2$ "reinflate" the low-frequency variation, so the spectrum at frequency 0 is nearly unchanged. 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))[21] 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.

### 4.2 DISCUSSION

The purpose of this section was to establish how temporal aggregation can substantially alter initial moving-average coefficients. While we believe this section has established compelling intuition for our results, the models are stylized and so we briefly discuss robustness. 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.

We next address how the *sign* of the impulse response can qualitatively change (panel 7b) under temporal aggregation. Given that the fundamental shock, $u_t$, is a linear combination of underlying monetary policy shocks, $u_t = f(\varepsilon_{t-s}, ..., \varepsilon_{t-m})$ for $s = 0, ..., m$, the sign and timing of these monetary policy shocks is critical to understanding the response of inflation to a structural shock. Panel 10a assumes that a contractionary monetary policy shock occurs throughout the aggregation period; that is, if $m = 10$, then a sequence of contractionary shocks occurs at each date $t = 0, 1, 2, ....$ Of course, this does not need to be the case. We now explore this issue.

[20] 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 10 continues to be relevant.

[21] Stram and Wei (1986) show this condition holds as long as the AR roots are distinct from the MA roots.

4.3 TEMPORAL AGGREGATION WITH LOCAL PROJECTIONS Consider the data-generating process of inflation,

$$\pi_t = \sum_{j=0}^{59} \Theta_j \varepsilon_{t-j}^{mp} + u_t \tag{5}$$
$$u_t = \rho^u u_{t-1} + \varepsilon_t^u$$

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 (with the value being equal to 0 on all other days), 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 (5) to obtain corresponding monthly data. We denote monthly variables as $\Pi_T$ and $\varepsilon_T^{mp}$, where $T$ is measured in months. 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 calibration is consistent with the local projection response of daily inflation to the NS shock series shown in figure 4.

Our parameterization accomplishes two tasks: first, it introduces what we refer to as an initial adversely-signed 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.[22] 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 adversely-signed inflationary response to materialize in the aggregate (monthly) data because a majority of the signs—20 out of 30—are negative instead of positive. The short-lived adversely-signed response should essentially be dominated by the theoretically-consistent response.

Table 5 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, $\epsilon_{T-1}$, does enter with a negative sign, so while the initial response could be adversely-signed, the subsequent moves are standard.[23]

[22] One can generate such an adversely-signed response assuming the monetary policy shocks are pure news. Specifically, if we assume the shock observed at date $t$ is given by $\varepsilon_{t-j}$, then inflation will increase in response to an *anticipated* contractionary shock over the foresight period, see Leeper and Walker (2011).

[23] Including additional controls could increase efficiency in finite samples, but would not alter the findings in this section

| | Panel A: Beginning | | | Panel B: Middle | | | Panel C: End | | |
|---|---|---|---|---|---|---|---|---|---|
| | $\varepsilon_T^{mp}$ | $\Pi_{T-1}$ | $\varepsilon_{T-1}^{mp}$ | $\varepsilon_T^{mp}$ | $\Pi_{T-1}$ | $\varepsilon_{T-1}^{mp}$ | $\varepsilon_T^{mp}$ | $\Pi_{T-1}$ | $\varepsilon_{T-1}^{mp}$ |
| $\Pi_T$ | -0.40 | 0.82 | | 0.29 | 0.82 | | 0.03 | 0.82 | |
| $\Pi_T$ | -0.50 | | -1.16 | 0.38 | | -0.85 | -0.06 | | -0.26 |
| $\Pi_{T+1}$ | -1.09 | 0.61 | | -0.92 | 0.60 | | -0.19 | 0.60 | |

Table 5: Local projection results. Three million observations of daily inflation simulated via (5) 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 second 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. Because we simulate three million observation we do not compute standard errors (which would be tiny).

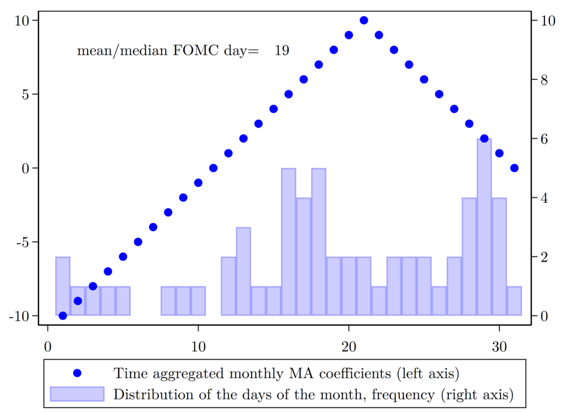
The timing of the monetary policy shock is important. Panel 11a plots the time-aggregated monthly moving average coefficients (i.e. the accumulated response to a monetary policy shock) (left, y-axis) against the timing of the monetary policy shock (x-axis).[24] The time-aggregated MA coefficients for any month can be written as $\Psi \equiv \sum_{t=0}^{29-j}(\mathbb{1}_{t\leq 9} - \mathbb{1}_{t>9})$ where $j = 29,\ldots,0$ is the day of the month when the monetary policy shock occurs. For example, when $j = 29$ the shock occurs on the last day of the month and $\Psi = 1$. As $j$ decreases, the shock occurs earlier in the month, and the monthly aggregated response $\Psi$ becomes larger. In fact, the largest positive response $\Psi = 10$ is 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 panel of figure 11 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 occurred after the 10th day of the month.[25] 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.[26]

because we have simulated such large samples to approximate population regressions.

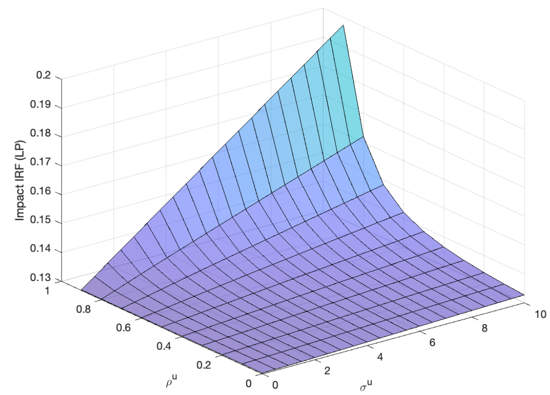
[24] Note that this accumulated response is not directly comparable to our estimates reported in table 5 since we assume in our simulations that there is only one monetary policy shock per month and in practice there are eight scheduled FOMC announcements per year.

[25] As noted previously, the FOMC schedule is typically set years in advance. It is therefore possible that the day of the month of an FOMC announcement is random, but unlikely in practice, especially since there is only one unscheduled announcement in our sample.

[26] Gertler and Karadi (2015) propose controlling for the timing of a monetary policy shock within a month by cumulating the shocks to announcements during the previous 31 days and then taking the monthly average of this trailing cumulative sum. Appendix B.4 shows estimates of the monthly impulse response in section 3.2 with the Gertler and Karadi (2015) transformation applied to the monetary shocks used in this paper. The point estimates are indeed attenuated over the first three months of the impulse response horizon relative to their counterparts shown in panels 4b-6b. In the case of the NS and target shocks, the initial positive responses are no longer statistically significant from zero and responses at month three are negative and significant. Although the transformation offers a partial remedy for temporal aggregation bias, there are several caveats. First, the error bands of these estimates overlap and second, the transformation may induce serial correlation as documented by Ramey (2016).




(a) Histogram of the days of the month for FOMC announcements




(b) Estimated Impact IRF

Figure 11: Robustness. Accumulated responses as a function of shock timing for August 2008 to January 2016 (left panel) and impact IRFs estimated via local projections as a function of autocorrelation ($\rho^u$) and standard deviation ($\sigma^u$) (right panel).

Finally, we note that the results are not contingent on the parameterization of the daily process, $u_t$. Panel 11b plots the initial response using the middle of the month timing as in panel B of table 5 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 adversely-signed response at daily frequency can be persistent and significant at monthly frequency.

### 4.4 Discussion

Of course, the econometrician would be better off using high-frequency data to estimate the response of inflation to a monetary policy shock. They would find an adversely-signed positive response that is quickly dominated by the negative response, consistent with the local projection impulse response of panel 4a. However, suppose only temporally aggregated data are available. One would expect the negative terms to dominate the temporal aggregation, eliminating the initial positive impulse response of monthly inflation. This does not happen in panel 4b and it does not happen in our simulation, hence temporal aggregation bias can have qualitative implications.

## 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 adversely-signed 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 adversely-signed response to monetary policy shocks with monthly or quarterly data when only a limited adversely-signed response is found at a higher frequency, we combine informal and formal empirical evidence with a simple model of temporal aggregation bias. Furthermore, our method of comparing impulse responses estimated from the same shock, but at different frequencies of response variables, allows us to maintain the same methodology for the construction of the shock when assessing the effects of information distortion on estimates of monetary policy transmission. Consequently, we can provide a more definitive assessment of whether or not a adversley-signed responses are a feature of a particular shock than studies that change the information set by comparing impulse responses across shocks.

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 2.

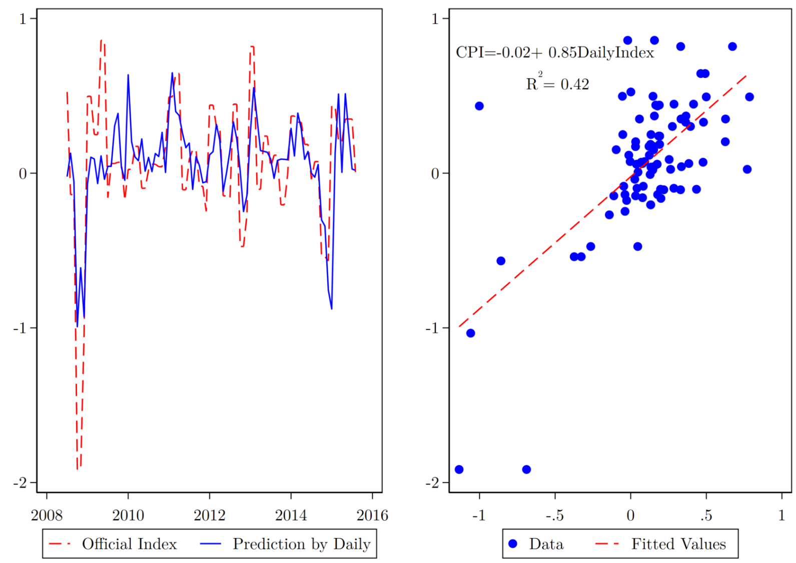



Figure 12: Nowcast of CPI using end of month values of the BPP, monthly and 30-day percentage change. For month $T$, $\Delta CPI_T = 100 \times (\log CPI_T - \log CPI_{T-1})$ and for day $m$ of month $T$, $\Delta BPP_T = 100 \times (\log BPP_m - \log BPP_{m-30})$.

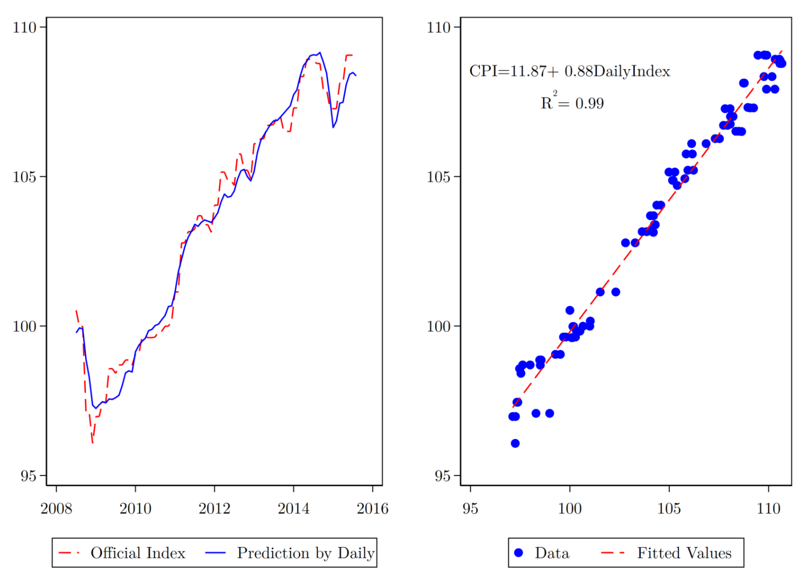



Figure 13: Nowcast of CPI using aggregated monthly values of the BPP index. For month $T$, $CPI_T = \log CPI_T$ and for day $t$ of month $T$, $\Delta BPP_T = \dfrac{1}{m} \sum_{t=1}^{m} \log BPP_t$ for $t = 1, \ldots m$ days in month $T$.

## A.2 CPI SUB-CATEGORIES

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

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

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

Table 6: Nowcast of CPI sub-categories using the BPP. For month $T$ and sub-category $i$, $\Delta CPI^i_T = 100 \times (\log CPI^i_T - \log CPI^i_{T-1})$; 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 for month $T$, $\Delta PCE_T = 100 \times (\log PCE_T - \log PCE_{T-1})$.

## A.3 SEASONALITY

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

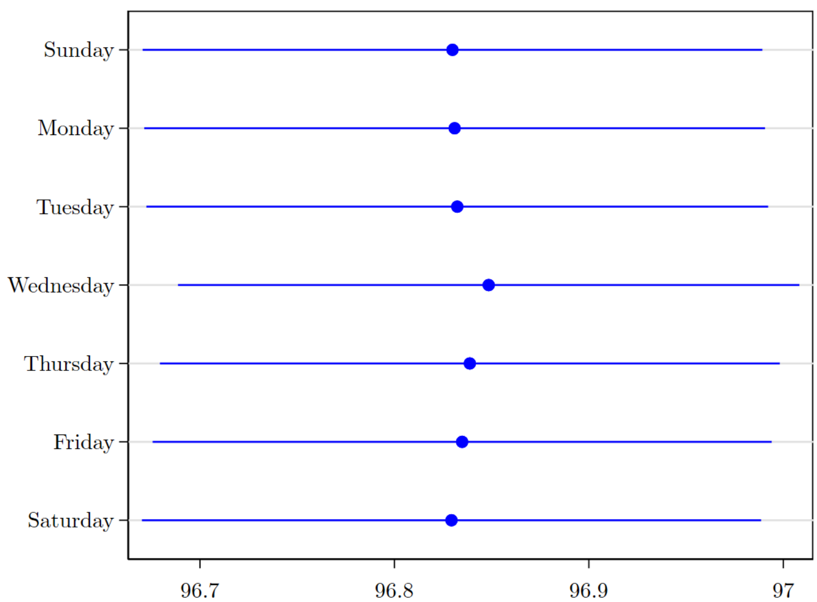
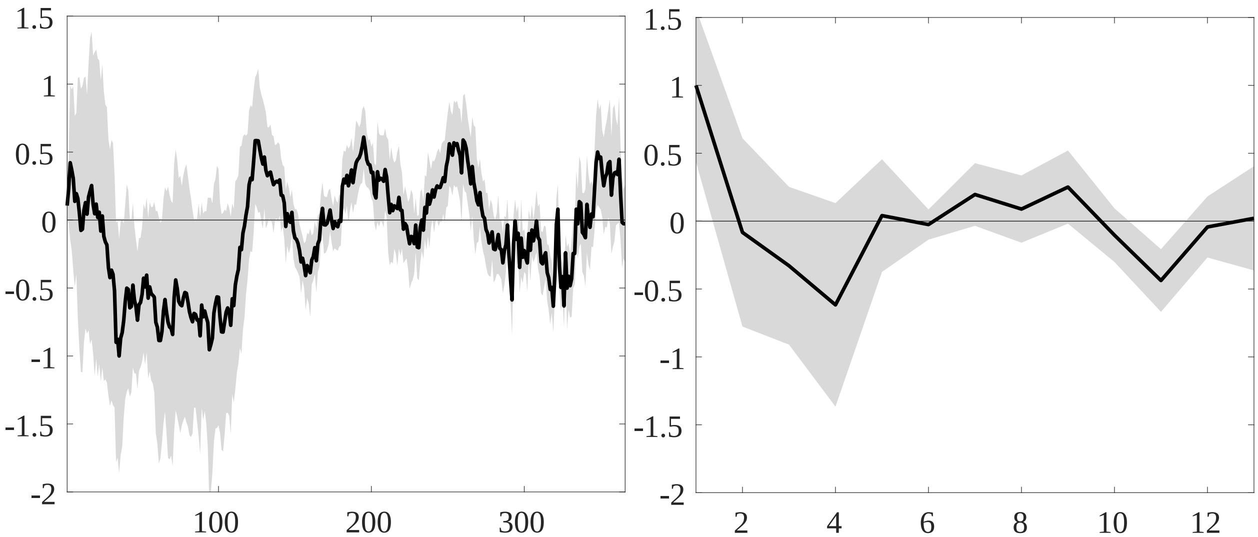



Figure 14: Day of week effects of the Billion Prices Project daily CPI.

# B Appendix: Local Projections

**B.1 Longer Impulse Response Horizon** This appendix shows versions of figures 4-6 with a 365 day impulse response horizon for panels 4a-6a. While these additional figures show that the impulse response becomes a bit erratic at longer horizons, figure 7 shows that this is not necessarily problematic when aggregating daily impulse response coefficients to a monthly frequency, as the coefficients are quite smooth. Additionally, the longer horizon shows that the inflation response occurs much earlier than the commonly understood 6 to 24 months.[27]

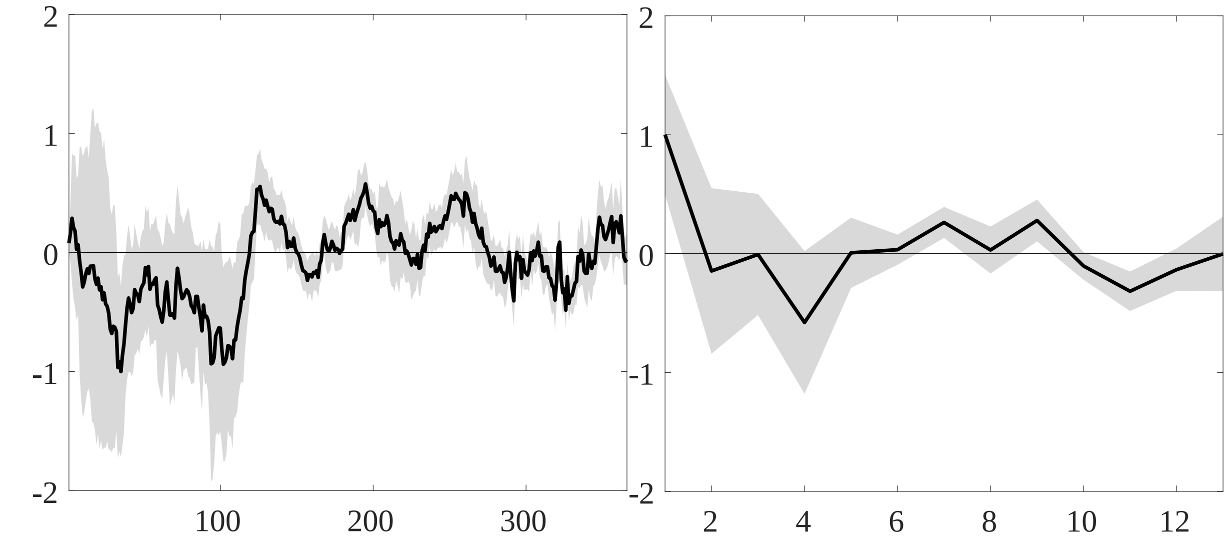



(a) Daily inflation response to a NS shock, 365 day horizon

(b) Aggregated (daily to monthly) inflation response

Figure 15: Impulse response of daily inflation (30-day percentage change) to a 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 percentage change of daily inflation, $BPP_T = \frac{100}{m}\sum_{t=1}^{m}(\log BPP_t - \log BPP_{t-30})$ for days $t = 1, \ldots, m$ of month $T$. 90% error bands.

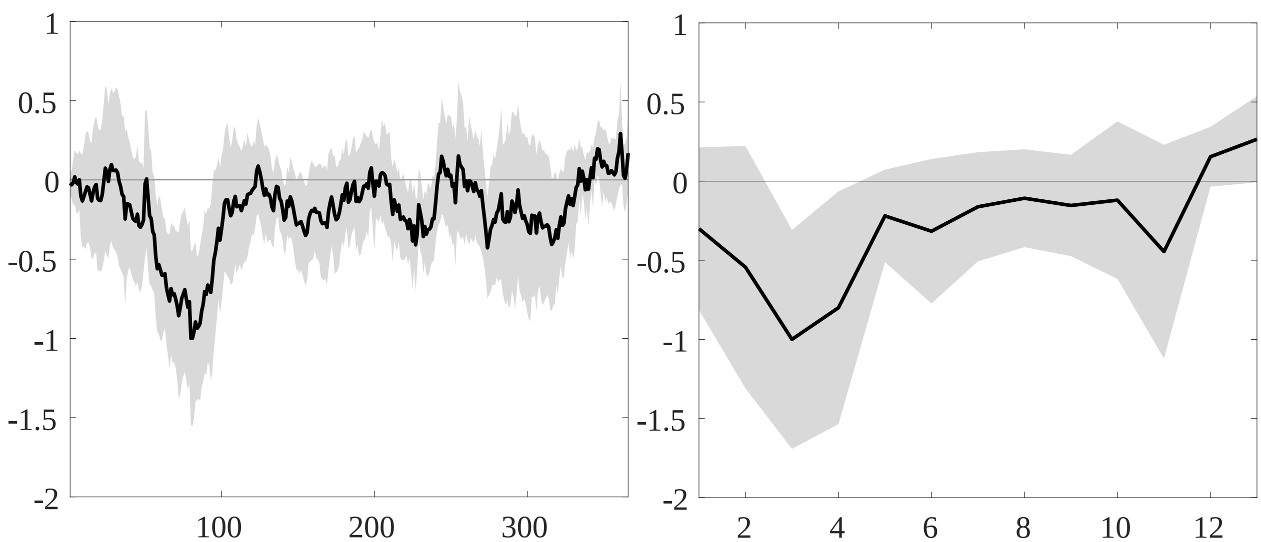
[27] We thank an anonymous referee for this insight.




(a) Daily inflation response to a target shock, 365 day horizon

(b) Aggregated (daily to monthly) inflation response

Figure 16: Impulse response of daily inflation (30-day percentage change) to a target 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 percentage change of daily inflation, $BPP_T = \frac{100}{m}\sum_{t=1}^{m}(\log BPP_t - \log BPP_{t-30})$ for days $t = 1, \ldots, m$ of month $T$. 90% error bands.

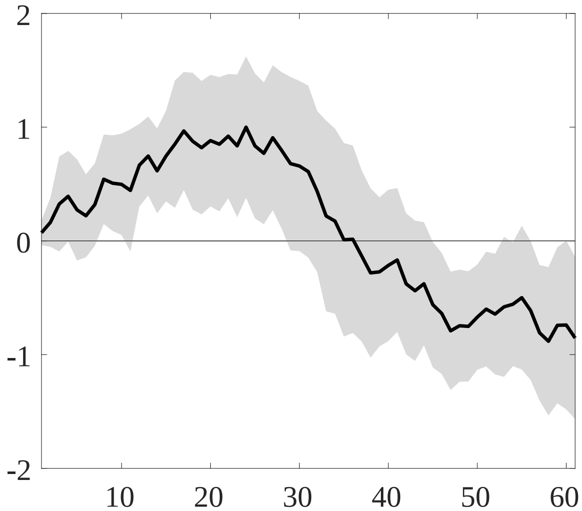



(a) Daily inflation response to a BRW shock, 365 day horizon

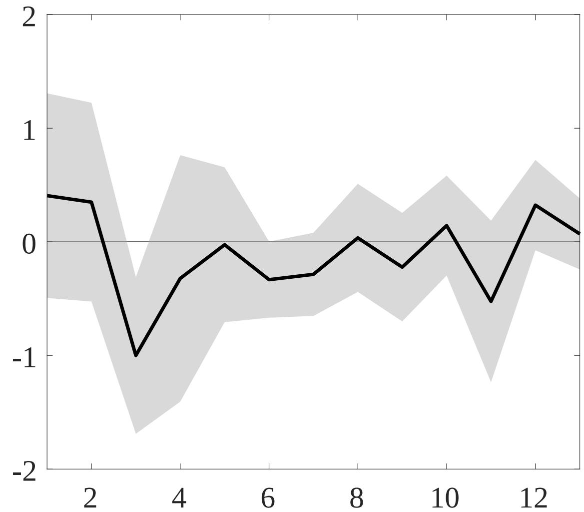
(b) Aggregated (daily to monthly) inflation response

Figure 17: Impulse response of daily inflation (30-day percentage change) to a 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 percentage change of daily inflation, $BPP_T = \frac{100}{m}\sum_{t=1}^{m}(\log BPP_t - \log BPP_{t-30})$ for days $t = 1, \ldots, m$ of month $T$. 90% error bands.

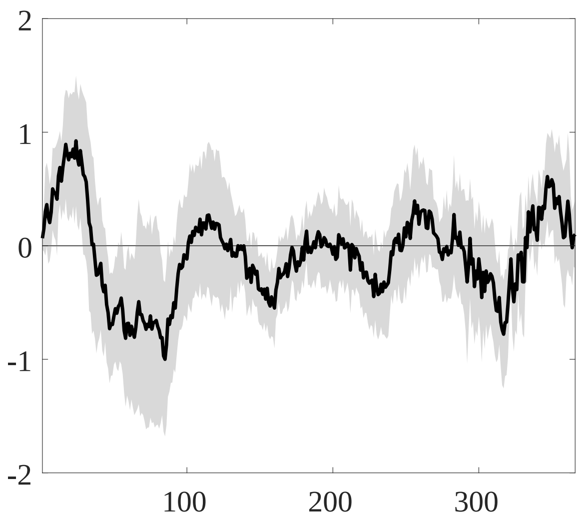
B.2 OTHER SHOCKS The impulse response of the path shock at a daily frequency (panel 18a) has a significant adversely-signed response for about 30 days before turning conventionally-signed. At a monthly frequency (panel 18b), the response is positive for two months and then turns negative. Because adversely-signed responses are often attributed to the Fed information effect's central bank signaling, one could expect an adversely-signed response to the path shock that capture surprise changes in forward guidance independent of the federal funds rate. Panel 18c is the same as panel 18a, but with a 365 day, instead of 60 day, response horizon.




(a) Daily inflation response to path shock, 60 day horizon



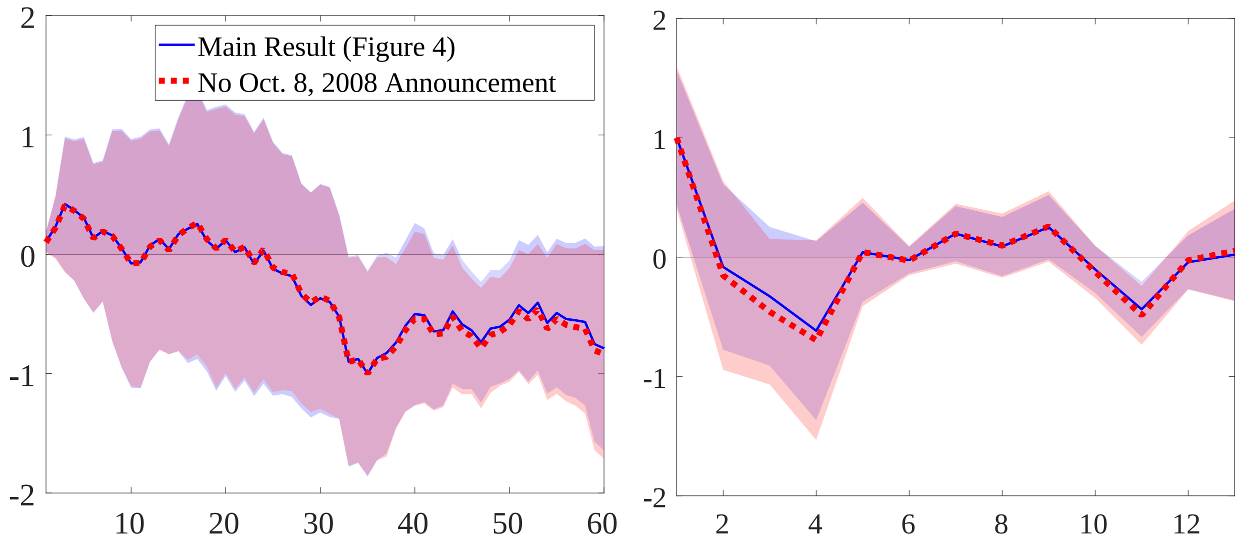

(b) Aggregated (daily to monthly) inflation response




(c) Daily inflation response to a path shock, 365 day horizon

Figure 18: Impulse responses of daily inflation (30-day percentage change) to Gürkaynak et al. (2005) path shock: aggregated vs. disaggregated. For a given month, the aggregate series are the sum of the monetary policy shocks and the average of 30-day percentage change of daily inflation, $BPP_T = \frac{100}{m}\sum_{t=1}^{m}(\log BPP_t - \log BPP_{t-30})$ for days $t = 1, \ldots, m$ of month $T$. Error bands are 90%.

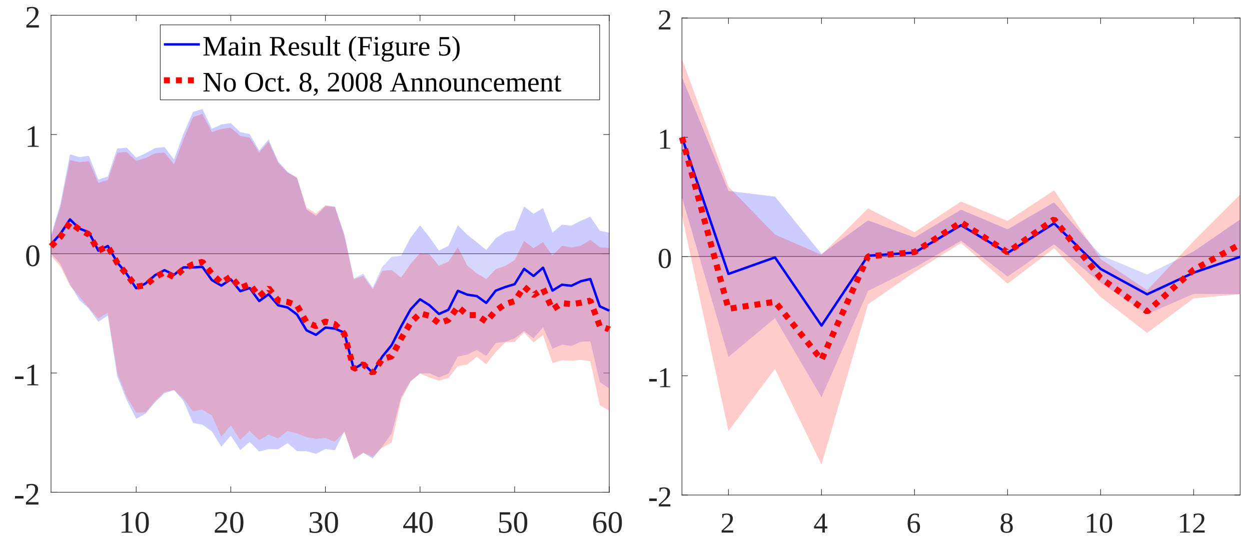
**B.3 SCHEDULED MEETINGS ONLY** Our sample of monetary policy shocks contains one unscheduled announcement on October 8, 2008. Figure 3 shows that the shock observations are quite large in magnitude for this unscheduled announcement. However, figures 19-22 shows that setting this observation to zero for all four of the shock series used has little material affect on impulse responses at either a daily or a monthly frequency.




(a) Daily inflation response to a NS shock

(b) Aggregated (daily to monthly) inflation response

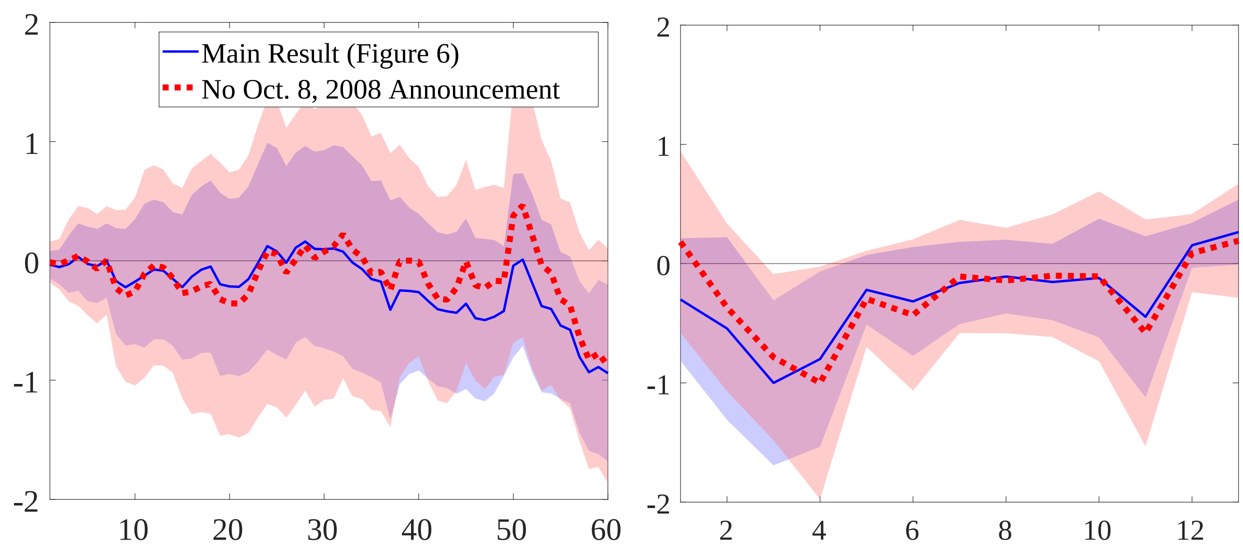
Figure 19: Impulse response of daily inflation (30-day percentage change) to a Nakamura and Steinsson (2018a) shock: aggregated vs disaggregated. For a given month, the aggregated series are the sum of the monetary policy shocks and the average of 30-day percentage change of daily inflation, $BPP_T = \frac{100}{m}\sum_{t=1}^{m}(\log BPP_t - \log BPP_{t-30})$ for days $t = 1,\ldots,m$ of month $T$. 90% error bands.




(a) Daily inflation response to a target shock

(b) Aggregated (daily to monthly) inflation response

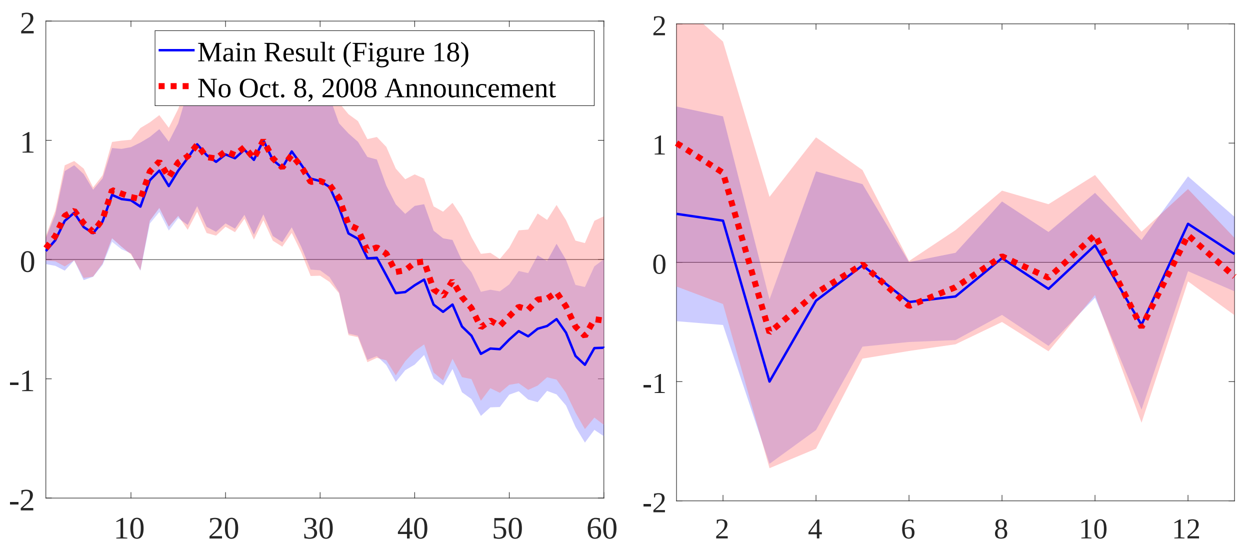
Figure 20: Impulse response of daily inflation (30-day percentage change) to a target shock: aggregated vs disaggregated. For a given month, the aggregated series are the sum of the monetary policy shocks and the average of 30-day percentage change of daily inflation, $BPP_T = \frac{100}{m}\sum_{t=1}^{m}(\log BPP_t - \log BPP_{t-30})$ for days $t = 1, \ldots, m$ of month $T$. 90% error bands.




(a) Daily inflation response to a BRW shock

(b) Aggregated (daily to monthly) inflation response

Figure 21: Impulse response of daily inflation (30-day percentage change) to a 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 percentage change of daily inflation, $BPP_T = \frac{100}{m}\sum_{t=1}^{m}(\log BPP_t - \log BPP_{t-30})$ for days $t = 1, \ldots, m$ of month $T$. 90% error bands.

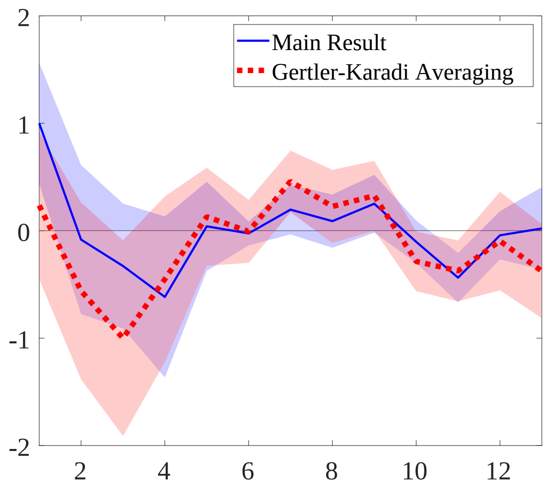



(a) Daily inflation response to a path shock

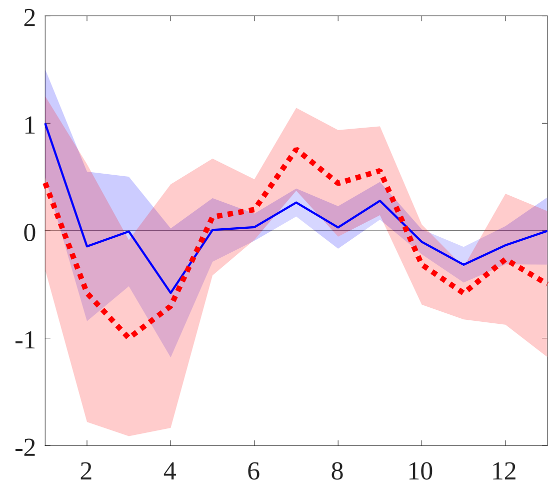
(b) Aggregated (daily to monthly) inflation response

Figure 22: Impulse responses of daily inflation (30-day percentage change) to Gürkaynak et al. (2005) path shock: aggregated vs. disaggregated. For a given month, the aggregate series are the sum of the monetary policy shocks and the average of 30-day percentage change of daily inflation, $BPP_T = \frac{100}{m}\sum_{t=1}^{m}(\log BPP_t - \log BPP_{t-30})$ for days $t = 1,\ldots,m$ of month $T$. Error bands are 90%.

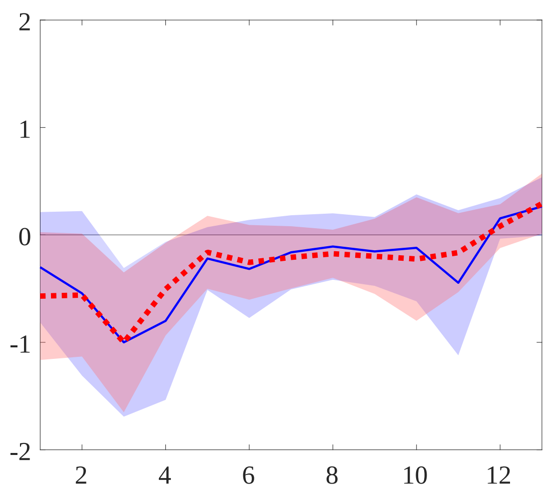
**B.4 GERTLER AND KARADI (2015) AVERAGING OF SHOCK SERIES** Gertler and Karadi (2015) propose controlling for the timing of a monetary policy shock within a month by cumulating the shocks during the previous 31 days for each announcement day and then taking the monthly average of this trailing cumulative sum. Figure 23 shows that the point estimates corresponding to the transformed shocks (dashed red lines) are indeed attenuated over the first three months of the impulse response horizon relative to their counterparts in the main text (solid blue lines). In the case of the NS and target shocks, the initial positive responses are no longer statistically significant from zero and responses at month three are negative and significant.



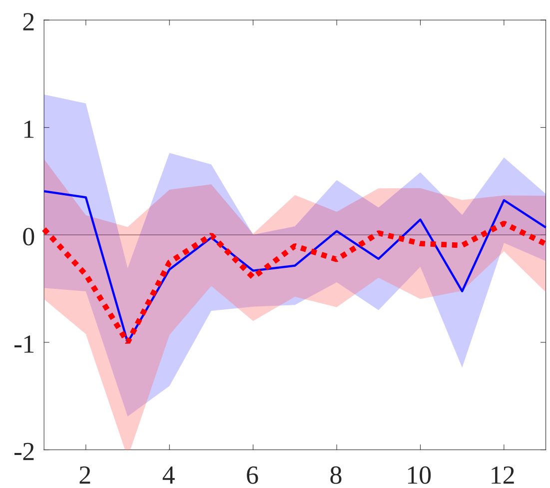

(a) Monthly inflation response to a NS shock



(b) Monthly inflation response to a target shock



(c) Monthly inflation response to a BRW shock



(d) Monthly inflation response to a path shock

Figure 23: Impulse responses of monthly inflation to monetary policy shocks. For a given month, the aggregate series are the sum of the monetary policy shocks and the average of 30-day percentage change of daily inflation, $BPP_T = \frac{100}{m}\sum_{t=1}^{m}(\log BPP_t - \log BPP_{t-30})$ for days $t = 1,\ldots,m$ of month $T$. The shock series in the main results are unadjusted while that have been transformed via Gertler and Karadi (2015) which entails cumulating the shocks to an announcements over the previous 31 days and then taking the monthly average of this trailing cumulative sum. Error bands are 90%.

## C 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 $0.25 \times 0.99^i$, where $i$ is the lag.

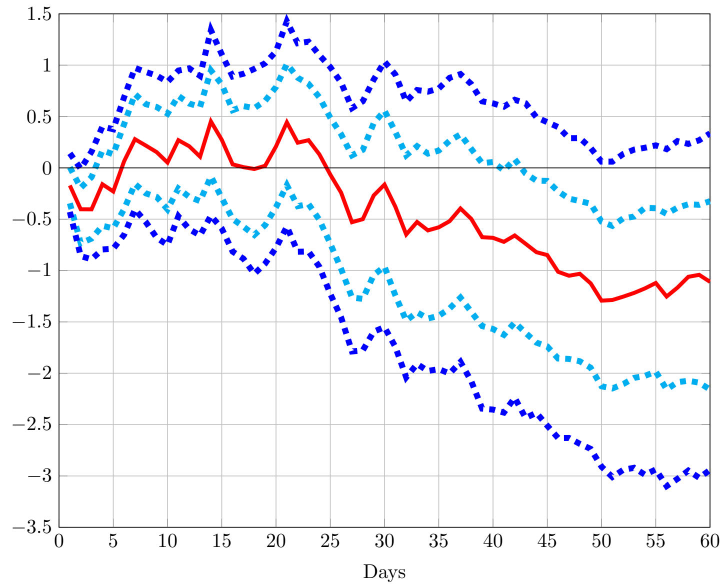



Figure 24: Impulse response of inflation ($\pi_t$) to a one standard deviation Nakamura and Steinsson (2018a) monetary policy shock. Error bands are 68% and 90% posterior bands centered at the median.

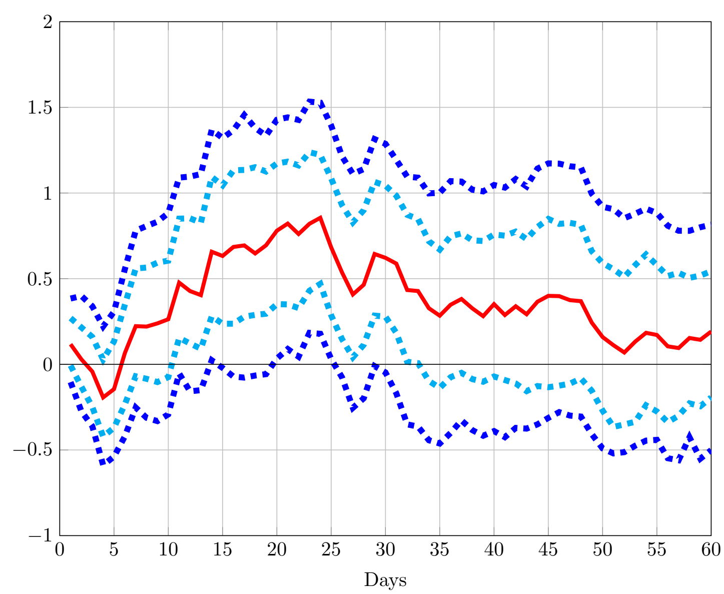



Figure 25: Impulse response of the transitory component of inflation ($g_t$) to a one standard deviation Nakamura and Steinsson (2018a) monetary policy shock. Error bands are 68% and 90% posterior bands centered at the median.

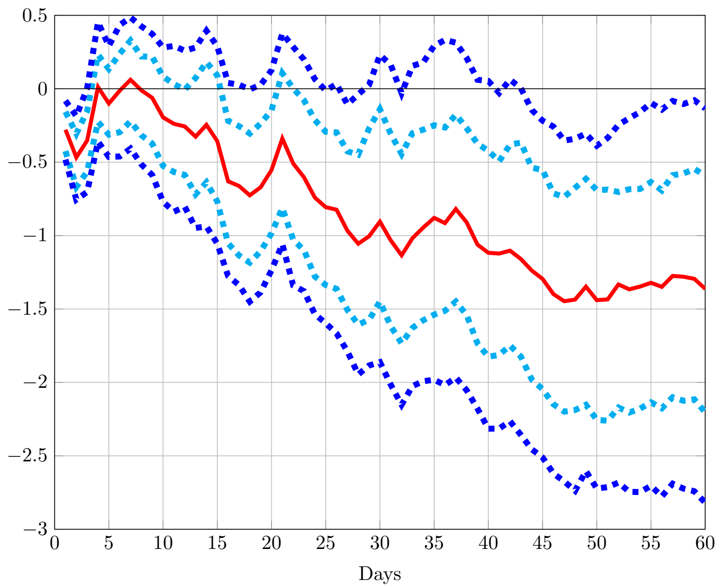



Figure 26: Impulse response of the permanent component of inflation ($\tau_t$) to aNakamura and Steinsson (2018a) monetary policy shock. Error bands are 68% and 90% posterior bands centered at the median.

# D APPENDIX: TEMPORAL AGGREGATION

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

1. *The temporally aggregated inflation series, $\Pi_T$, 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, $\Pi_T$.*

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

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

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

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

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, $\text{Var}(\Pi_T) \to \sigma_\pi^2$ and $\text{Var}(\Pi_T) \in (0, \sigma_\pi^2)$. Further, the parenthetic term in (8) converges to $m$ as $\rho \to 1$, and $\text{Cov}(\Pi_t, \Pi_{t+s}) \to \sigma_\pi^2$.

| | $\pi_t$ | $\pi_{t-1}$ | $\pi_{t-2}$ | $\cdots$ | $\pi_{t-m}$ |
|---|---|---|---|---|---|
| $\pi_t$ | 1 | $\rho$ | $\rho^2$ | $\cdots$ | $\rho^{m-1}$ |
| $\pi_{t-1}$ | $\rho$ | 1 | $\rho$ | $\cdots$ | $\rho^{m-2}$ |
| $\pi_{t-2}$ | $\rho^2$ | $\rho$ | 1 | $\cdots$ | $\rho^{m-3}$ |
| $\vdots$ | | | | | |
| $\pi_{t-m}$ | $\rho^{m-1}$ | $\rho^{m-2}$ | $\rho^{m-3}$ | $\cdots$ | 1 |

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

### D.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 panel 10b.

# E APPENDIX: DATA

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

**OFFICIAL CPI INDEX** Analysis in sections 2.2 use the BLS' seasonally adjusted Consumer Price Index (`FRED: CPIAUCSL`) at a monthly frequency. Results in section 3.4 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.[28] 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 CPI can be obtained via Cavallo and Rigobon (2016) for July 2008 through August 2015.[29] The index is not seasonally adjusted constructed from webscraped prices of multichannel retailers that sell both online and offline.

**BREAKEVEN 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.[30]

**NAKAMURA AND STEINSSON (2018A) MONETARY POLICY SHOCK** High-frequency monetary policy shocks are originally available from 1995 to 2014.[31] 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. The construction of the shock series follows that of Gürkaynak et al. (2005) as described in Nakamura and Steinsson (2018a) and Brennan et al. (2024). The shocks are the first principal component of changes in high-frequency federal funds rate futures and Eurodollar futures:

[28] 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

[29] 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.

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

[31] Series `FFR_shock` from the spreadsheet `PolicyNewsShocksWeb.xlsx` https://eml.berkeley.edu/~jsteinsson/papers/PolicyNewsShocksWeb.xlsx and the code https://eml.berkeley.edu/~jsteinsson/papers/realratesreplication.zip.

$$MP1_s = \begin{cases} \dfrac{D^s}{D^s - d^s}(ff^1_{s,t} - ff^1_{s,t-\Delta t}) & \text{if} \quad D^s - d^s > 7 \\ ff^2_{s,t} - ff^2_{s,t-\Delta t} & \text{otherwise} \end{cases} \tag{14}$$

$$MP2_s = \begin{cases} \dfrac{D^{s'}}{D^{s'} - d^{s'}}\left[(ff^j_{s',t} - ff^j_{s',t-\Delta t}) - \dfrac{d^{s'}}{D^{s'}} MP1_s\right] & \text{if} \quad D^{s'} - d^{s'} > 7 \\ ff^{j+1}_{s',t} - ff^{j+1}_{s',t-\Delta t} & \text{otherwise} \end{cases} \tag{15}$$

$$\Delta ed^2_q = ed^2_{q,t} - ed^2_{q,t-\Delta t} \tag{16}$$

$$\Delta ed^3_q = ed^3_{q,t} - ed^3_{q,t-\Delta t} \tag{17}$$

$$\Delta ed^4_q = ed^4_{q,t} - ed^4_{q,t-\Delta t} \tag{18}$$

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.[32] 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 $ff^j$ denote the duration $j$ of the federal funds futures contract $ff$. For example, $j = 1$ denotes the contract expiring in the current month, $j = 2$ the contract expiring next month, etc. For month $s$, $D^s$ and $d^s$ are the number of total days in the month and the day of the FOMC announcement, respectively. If a monetary policy announcement occurs in the first 23 days of the month, then that month's federal funds future $j = 1$ is used to calculate $MP1_s$. Because the settlement prices are based on the average of the effective overnight federal funds rate in month $s$ rather than the federal funds rate on a specific day, one must correct for time averaging and scale by the inverse of the share of days remaining in the month, $\frac{D^s}{D^s - d^s}$. Otherwise, if the FOMC announcement occurs in the last seven days of the month, next month's future $j = 2$ is used to calculate $MP1_s$.

$MP2_s$ captures the unexpected change in the federal funds futures contracts that expire at the end of month $s'$ which is the month of the next scheduled FOMC meeting. Brennan et al. (2024) show that in practice the next or following month's federal funds future $j = 2, 3$ is used to calculate $MP2_s$.

Because federal funds futures are highly liquid for contracts expiring in the next three months but less liquid for contracts thereafter, researchers use Eurodollar futures to cover the remaining first year of the term structure. Eurodollar futures were listed quarterly and mature in March, June, September, and December. They are an agreement to exchange, on the second London business day before the third

[32] As shown by Brennan et al. (2024), the windows are not always this precise in practice 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.

Wednesday of the last month of the quarter, the price of the contract minus the three-month US dollar BBA LIBOR interest rate. Because the BBA LIBOR interest rate is discontinued, Eurodollar futures ceased trading in April 2023 which does not affect our construction because we only need a series that ends in 2015. 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.

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.

GÜRKAYNAK ET AL. (2005) MONETARY POLICY SHOCKS The target and path shocks of Gürkaynak et al. (2005) are constructed using principal component analysis over the same instrument set of Nakamura and Steinsson (2018a)—expressions (14)-(18). Rather than extracting just the first principal component, Gürkaynak et al. (2005) extract the first two principal components and then rotate these principal components so that the second has no effect on the federal funds rate. The first rotated principal component is called the target shock and is normalized so that it is one-for-one with the federal funds rate. The second is the called path shock which is normalized to be one-for-one with the four-quarter ahead change in the Eurodollar futures ($ed4_s$ in expression (18)) and captures all forward guidance surprises.

BU ET AL. (2021) MONETARY POLICY SHOCK Daily monetary policy shocks are available from 1994 to 2020.[33] We construct this series to include unscheduled announcements in our sample and do so via a Fama and MacBeth (1973) two-step regression that extracts unobserved monetary policy shocks $\Delta i_s$ from the common component of the daily change in zero-coupon yields $\Delta R^j_s$.

1. Estimate the responsiveness of zero-coupon yields $\Delta R^j_s$ with maturities $j = 1, ..., 30$ years to policy indicator $\Delta i_s$ for each monetary policy announcement $s$ via time-series regressions. For maturities $j = 1, ..., 30$ there will be 30 regressions.

$$\begin{aligned}\Delta R^1_s =& \alpha_1 + \beta_1 \Delta i_s + \epsilon^1_s \\ &\vdots \\ \Delta R^{30}_t =& \alpha_{30} + \beta_{30} \Delta i_s + \epsilon^{30}_s\end{aligned}$$

   The implementation assumes $\Delta i_s$ is one-to-one with the daily change in the two-year constant maturity Treasury yield $\Delta R^2_s$. For each maturity $j = 1, ..., 30$, the above expression becomes:

$$\Delta R^j_s = \theta_j + \beta_j \Delta R^2_s + \underbrace{\epsilon^j_s - \beta_j \epsilon^2_s}_{\xi^j_s}$$

   The endogeneity arising from $corr(\Delta R^j_s, \xi^j_s) > 0$ due to $\beta_j \epsilon^2_s$ being a component of $\xi^j_s$ can be reconciled with IV or the heteroskedasticity-based estimator of Rigobon (2003). The time-series regres-

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

sions instrument $\Delta i_s$ with $(-1) \times \Delta i_{s-7}$, the negative change in the chosen policy indicator seven days before FOMC announcement $s$. Using $(-1) \times \Delta i_{s-7}$ as an instrument should cancel out the $\beta_j \epsilon_s^2$ that would exist in any given day without monetary policy news.

2. Estimate monetary policy shock $\Delta \hat{i}_s$ from repeated cross-sectional regressions of $\Delta R_s^j$ on the responsiveness index $\hat{\beta}_j$ for each FOMC announcement $s$ estimated in step 1.

$$\Delta R_s^j = \alpha_j + \Delta i_s \hat{\beta}_j + v_s^j, \quad s = 1, \ldots, T \quad \text{FOMC announcements}$$

3. Re-scale the estimated shock $\Delta \hat{i}_s$ by the assumed normalization in step 1. We follow Bu et al. (2021) and use the daily change in the 2-year Treasury, but our results are robust to scaling by the 1-year to match the scaling of the NS monetary policy shocks.