Finance and Economics Discussion Series

Federal Reserve Board, Washington, D.C.
ISSN 1936-2854 (Print)
ISSN 2767-3898 (Online)

Monetary Policy Shocks: Data or Methods?

Connor M. Brennan, Margaret M. Jacobson, Christian Matthes, Todd B. Walker

2024-011

Please cite this paper as:
Brennan, Connor M., Margaret M. Jacobson, Christian Matthes, and Todd B. Walker (2024). "Monetary Policy Shocks: Data or Methods?," Finance and Economics Discussion Series 2024-011r1. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/FEDS.2024.011r1.

Monetary Policy Shocks: Data or Methods?*

Connor M. Brennan† Margaret M. Jacobson‡ Christian Matthes§ Todd B. Walker¶

October 2024

Abstract

Different series of high-frequency monetary shocks can have a correlation coefficient as low as 0.3 and the same sign in only one half of observations. Both data and methods drive these differences, which are starkest when the federal funds rate is at its effective lower bound. After documenting differences in monetary shock series, we explore their consequence for inference in several specifications. We find that empirical estimates of monetary policy transmission have few qualitative differences. We caution that inference may not be entirely robust to all shock constructions because qualitative differences can emerge when we interchange data and methods.

Keywords: high-frequency monetary policy shocks; monetary policy transmission; empirical monetary economics.
JEL Codes: E52, E58, E31, E32.

*This material reflects the views of the authors and not those of the Federal Reserve Board of Governors. The authors thank Aeimit Lakdawala for an excellent discussion. The authors also thank Miguel Acosta, Ben Johannsen, Ellis Tallman, and audiences at the Federal Reserve Board, Midwest Macro Spring Meetings, the Barcelona Summer Forum, the North American Econometric Society, the Society for Economic Dynamics, and the Wake Forest University Empirical Macro Workshop for helpful comments. Finally the authors thank Miguel Acosta for help extending the Nakamura and Steinsson (2018) shock series, Jenny Tang and Ricardo Nunes for help with the $FF4$ shock series, and John Rogers and Wenbin Wu for help reconstructing their BRW shock series.

†University of Chicago; cmbrennan@uchicago.edu. 5757 S University Ave, Chicago, IL 60637.

‡Federal Reserve Board; Margaret.M.Jacobson@frb.gov. 20th and Constitution; Washington, DC 20551. Corresponding author.

§Department of Economics, Indiana University, matthesc@iu.edu. 100 S Woodlawn Ave; Bloomington, IN 47405.

¶Department of Economics, Indiana University, walkertb@indiana.edu. 100 S Woodlawn Ave; Bloomington, IN 47405

1 Introduction

Because monetary policy simultaneously affects and responds to economic conditions, identifying its exogenous variation is an ongoing challenge. Any instrument that estimates monetary shocks must be orthogonal to economic conditions and control for all available information to isolate unanticipated decisions from anticipated. Since at least Kuttner (2001), high-frequency environments have proven useful to fine-tune information sets to extract market surprises. Asset prices observed minutes before a monetary policy decision presumably contain all available information and hence control for any anticipated decision. Asset prices observed minutes after a monetary policy decision reflect the market reaction to the decision. Because only monetary news is released in the narrow time window surrounding a decision, researchers can presumably isolate monetary surprises from non-monetary news.

Given that various high-frequency monetary shock series are constructed from highly correlated changes in asset prices in similar narrow time windows around the same monetary policy announcements, one could expect the series to have similar magnitudes and signs even if underlying data or statistical methods differ. We find that differences emerge in practice, especially when the federal funds rate is at its effective lower bound (ELB). We ask if data or methods drive these differences in high-frequency monetary shock series for the United States. For researchers studying the transmission of monetary policy to either financial markets or the macroeconomy, differences in monetary shock series could be particularly troubling *if* they lead to differences in estimates of the effect of monetary policy. In practice, we find that differences in monetary shock series affect the magnitudes of point estimates but only affect the sign in certain specifications. This finding is only robust to commonly used monetary policy shock series, as constructions that interchange data and methods—i.e. take the data from one series and use it in the method of another—have different signs of their point estimates.

The first contribution of this paper is to construct and compare commonly used monetary shock series from high-frequency trades so that readers without access to the underlying intraday tick-by-tick data can better understand the differences. Although high-frequency constructs are widely used, limited data availability often precludes construction from scratch [see Nakamura and Steinsson (2018), Acosta (2023), Boehm and Kroner (2023) and Nunes et al. (2023) for notable exceptions]. Among all of the numerous high-frequency series, we focus on six: four that are commonly used—Kuttner (2001), Gertler and Karadi (2015), Nakamura and Steinsson (2018), and Bu et al. (2021)—and two that interchange data and methods. Like Swanson (2023) and Bu et al. (2021), we find that asset prices with longer maturities can be a driver of differences, especially since central bank toolkits expanded beyond the main tool of targeting short-term interest rates in recent decades. In fact, shock series constructed from the shortest and longest maturities of data—Kuttner (2001) and Bu et al. (2021), respectively—are the most different with only a 0.3 correlation coefficient and the same sign for only one half of observations. In their comparison of the forward guidance components of high-frequency monetary policy shocks, Bundick and Smith (2020, Appendix A.4) similarly find low correlations and differences in signs.

The second contribution of this paper is to document that monetary shock series become even more different when the federal funds rate is at its effective lower bound (ELB) due to data. Monetary shock series calculated from asset prices with maturities of a year or less—those of Kuttner (2001), Gertler and

Karadi (2015), and Nakamura and Steinsson (2018)—yield estimates that are relatively smaller in magnitude at the ELB. By contrast, estimates based on asset prices with longer maturities—those of Bu et al. (2021)—yield monetary shocks series that have similar magnitudes in ELB and non-ELB periods. While the federal funds rate affects shorter rates more strongly, forward guidance and LSAPs specifically target longer rates. Therefore, high-frequency monetary shock series constructed from only short-term rates may be less equipped to capture the effects of these newer policy tools.

We note that data on long-term rates are not the only determinant of differences in monetary shock series: methods are also important for capturing the effects of the 21st-century monetary policy toolkit. We show that expanding the methods developed in the 2000s, when the federal funds rate was the primary policy tool, to simply include long-term rates targeted by newer policy tools may be ineffective at exploiting additional information. By contrast, we argue that the Fama-MacBeth regression used by Bu et al. (2021) is effective at exploiting additional information from long-term rates because it relies on the differential responsiveness of short- and long-term rates to monetary policy. Given that long-term rates are less responsive, on average, to monetary policy than short-term rates, methods such as the principal component analysis of Nakamura and Steinsson (2018) that weight by the averages across the sample are less equipped to extract information from long-term rates.

This paper's third contribution is to analyze how differences in data and methods affect estimates of monetary policy transmission. We find that differences affect the sign of estimates of monetary policy transmission in specifications that rely on forecast revisions. By contrast, in some VARs and local projections the signs are similar across shock series while the magnitudes may differ. We only find these similarities for commonly used shock series. Qualitative differences in estimates emerge when we interchange data and methods suggesting that some constructions may result in non-robust inference.

Because many commonly used monetary shock series have been shown to be predictable and hence not entirely exogenous, we carry out several predictability tests standard in the literature and find that only a subset of shock series constructed from short-term asset prices are predictable [see Karnaukh and Vokata (2022), Bauer and Swanson (2022, 2023), Caldara and Herbst (2019), Sastry (2021), Miranda-Agrippino and Ricco (2021)]. However, in our study of monetary policy transmission, we find that the predictable shocks series do not have drastically different impulse responses than those that are unpredictable. While predictability is inherently undesirable, we find that its practical consequences for inference may depend on the specification.

Next, we estimate monetary transmission using the specification of Campbell et al. (2012) and Nakamura and Steinsson (2018) that predicts forecast revisions from monetary policy shock series. This specification yields transmission estimates with signs and magnitudes affected by the choice of monetary shock series. While the monetary shock series of Bu et al. (2021) is the most likely to deliver signs and magnitudes in line with theoretical predictions, the shock series of Kuttner (2001) is the next best. Of all of the shock series studied, these two are some of the simplest to construct in terms of both data and methods but the most different in terms of correlation coefficients and signs. A potential reason for the lack of an opposite-signed response found in the other series despite their differences may be that they are the least likely to contain central bank signals about the future state of the economy, i.e. the so-called

“Fed information effect" or “Fed response to news" channel [Bauer and Swanson (2022)].

Finally, we find that estimates of monetary transmission from local projections and vector autoregressions (VARs) are more similar across shock series than their counterparts estimated via forecast revisions. The daily local projections specification of Jacobson et al. (2022) controls for temporal aggregation by matching the frequency of shocks and response variables, and delivers impulse response functions with a negative sign predicted by theory in the four main shock series studied. Positive responses that contradict theoretical predictions are neither statistically significant nor long-lived. VAR specifications can yield similar findings: impulse response functions vary in magnitude across the four main shock series, but all have signs consistent with theoretical predictions. Accordingly, differences in shock series are less likely to affect transmission estimates in dynamic specifications like VARs relative to more static treatments. Therefore, whether or not differences in commonly used monetary shock series matters for estimates of monetary policy transmission depends on the specification used by the researcher. Qualitative differences in estimates of monetary transmission do emerge when using monetary policy shock series that interchange data and methods, as these tend to be quite different from the commonly used series. As such, we suggest that researchers proceed with caution when varying certain components of shock construction as it could lead to non-robust inference.

1.1 Connection to the Literature

While there are numerous approaches to identifying exogenous variation in monetary policy, we focus on four commonly used high-frequency series and two that interchange data and methods. All six series rely on asset price data that are either at an intraday or a daily frequency and are constructed either directly from raw data or from simple statistical procedures. The data used in construction consist of short-term futures and the full term structure of Treasury yields. Although there are complementary non-high frequency approaches and add-on techniques that further purge high-frequency series from contamination, we focus on four core series to highlight their differences and similarities as simply as possible. In a similar appeal to simplicity, we follow Bauer and Swanson (2022) and focus on shock series that summarize monetary policy in a single series rather than multiple dimensions. As Bauer and Swanson (2022) explain, a single series can often be interpreted as a weighted average of multiple dimension that parsimoniously captures certain aspects of the dimensions.

Complementing our study of the implication of differences within high-frequency monetary policy shock series are those that compare across types of shock series. Rudebusch (1998) compares monetary shock series estimated as a VAR residual [Christiano et al. (1996, 2005)] to high-frequency shock series and finds that these series are quite different. Similarly, Ettmeier and Kriwoluzky (2019) compare the performance of narrative identification achieved by parsing FOMC policy documents for intended changes in the federal funds rate [Romer and Romer (1989), Romer and Romer (2004), Wieland and Yang (2020), Aruoba and Drechsel (2023)] to high-frequency shocks and find differences in inference. Finally, Ramey (2016) also documents differences within and across types of shocks. McKay and Wolf (2023) appeal to Sims's (1998) argument that monetary policy shocks need not necessarily be correlated across different types of identification as they could be capturing different sources of exogenous variation in monetary policy. However, within high-frequency monetary policy shocks, one could expect similarity given that they are constructed from highly correlated asset prices.

Because high-frequency identification explicitly relies on monetary policy announcements, most researchers are limited to starting their sample in 1994 when the Federal Reserve's Federal Open Market Committee (FOMC) began regularly announcing its monetary policy decisions (exceptions include Bauer and Swanson (2022) and Bu et al. (2021)). Other approaches typically extract longer monetary shock series because they are not constrained to explicitly announced FOMC decisions. However, judgment plays a larger role in determining the time and date of a monetary shock in the absence of an explicit announcement. Therefore, relying on explicitly announced decisions may lend to greater reproducibility, as it is straightforward for researchers to look up the date and time of the announcement and calculate a fixed time window around that announcement. See Appendix D for details on FOMC announcement dates and times.

Researchers have focused on refining high-frequency monetary shock series with add-on techniques because estimates of monetary transmission often have signs that are opposite of what theory predicts.[1] By controlling for information mismatches between central banks and private agents, high-frequency monetary shock series and their associated monetary transmission estimates can be purged of this so-called "Fed information effect" [see Miranda-Agrippino and Ricco (2021), Bauer and Swanson (2023, 2022), Jarocinski and Karadi (2020), Nunes et al. (2023), Zhu (2023), and others]. Because there are many solutions to control for potentially endogeneity, we leave our monetary shock series in their simplest form without any additional refinements, permitting more straightforward and transparent comparisons across data and methods.

Because today's monetary policy has many tools in addition to the federal funds rate, researchers have often extracted multi-dimensional high-frequency monetary shock series [Gürkaynak et al. (2005), Lewis (2023), Swanson (2021, 2023), Acosta (2023), Jarociński (2024) and others]. We follow Bauer and Swanson (2022) and focus on single monetary shock series for easier comparisons, especially for exercises that interchange data and methods.[2] Furthermore, a single series allows us to parsimoniously identify the joint effects of monetary policy tools and may combine different dimensions of monetary policy that are not necessarily independent, like those identified by Jarociński (2024).

Although we focus on high-frequency monetary shock series for the United States, the data and methods described in this paper can be extended to other settings. Altavilla et al. (2019), Cieslak and Schrimpf (2019), Andrade and Ferroni (2021), Bu et al. (2021), and others construct shock series for Europe while Braun et al. (2024) and Cieslak and Schrimpf (2019) construct shock series for the United Kingdom. Like us, these researchers start from raw data to highlight the choices faced by researchers and how these choices affect estimates of monetary transmission.

---

[1] Bauer and Swanson (2023) and Jacobson et al. (2022) are notable exceptions that instead explore features of response variables that may explain opposite-signed responses.

[2] Bauer and Swanson (2022) explain, "Rather than focus on two dimensions of monetary policy, as in Gürkaynak et al. (2005), we follow Nakamura and Steinsson (2018) and take just the first principal component of the changes in ED1–ED4 around FOMC announcements... Gürkaynak et al. (2005) showed that FOMC announcements cause surprises about both the current federal funds rate target and the expected path of the federal funds rate for the next several months (i.e., their "target" and "path" factors). Because the first principal component is essentially equal to a weighted average of the target and path factors, it parsimoniously captures some of the main features of both types of monetary policy surprises."

2 SHOCK CONSTRUCTION

We focus on the commonly used high-frequency monetary shock series that rely on tick-level intraday or daily data of the federal funds rate futures, eurodollar futures, and Treasury yields. Some of these series are first-differences of raw or scaled data while others rely on statistical procedures like principal component analysis or Fama-MacBeth regression. Careful assessment necessitates constructing these shock series by selecting suitable trades from tick data so that we can best understand how various components of the underlying assets and statistical methodology contribute to final estimates. Our underlying data closely match those of Acosta (2023) and Acosta et al. (2024) which are similarly constructed from tick data. Compared to the original series available on the authors' websites of Nakamura and Steinsson (2018) and Bu et al. (2021), our series have a 0.99 and a 0.99 correlation, respectively. The correlation is 0.98 and 0.97 for the $MP1$ and $FF4$ series, respectively, available from Gürkaynak et al. (2024) at (http://www.bilkent.edu.tr/~ refet/replication_GKL.zip).

To that end, we first provide a brief description of the financial assets used in the shock construction with notation: superscripts j are the duration of an asset; subscripts s and q are the month and quarter, respectively, of an FOMC announcement; and subscripts t are the time of measurement with Δt the duration of time between measurements. All intraday data is from CME Group Inc. DataMine (https://datamine.cmegroup.com/) at the Federal Reserve Board which is available starting in 1995. Although it may be possible to construct monetary policy shock series back to 1994 or 1988 with other data sources, we prefer to truncate our data sample than merge it with data we are unable to replicate and verify on a trade-by-trade basis.

Our January 1995 to September 2024 sample includes 244 FOMC announcements, 7 of which are unscheduled. We drop intermeeting announcements that are notational votes or about topics not directly related to monetary policy actions such as: swap lines, financial crisis facilities, the debt ceiling, the monetary policy framework review, foreign economic crises, the outbreak of war in Iraq, or swap lines. We drop the announcements following 9/11 (as is common in the literature) and drop the March 15, 2020 announcement that occurred on a Sunday which precludes the availability of trades.

Federal Funds Futures are futures contracts traded on the Chicago Mercantile Exchange since 1988. The contract index, following International Monetary Market (IMM) convention, is priced as $ff^j = 100 - R$, where R is the arithmetic average of the daily effective federal funds rates during the contract month j for $j > 0$. For example, a price quote of 95.75 is equivalent to an average daily rate of 4.25 over the course of the month in which the contract matures. See Appendix A.1 for additional contract details.

As documented by Barakchian and Crowe (2013), the federal funds futures market is highly liquid for contracts expiring in the next three months and less liquid for contracts expiring in several years. Because the federal funds rate futures are more liquid at shorter horizons, only horizons up to three months ahead are typically used in the construction of monetary shock series. Trading volume was relatively low during ELB episodes, but has roughly tripled from 2014 as shown in Appendix Figure (A.11).

Following the literature, we measure the change in federal funds rate futures around monetary policy announcements in month s and time t as $\Delta ff_s^j = ff_{s,t}^j - ff_{s,t-\Delta t}^j$ where Δt measures the length of the high-frequency window and j is the duration of the futures contract. For example, if s = March 2014 then $j = 1$ is the contract that expires March 31 2014, $j = 2$ expires April 30 2014, and so on. In the shock series studied below, as in the literature, we only examine $j = 1,2,3,4$. We discuss the length of the high-frequency window in more detail below.

Eurodollar Futures were quarterly futures contracts traded on the Chicago Mercantile Exchange from 1981 to April of 2023. Eurodollars is a generic term to describe U.S. dollar-denominated deposits at foreign banks or at the overseas branches of American banks that are outside of the purview of the U.S. financial regulatory framework. Prior to their discontinuation in April of 2023, Eurodollar futures had a payout at expiration based on the three-month maturity U.S. dollar London Inter-Bank Offer Rate (LIBOR). See Appendix A.1 for additional contract details.

Eurodollar futures were one of the most actively traded futures contracts in the world as measured by open interest. The extended duration of the contract, relative to fed funds futures, is the primary benefit of using eurodollar futures to identify exogenous variation in monetary policy. The duration at which the fed funds futures market liquidity begins to dry up is where eurodollar futures were most heavily traded. Gürkaynak et al. (2007) confirm that the combination of federal funds and eurodollar futures are the best financial instruments to predict changes in the federal funds rate one year ahead.

SOFR Futures based on the Secured Overnight Financing Rate (SOFR) have successfully replaced eurodollar futures on the Chicago Mercantile Exchange. The SOFR rate is based on the cost to borrow USD overnight using Treasury securities as collateral. Because SOFR futures are designed to replace eurodollar futures, they can be spliced into shock construction when they are available. Acosta et al. (2024) recommend January 2022 as a start date for SOFR futures, but also note that the choice of start date has little effect on the construction of final estimates.

We measure the change in eurodollar/SOFR futures around monetary policy announcement in quarter q at time t as: $\Delta ED_q^j = ED_{q,t}^j - ED_{q,t-\Delta t}^j$, where $j = 2,\ldots,4$ represent the 2nd, 3rd, and 4th expiring eurodollar contracts, i.e. six-, nine-, and 12-months ahead. The corresponding contracts for SOFR futures are the 3rd, 4th, and 5th expiring contracts, $\Delta SF_q^j = SF_{q,t}^j - SF_{q,t-\Delta t}^j$ for $j = 3,...,5$.[3] As before, the length of the high-frequency window, Δt, is such that t indicates the time after the FOMC announcement and $t - \Delta t$ the time before.

US Treasury securities have maturities of one to 30 years and are so well known that they do not require a thorough description. Because Hansen et al. (2019) and Hanson and Stein (2015) document that Treasuries react to monetary policy announcements with varying degrees of responsiveness depending on the maturity, Treasuries are well suited to capture monetary surprises. Bu et al. (2021) use the daily change in zero-coupon Treasury yields to construct a high-frequency monetary shock series. The zero-coupon yields, as calculated by Gürkaynak et al. (2007) (https://www.federalreserve.gov/pubs/feds/2006/200628/200628abs.html), harmonize Treasury yields

[3]While eurodollar futures were based on expected interest rates over three months after the settlement date, SOFR futures are based on interest rates over the three months before. As a result, the first-outstanding Eurodollar future and the second-outstanding SOFR future are called the $q+1$ contract. Eurodollar and SOFR futures are named based on the quarter of their interest rate exposure, they can be matched based on their contract names. Alternatively, one can match the nth-outstanding SOFR contract with the (n-1)st-outstanding eurodollar contract.

of various maturities to reflect what the discount would be if interest payments were not made until maturity. We measure the change in Treasury yields around each monetary policy announcement s as $\Delta R_s^j = R_{s,t}^j - R_{s,t-\Delta t}^j$ where $j = 1,\ldots 30$ represents yields of maturities ranging from one to 30 years. The length of the window is Δt and t is the time after the FOMC announcement and $t-\Delta t$ the time before.

2.1 KUTTNER (2001), *MP1*

Kuttner (2001) was one of the first to rely on the federal funds futures market to disentangle anticipated from unanticipated changes to the federal funds rate. For FOMC announcement in month s, Kuttner (2001) uses the scaled change in the current month federal funds futures ($j = 1$) unless the monetary policy announcement is in the final seven days of the month, then he uses the unscaled next month federal funds futures ($j = 2$). Label this instrument as $MP1$ and in month s we have,

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

D^s is the number of days in month s and d^s is the day of the FOMC announcement. Kuttner (2001) notes that because the settlement prices of the federal funds futures 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 the time averaging and scale by the inverse of the share of days remaining in the month after an FOMC announcement occurs. For this reason, Δff_s^1 is scaled by $\frac{D^s}{D^s-d^s}$. Kuttner's (2001) original specification differed three ways from this paper: 1) he used a daily window so that $t-\Delta t$ was the market close the day before an announcement and t was the close on the announcement day, 2) he switched to the one-month ahead future if the FOMC announcement was in the final three days of the month, and 3) he included FOMC decisions back to the 1970s. In this paper we use the more popular 1) narrow 30-minute time window put forth by Gürkaynak et al. (2005) where $t-\Delta t$ indexes the 10 minutes before and FOMC announcement and t indexes 20 minutes after, 2) seven day threshold for the switch to the next month's future, and 3) a sample that starts after the introduction of announcements of FOMC decisions in February of 1994.[4]

Panels (4a) and (5a) show the *MP1* shock series from January 1995 to September 2024. Although the *MP1* shock series has some of the largest negative shocks in our sample, it is close to zero throughout both ELB periods. When the federal funds rate is at the ELB—as it was from December 16, 2008 to December 16, 2015 and again from March 15, 2020 to March 16, 2022—the FOMC has used date- or threshold-based forward guidance to communicate expected liftoff [see Carlstrom and Jacobson (2013) for an overview]. An expected liftoff date far into the future or macroeconomic indicators far from their policy thresholds has resulted in market participants perceiving a change in the federal funds rate as unlikely at the upcoming meeting. As a result, there may be either little trading in federal funds futures contracts expiring in the current or next month, or no monetary news that surprises markets. For exam-

[4] Gürkaynak et al. (2005) advocate using an intraday frequency because a daily frequency may not be able to purge monetary news from its non-monetary policy counterpart on days when there are both economic data releases and FOMC announcements. Nakamura and Steinsson (2018) detect substantial background noise that can bias inference when using daily instead of intraday data. Furthermore, because federal funds futures contain low-frequency risk premia, high-frequency changes can essentially remove this potentially confounding element, as shown by Piazzesi and Swanson (2008).

ple, panel 3 of table (2) shows that about 40 percent of ELB observations are 0 for the $MP1$ shock series. Moreover, the magnitudes of these shocks at the ELB are at a maximum of about five basis points.

With estimates of the $MP1$ shock series close to zero in the ELB periods, estimates of monetary transmission may be quite small or imprecise, leading researchers to conclude that there is no effect of monetary policy on the economy, as shown in Appendix figure (B.18). These findings could be potentially problematic because other evidence such as the work by Swanson and Williams (2014) finds that monetary policy can have an effect at the ELB, just through longer horizons than the very short horizons used to calculate the $MP1$ shock series.

In light of these shortcomings, the $MP1$ shock series has the advantage of reducing bias from either the so-called “Fed information effect" or Fed forward guidance, as noted by Paul (2020). Because either of these features could be operating in the opposite direction of direct changes in the federal funds rate, researchers concerned about contamination may find the $MP1$ shock series appealing.

2.2 NAKAMURA & STEINSSON (2018), *NS*

Nakamura and Steinsson (2018) use the first principal component of the financial instruments employed by Gürkaynak et al. (2005) (*MP1*, *MP2*, *ED2*, *ED3*, *ED4*) to identify exogenous variation in monetary policy. To exploit information beyond the immediate horizon, Gürkaynak et al. (2005) build off Kuttner's (2001) work by creating composite measures of changes in interest rate futures that span the first year of the term structure. They include Kuttner's current-month surprise $MP1$ along with the surprise for the next FOMC meeting $MP2$ and Eurodollar futures (*ED2*, *ED3*, *ED4*) which we update with SOFR futures ($SF3$, $SF4$, $SF5$) starting in January 2022. As before, t index the 20 minutes after an FOMC announcement and $t-\Delta t$ 10 minutes before, resulting in a 30-minute time window.[5]

Specifically, the five Gürkaynak et al. (2005)/Nakamura and Steinsson (2018) futures—along with their SOFR futures counterparts—are:

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

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

$$\Delta ED^2_q / SF^3_q = \begin{cases} ED^2_{q,t} - ED^2_{q,t-\Delta t} & \text{if} \quad q < 2022:Q1 \\ SR^3_{q,t} - SR^3_{q,t-\Delta t} & \text{otherwise} \end{cases} \tag{3}$$

$$\Delta ED^3_q / SF^4_q = \begin{cases} ED^3_{q,t} - ED^3_{q,t-\Delta t} & \text{if} \quad q < 2022:Q1 \\ SR^4_{q,t} - SR^4_{q,t-\Delta t} & \text{otherwise} \end{cases} \tag{4}$$

$$\Delta ED^4_q / SF^5_q = \begin{cases} ED^4_{q,t} - ED^4_{q,t-\Delta t} & \text{if} \quad q < 2022:Q1 \\ SR^5_{q,t} - SR^5_{q,t-\Delta t} & \text{otherwise} \end{cases} \tag{5}$$

[5] Appendix A.2 shows that time windows are often larger than 30 minutes due to a lack of suitable trades exactly 10 minutes before an FOMC announcement and 20 minutes after. In practice, we find that the lack of time window uniformity has little material effect on shock construction.

Where $MP1$ is as before and captures the unexpected change in the federal funds futures contracts expiring at the end of the month s of an FOMC announcement. $MP2$ captures the unexpected change in federal funds futures that expire at the end of the month s' which is the month of the next scheduled FOMC meeting.[6] For example, let s =March 2014 then s'=April 2014. The next scheduled FOMC meeting may be in the next month or up to two months after the current announcement, as shown by column 1 of table (1). Column 2 shows that the futures used to calculate $MP2$ may be as far as three months after the current announcement because of the convention of using the following month's future when an FOMC announcement is in the final seven days of a month. Overall, the table shows that most of the meetings used to calculate $MP2$ are either one- or two-months ahead such that $j = 2, 3$. As noted previously, limited trading in federal funds futures at horizons beyond four months has led researchers to rely on eurodollar futures to capture the remaining horizons of the first year of the term structure. Because eurodollars/SOFR futures are quarterly, q indexes the quarter of the current FOMC announcement. For example, if q=2014:Q1, $ED2/SF3$, $ED3/SF4$, and $ED4/SF5$ in equations (3)-(5) represent contracts expiring in 2014:Q2, 2014:Q3, and 2014:Q4, respectively.

		Next scheduled FOMC announcement			
		(1)		(2)	
Future		Percent	Number	Percent $MP2$	Number $MP2$
$FF1$	in current month	1%	3	0%	0
$FF2$	1-month ahead	50%	122	22%	53
$FF3$	2-months ahead	49%	119	76%	185
$FF4$	3-months ahead	0%	0	2%	6
Total			244		244

Table 1: Months ahead of the next scheduled FOMC meeting.

Note: The next scheduled FOMC meeting occurs in the current month when an unscheduled meeting occurs before a scheduled meeting as happened in January 2008 when there was an unscheduled conference call on January 21st that announced an interest rate cut and a scheduled announcement on January 30, 2008. 1-month ahead implies that the next scheduled meeting is the month following that of the current FOMC meeting and 2-months ahead implies two months, etc. The futures used in $MP2$ (column 2) may differ from those in column 1 because the future for the month following that of the next scheduled FOMC announcement is used when that announcement is scheduled in the final seven days of the month. For example, the announcement following the March 18, 2015 announcement is on April 29, 2015. Because April 29 is in the last seven days of April, $FF3$ instead of $FF2$ would be used to represent the next month's FOMC announcement. The sample is from January 1995 to September 2024.

Whether or not monetary policy has multiple dimensions or can be summarized by a single series is debated. Gürkaynak et al. (2005) extract and rotate two factors—the target and path—from the instrument set {*MP1*, *MP2*, *ED2*, *ED3*, *ED4*}. These factors correspond to the level and slope of the yield curve for one year ahead interest rates and explain 80 and 15 percent of the variation, respectively. Gürkaynak et al.'s (2005) multiple factors with suitable rotations can identify the independent effects of each monetary policy tool which may be useful for researchers studying the effects of forward guidance, or other policy tools, separate from that of the federal funds rate [see Gürkaynak et al. (2005), Jarociński (2024),

[6] Gürkaynak et al. (2005) explain that the equation for the futures at the next scheduled FOMC meeting s' can be written as, $ff^{j}_{s',t} = \frac{d^{s'}}{D^{s'}}\mathbb{E}_t[r_s] + \frac{D^{s'}-d^{s'}}{D^{s'}}\mathbb{E}_t[r_{s'}] + \rho 2_t$ where r_s is the expected Federal Funds rate the current FOMC meeting and s' is for the next scheduled FOMC meeting and $\rho 2$ is any risk premium. Differencing this equation by $t - \Delta t$ yields the expression in (2).

Swanson (2021, 2023) and Acosta (2023) for additional multi-dimensional examples].

By contrast Nakamura and Steinsson (2018) use a single factor from the same instrument set (*MP1*, *MP2*, *ED2*, *ED3*, *ED4*) which can parsimoniously capture the joint effects of different policy tools, which is more advantageous when estimating monetary transmission in more complicated frameworks. We follow the approach of Nakamura and Steinsson (2018), which is also used by Bauer and Swanson (2022), and focus on the single series to simplify the comparison of shocks and interchanging exercises.

The first principal component of the Gürkaynak et al. (2005)/Nakamura and Steinsson (2018) instrument set updated with SOFR futures ($MP1$, $MP2$, $ED2/SF3$, $ED3/SF4$, $ED4/SF5$) explains about 80 percent of the variation. The estimated loadings are relatively equal which likely stems from all futures in the instrument set having maturities of less than a year and moving in lock-step. Otherwise, one could expect a particular instrument to be associated with a higher loading if its movements were typically outliers relative to the others.

A final step in the construction of the *NS* shock series consists of re-scaling the first principal component of equations (1)-(5) into interpretable units. Unlike the *MP1* shock series that is simply a percentage point surprise in the federal funds rate, a principal component is not so straightforward. Following Nakamura and Steinsson (2018), we use the fitted value from the regression of the daily change in the one-year zero-coupon Treasury yield on the first principal component.[7] The coefficients from this regression are quite small with a value of about 0.02 for the slope and zero for the constant.

With a 0.8 correlation coefficient, the Nakamura and Steinsson (2018) shock series is similar to the $MP1$ shock series, as shown in panels (4b) and (5b). Like the $MP1$ shock series, the NS shock series is tightly distributed around zero throughout the ELB periods. In contrast to the $MP1$ shock series where most ELB observations were 0, 78 percent of the NS shock series observations are positive at the ELB, as shown in panel 2 of table (2). The principal component analysis used to calculate the NS shock series can explain this difference. At the ELB, the federal funds rate target range is 0 to 25 basis points with a lower limit of zero. The average effective federal funds rate is near the midpoint of this range or below.[8] Therefore, the maximum downward surprise at the ELB is about 12.5 basis while upside surprises are not censored to the same degree.[9] Because principal component analysis is a linear combination of the underlying instrument set, and this instrument set is left-censored, it is not surprising that there is a rightward shift from zero observed in the distribution of the NS shock series at the ELB.

Given that the Federal Reserve has deployed record monetary stimulus at the ELB, what is the interpretation of the 78 percent positive observations of the NS shock series? One could interpret unantici-

[7] See Appendix figure (A.16a) for comparisons of the NS shock series under different scaling assumptions. Because the shock series have a correlation coefficient close to one, transmission estimates are largely unaffected by scaling choice. Appendix figure (A.14a) shows that the correlation coefficient between the NS series and version constructed from real-time estimates is also near perfect.

[8] In contrast to other central banks that have had a negative policy rate, it is unclear if it would be legal for the federal funds rate to be negative. Former Fed Chair Janet Yellen explained in her 2016 Congressional testimony that, "I would say that [a negative federal funds rate] remains a question that we still would need to investigate more thoroughly." See https://www.govinfo.gov/content/pkg/CHRG-114hhrg23566/html/CHRG-114hhrg23566.htm.

[9] Because it may be optimal for central banks to smooth interest rate increases to safeguard financial stability, upside surprises are not indefinitely large. See a October 14, 2024 speech by Federal Reserve Governor Christopher J. Waller https://www.federalreserve.gov/newsevents/speech/waller20241014a.htm.

pated contractionary monetary news as markets expecting a larger stimulus than what was announced or implemented. Vissing-Jorgensen and Krishnamurthy (2011) note that the LSAP program known as "QE II" announced on November 3, 2010 was about $150 billion less than market expectations. However, it is unlikely that markets expected a larger stimulus in nearly four out of five announcements.

2.3 GERTLER & KARADI (2015), *FF4* Gertler and Karadi (2015) find that the three-month ahead federal funds futures, $FF4$, perform strongly as an external instrument in VAR analysis over the January 1991 to June 2012 period. As before, t index the 20 minutes after an FOMC announcement and $t-\Delta t$ 10 minutes before, resulting in a 30-minute time window.

$$\Delta ff_s^4 = ff_{s,t}^4 - ff_{s,t-\Delta t}^4 \tag{6}$$

For example, if the month s of an FOMC meeting is March 2014, *FF4* is the expected federal funds rate at the end of June 2014. In contrast to the construction of the $MP1$ and NS shock series, Gertler and Karadi (2015) do not scale the $FF4$ shock series by $D^s/(D^s - d^s)$. Because they use the $FF4$ shock series as an external instrument in a monthly VAR, they instead use a moving average representation.[10] We report the unscaled version of the $FF4$ shock series because the scaled version has been shown by Ramey (2016) and Miranda-Agrippino and Ricco (2021) to induce predictability and serial correlation.

Because the three-month ahead horizon of $FF4$ covers the next scheduled FOMC announcement as shown by table (1), the $FF4$ shock series can be interpreted as capturing the effects of both federal funds rate decisions and forward guidance in a single instrument. Figure (1) shows how $FF4$ covers the next FOMC announcement and can cover up to three FOMC announcements which is the case about 10 percent of the time. Furthermore, table (1) shows that $FF4$ is occasionally used in the calculation of $MP2$ and therefore contained in the NS instrument set.

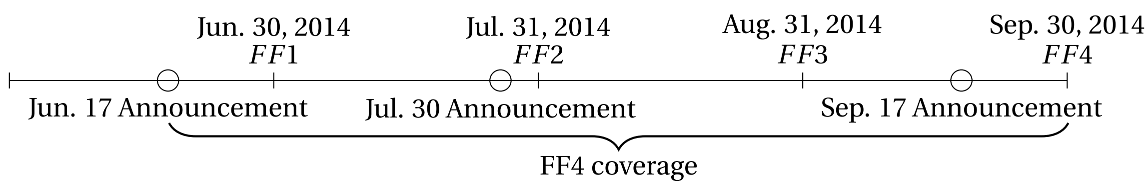


Figure 1: Timing of futures and FOMC announcements

Panels (4c) and (5c) show that the $FF4$ shock series is similar to the $MP1$ and NS shock series. Although the distribution of the $FF4$ shock series similarly narrows at the ELB, it is more centered at zero than the NS shock series. In fact, panel 3 of table (2) shows that 45 percent of the $FF4$ shock observations are zero at the ELB and another 27 percent are positive, which is much less than the 78 percent positive observations of the NS shock. Even though the $FF4$ shock series avoids suggesting more contractionary

[10] In footnote 11 they explain, “First, for each day of the month, we cumulate the surprises on any FOMC days during the last 31 days (e.g., on February 15, we cumulate all the FOMC day surprises since January 15), and, second, we average these monthly surprises across each day of the month. Or, equivalently, we can first create a cumulative daily surprise series by cumulating all FOMC day surprises (similarly as was done by Romer and Romer (2004) and Barakchian and Crowe (2013)), then, second, we can take monthly averages of these series, and, third, obtain monthly average surprises as the first difference of this series."

monetary news than expected in a time of record stimulus, the preponderance of zero observations at the ELB suggests that $FF4$ may still struggle to capture monetary policy actions at the ELB.

Panel 1 of table (2) shows that the previously discussed shock series—*MP1*, *NS*, *FF4*—are tightly correlated with correlation coefficients ranging from about 0.8 to above 0.9. This tight correlation is not surprising given that they are all calculated over the same high-frequency intervals and rely on futures with maturities of year or less. Moreover, sometimes these series even use the same underlying data, which is especially true for $MP1$ in the NS instrument set.

2.4 BU, ROGERS, & WU (2021), *BRW* Bu et al. (2021) note the following two shortcomings of the previously discussed high-frequency monetary shock series constructed from futures with maturities of one year or less. First, obtaining futures data at an intraday frequency can be difficult and second, shorter maturities may be less suited to capturing policies deployed at the ELB to affect longer maturity assets.

By constructing monetary shock series from changes in daily Treasuries yields that span the full one- to 30-year term structure, Bu et al. (2021) overcome these challenges.[11] While intraday data assure the crispest separation of monetary news from its non-monetary counterpart, daily data like that originally used by Kuttner (2001) may only be problematic on all but a few FOMC meetings as explained by Gürkaynak et al. (2005). However, because Nakamura and Steinsson (2018) find that changes in long-term interest rates can be confounded by background noise when used at daily frequency, Bu et al. (2021) use a Rigobon (2003) heteroskedasticity-based estimator in shock construction to avoid overstating statistical precision. Finally, we note that daily data have the advantage of uniform time windows throughout the sample. Appendix A.2 shows that intraday time windows bracketing FOMC announcements can often be larger than 30 minutes when there is a shortage of suitable trades.

Not only is the BRW shock series constructed from different underlying data, it also relies on a different method than the three shock series previously discussed. The Fama and MacBeth (1973) two-step regression extracts unobserved monetary policy shocks Δi_s from the common component of the change in zero-coupon yields ΔR_s^j. The first step estimates the average responsiveness of each maturity $j = 1,...,30$ on days of FOMC announcements s. The second step obtains repeated cross-sectional estimates for each FOMC announcement by regressing the daily change in maturities one to 30 onto the first step's average responsiveness coefficients for maturities one to 30. The resulting second step coefficients are the BRW monetary shock series. Note the slight change in notation in that regression coefficients will have maturity j as a subscript instead of a superscript.

1. Estimate responsiveness of zero-coupon yields ΔR_s^j with maturities $j = 1,\ldots,J$ to policy indicator Δi_s for monetary policy announcement s via time-series regressions. For maturities $j = 1,\ldots 30$ years there will be 30 regressions.

[11] Series `BRW_fomc` of spreadsheet `brw-shock-series.csv` (https://www.federalreserve.gov/econres/feds/files/brw-shock-series.csv). The zero-coupon Treasury yields are those calculated by Gürkaynak et al. (2007) (https://www.federalreserve.gov/pubs/feds/2006/200628/200628abs.html)

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

This implementation assumes Δi_s is one-to-one with a particular tenure of interest rate. Bu et al. (2021) choose the 2-year constant maturity Treasury yield ΔR_s^2. For each maturity $j = 1, \ldots J$, the above expression can be written as:

$$
\Delta R_s^j = \theta_j + \beta_j \Delta R_s^2 + \underbrace{\epsilon_s^j - \beta_j \epsilon_s^2}_{\xi_s^j} \tag{7}
$$

The endogeneity arising from $\text{corr}(\Delta R_s^j, \xi_s^j) > 0$ stems from $\beta_j \epsilon_s^2$ being part of ξ_s^j and can be reconciled with IV or the heteroskedasticity-based estimator of Rigobon (2003). The time-series regressions instrument Δi_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.

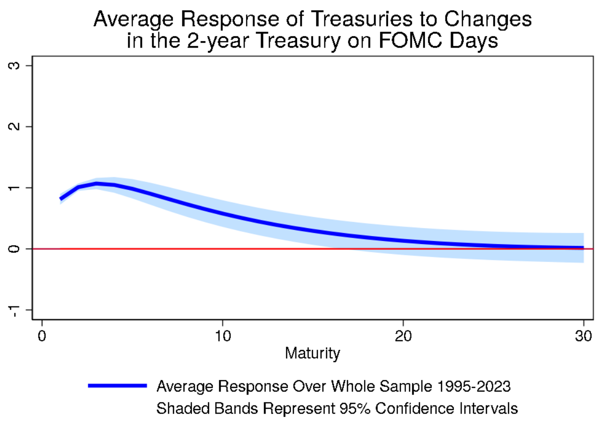
2. Recover monetary policy shock $\Delta \hat{i}_s$ from $s = 1, \ldots, T$ repeated cross-sectional regressions of ΔR_s^j on the responsiveness index $\hat{\beta}_j$ for each FOMC announcement s estimated in step 1.

$$
\Delta R_s^j = \alpha_j + \Delta i_s \hat{\beta}_j + v_s^j, \quad s = 1, \ldots, T \quad \text{FOMC announcements} \tag{8}
$$

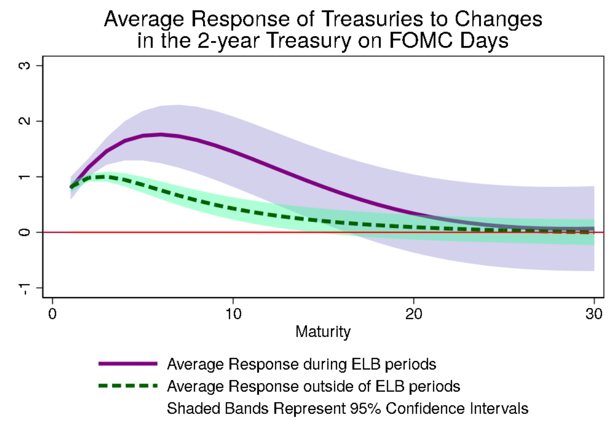
3. Re-scale the shock series by the assumed normalization in step 1, i.e. the daily change in the 2-year constant maturity ΔR_s^2 Treasury yield in the original formulation.

In contrast to the other high-frequency monetary shock series previously described, panels (4d) and (5d) show that the distribution of the *BRW* shock series is similar across ELB and non-ELB periods. Furthermore, panel 3 of table (2) shows that shock estimates are never zero throughout the ELB period and about 66 percent are negative and hence expansionary in periods of record monetary stimulus. The largest negative observations occurred when the Federal Reserve extended or announced LSAP programs in March 2009 and March 2020, respectively.

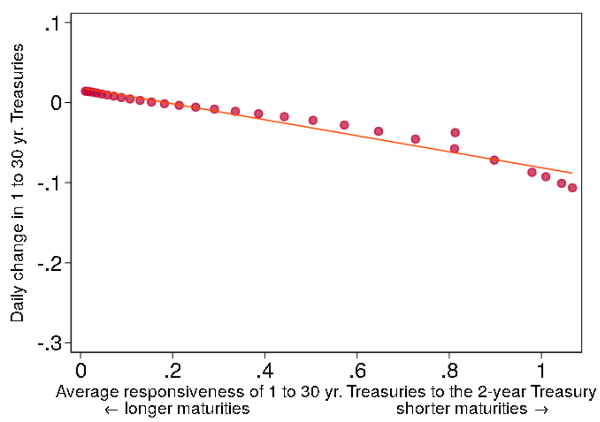
Because forward guidance and LSAPs affect maturities longer than the one-year horizon of the *NS* instrument set, shocks constructed from data with maturities up to 30 years should intuitively better capture the effects of these policies. However, including data on longer maturities may be insufficient as these data may be unresponsive to monetary policy on average. Figure (2a) shows the responsiveness coefficients from the first step of the Fama-MacBeth regression given by equation (7). On average, Treasuries with relatively shorter maturities are more responsive to changes in the two-year Treasury on FOMC announcement days. In fact, Treasuries with maturities beyond 15 years do not have a statistically significant average responsiveness. For this reason, simply including longer term rates in the *NS* instrument set via principal component analysis does not materially change the final series as shown in Appendix A.4. In fact, augmenting the NS instrument set with one-, five-, ten- and 30-year intraday Treasury yields results in a shock series that has a 0.95 percent correlation coefficient with the original NS series. We note that this correlation coefficient is higher than quite a few of the other series studied in this paper.



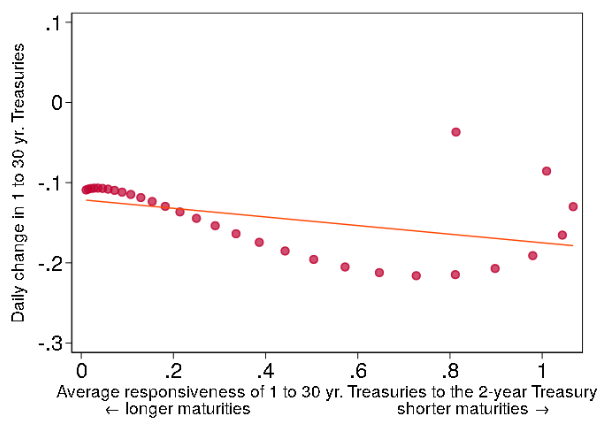
(a) Average responsiveness of the BRW data to 2-year Treasuries, full sample



(b) Average responsiveness of the BRW data to 2-year Treasuries, ELB and non-ELB samples



(c) Second-step Fama-MacBeth for Mar. 16, 2016, $\Delta\hat{i} = -0.08$



(d) Second-step Fama-MacBeth for Aug. 9, 2011, $\Delta\hat{i} = -0.05$

Figure 2: Construction of the Bu et al. (2021) shock series.

Panels (a) and (b) show estimates $\{\hat{\beta}_j\}_{j=1}^{30}$ from equation (7), $\Delta R_s^j = \theta_j + \beta_j \Delta R_s^2 + \xi_s^j$ for maturities $j = 1, \ldots, 30$ years are obtained by regressing daily changes in zero-coupon Treasury yields from maturities $j = 1, \ldots, 30$ on the daily change in the constant maturity two-year Treasury. Estimates are obtained via OLS with robust standard errors. Because response variables are zero-coupon and the independent variable is constant maturity, the coefficient $\hat{\beta}_2$ for the two-year will be close to one, but not exactly. The effective lower bound of the federal funds rate (ELB) is defined as defined as December 16, 2008 to December 16, 2015 and March 15, 2020 to March 16, 2022. Panels (c) and (d) show the second step of the BRW Fama-MacBeth regression in equation (8), $\Delta R_s^j = \alpha_j + \Delta i_s \hat{\beta}_j + \upsilon_s^j$ where s =March 16, 2016 and August 9, 2011, respectively. The x-axis in panels (c) and (d) is $\{\hat{\beta}_j\}_{j=1}^{30}$, the coefficient estimates from the first-step in equation (7) for one- to 30-year maturities plotted in panels (a) and (b). $\hat{\beta}_j$ close to 1 are short-term yields and $\hat{\beta}_j$ close 0 are long-term yields. The y-axis in panels (c) and (d) is the daily change in zero-coupon Treasury yields $\{\Delta R_s^j\}_{j=1}^{30}$ for maturities $j = 1, \ldots, 30$ years. The estimated linear fit $\Delta\hat{i}_s$ is the monetary shock. The sample is from January 1995 to September 2024.

If long-term data alone cannot account for the differences in monetary shock series, what is the role of methods? In contrast to principal component analysis, Fama-MacBeth regression allows for the weights on underlying instruments to be time varying so that long-term rates may matter more than short-term for certain announcements and the opposite for others. By relying on the differential responsiveness of short- and long-term Treasuries, the Fama-MacBeth regression can therefore exploit information from long-term rates despite their overall average low responsiveness shown in panel (2a). The second step of the method projects the change in Treasuries for each maturity on the day of an FOMC announcement onto their average responsiveness shown in figure (2a). If the changes across all maturities on FOMC announcement day s were equal such that $\Delta R_s^j = \Delta R_s^{j+1}$ for all maturities $j+1$, then the estimated monetary shock $\Delta\hat{i}_s$ from equation (8) would be equal to zero. On the other hand, if the change in all maturities equaled their average responsiveness, i.e. $\Delta R_s^j = \hat{\beta}_j$ for all maturities j, then $\Delta\hat{i}_s = 1$. A more practical example than either of these two extremes would be one like that shown in panel (2c) where the change in long-term rates is close to zero, but short-term rates fall. The BRW Fama-MacBeth method would then estimate a negative shock $\Delta\hat{i}_s < 0$ even though long rates are little changed.

Furthermore, identifying monetary shocks via the differential responsiveness of short- and long-term rates is particularly useful when the federal funds rate is at the ELB. Although short-term rates may be relatively unchanged due to forward guidance communicating no expected change in the federal funds rate, medium- to long-term rates may still be adjusting, especially since forward guidance and LSAPs may be targeting these rates. In fact, panel (2b) shows that medium-term rates became relatively more responsive at the ELB changing more than one-for-one relative to a change in the two-year rate. Panel (2d) confirms these differential changes by showing a particular FOMC announcement where long-term rates drop by more than short-term rates and medium-term rates are the most responsive. With roughly a -0.03 percentage point change, the one-year Treasury is the least responsive on this particular FOMC announcement during an ELB episode.

Compared to other methods of incorporating information from policy actions that target long-term interest rates, the single-series of Bu et al. (2021) has the advantage of parsimony and flexibility in assumptions. By contrast, Swanson (2023) defines multiple independent dimensions of monetary policy and only allows for the effect of large-scale asset purchase shocks during certain periods. Jarociński (2024) and Lewis (2023) define multiple dimensions via additional information from financial markets.

Appendix figures (A.14b) and (A.16b) show that the BRW shock is tightly correlated with versions constructed from real-time estimates and different normalizations, respectively.

2.5 INTERCHANGING DATA AND METHODS

To confirm that both data and methods drive the differences in the *BRW* shock series relative to the other shocks series studied, we follow Bu et al. (2021) and interchange data and methods of the NS and BRW shock series. Overall, we find that differences become more pronounced with the largest correlation coefficient at 0.24 and the lowest at -0.40 as shown in table (2).

Using the NS data—changes in five interest rate futures with maturities of a year or less—in the BRW Fama-MacBeth method produces shocks that have only a correlation coefficient of only about 0.2 with either of the original series, as shown in table (2). This series has the lowest correlation coefficient in the entire table, −0.40 with the $MP1$ shock series.

Panels (4e) and (5e) show that the NS data with BRW method results in distributions that are similar in the ELB and non-ELB periods. By contrast shock series based on raw data or principal component analysis have distributions that narrow at the ELB. In support of these findings, figure (3) shows the average responsiveness of the five NS interest rate futures to the two-year Treasury on FOMC days is not significantly different in ELB episodes relative to non-ELB episodes. We do note that the responsiveness of the instruments with the shortest maturities—$MP1$ and $MP2$—is relatively lower in ELB episodes.

Furthermore, like the original BRW shock series, the version with NS data is mostly symmetric around zero at the ELB as shown in panel (5e). Although the underlying short-term data may be left-censored, because the Fama-MacBeth regression calculates the differential variation across underlying instruments, it may not always prescribe a positive shock if all rates rise. In fact, table (2) shows that only 52% of observations are positive at the ELB compared with 78% using the original principal component analysis. Finally, figure (3) supports the findings of Swanson and Williams (2014) that monetary policy can still have effects at the ELB.

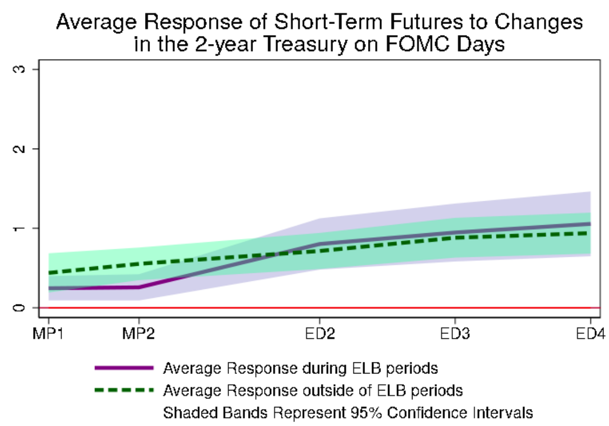
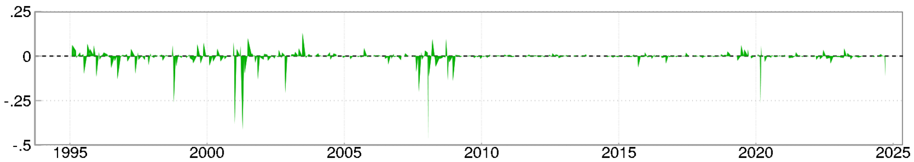


Figure 3: Average responsiveness of the NS data to 2-Year Treasuries.

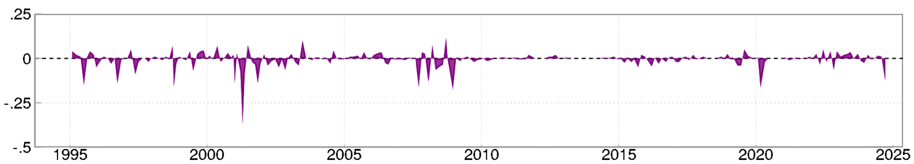
Estimates $\hat{\beta}_j$ from equation (7), but with the updated NS instrument set $\{MP1, MP2, ED2/SF3, ED3/SF4, ED4/SF5\}$ regressed on the daily change in the constant maturity two-year Treasury. Estimates are obtained via OLS with robust standard errors. The effective lower bound of the federal funds rate (ELB) is defined as defined as December 16, 2008 to December 16, 2015 and March 15, 2020 to March 16, 2022. The sample is from January 1995 to September 2024.

Panels (4f) and (5f) show that using the BRW data—changes in one- to 30-year zero-coupon Treasury yields—with the NS principal component analysis results in shock series that are not as small in magnitude as the other interchanged shock series shown in panels (4e) and (5e). Like the NS shock series, these interchanged shock series also have a positive mass—68 percent of observations—during the ELB periods. Because the principal component analysis is a linear combination of the underlying instruments, it will prescribe positive shock if all rates rise in response to the monetary policy announcement. Like the previously discussed interchanged shock, the shock series constructed from the BRW data with NS method has a relatively low correlation coefficient of at most 0.24 with the commonly used shocks we study.

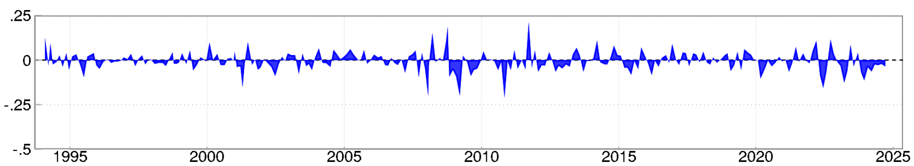


(a) Kuttner (2001) Shock Series, $MP1$

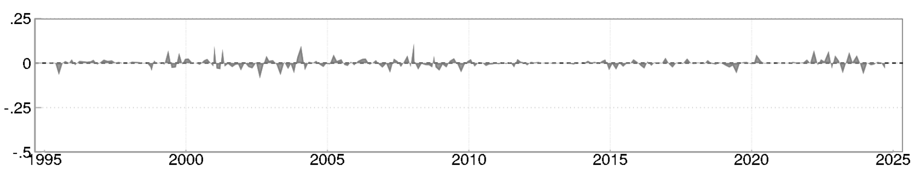
(b) Nakamura and Steinsson (2018) Shock Series, NS



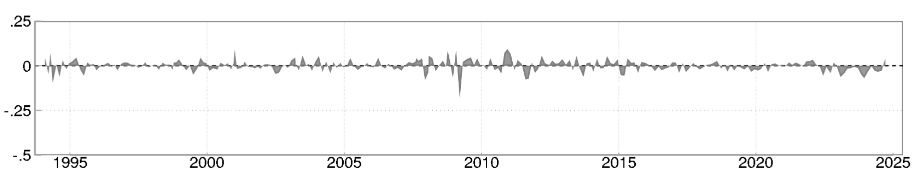
(c) FF4 Shock Series, $FF4$



(d) Bu et al. (2021) Shock Series, BRW



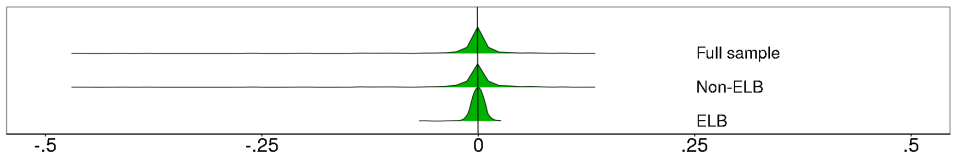
(e) Nakamura and Steinsson (2018) data, Bu et al. (2021) method



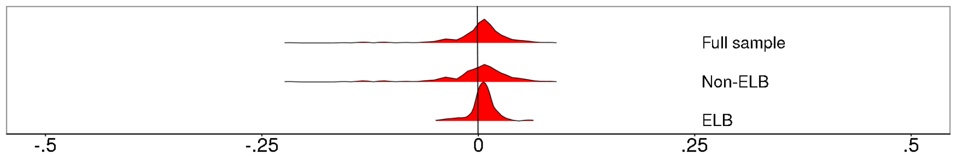
(f) Bu et al. (2021) data, Nakamura and Steinsson (2018) method

Figure 4: Time series of monetary shock series, January 1995 to September 2024.

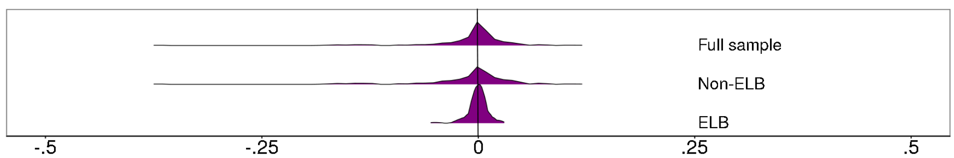
$MP1$ is the 30-minute change around an FOMC announcement in the current month's federal funds future if the FOMC announcement is in the first 23 days of the month with an adjustment or the next month's federal funds future if the FOMC announcement is within the last seven days of the month. $FF4$ is the change in the three-month ahead federal funds futures within 30-minutes of an FOMC announcement. NS is the first principal component of the instrument set $\{MP1, MP2, ED2/SF3, ED3/SF4, ED4/SF5\}$ which is the 30-minute change in these futures around an FOMC announcement. BRW is a Fama-MacBeth regression of the daily change in one- to 30-year constant maturity Treasury yields. NS data/BRW method is a Fama-MacBeth regression of the NS data. BRW data/NS method is the first principal component of the BRW data.



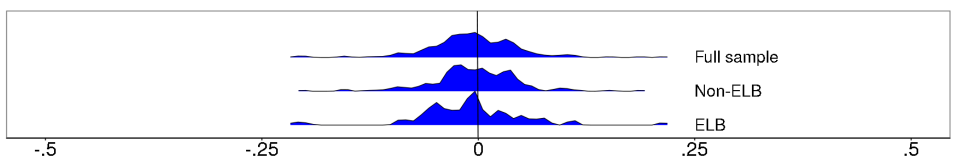
(a) Kuttner (2001) Shock $MP1$



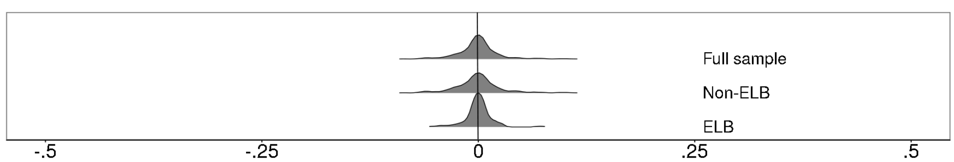
(b) Nakamura and Steinsson (2018) Shock



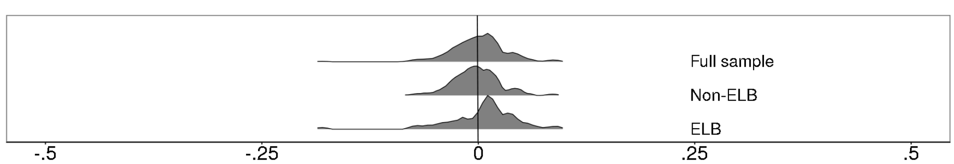
(c) FF4 Shock



(d) Bu et al. (2021) Shock



(e) Nakamura and Steinsson (2018) data, Bu et al. (2021) method



(f) Bu et al. (2021) data, Nakamura and Steinsson (2018) method

Figure 5: Distributions of monetary shock series, January 1995 to September 2024

$MP1$ is the 30-minute change around an FOMC announcement in the current month's federal funds future if the FOMC announcement is in the first 23 days of the month with an adjustment or the next month's federal funds future if the FOMC announcement is within the last seven days of the month. $FF4$ is the change in the three-month ahead federal funds futures within 30-minutes of an FOMC announcement. NS is the first principal component of the instrument set $\{MP1, MP2, ED2/SF3, ED3/SF4, ED4/SF5\}$ which is the 30-minute change in these futures around an FOMC announcement. BRW a the Fama-MacBeth regression of the daily change in one- to 30-year constant maturity Treasury yields. NS data/BRW method is a Fama-MacBeth regression of the NS data. BRW data/NS method is the first principal component of the BRW data. The ELB is defined as December 16, 2008 to December 16, 2015 and March 15, 2020 to March 16, 2022.

Shock	Panel 1) Correlation Coefficient *MP1*	*NS*	*FF4*	*BRW*	*NS data BRW meth.*	*BRW data NS meth.*	Panel 2) Same Sign, % *MP1*	*NS*	*FF4*	*BRW*	*NS data BRW meth.*	*BRW data NS meth.*
MP1	1.00						100%					
NS	0.77	1.00					47%	100%				
FF4	0.80	0.92	1.00				59%	67%	100%			
BRW	0.27	0.50	0.42	1.00			42%	65%	53%	100%		
NS data/BRW meth.	−0.40	0.22	0.02	0.28	1.00		32%	70%	52%	61%	100%	
BRW data/NS meth.	−0.03	0.14	0.05	0.22	0.24	1.00	35%	57%	41%	52%	59%	100%

Shock	Panel 3) Sign at the ELB, % zero	negative	positive
MP1	38%	37%	25%
NS	0%	22%	78%
FF4	45%	27%	27%
BRW	0%	66%	34%
NS data/BRW meth.	3%	45%	52%
BRW data/NS meth.	0%	32%	68%

Table 2: Statistics of various shock series.

For high-frequency monetary policy shock series, the three panels display their 1) correlation coefficient, 2) percentage of occurrences when the shocks have the same sign, and 3) percentage of occurrences when they are either equal to zero, positive, or negative during the ELB episodes which are defined from December 16, 2008 to December 16, 2015 and March 15, 2020 to March 16, 2022. $MP1$ is the 30-minute change around an FOMC announcement in the current month's federal funds future if the FOMC announcement is in the first 23 days of the month with an adjustment or the next month's federal funds future if the FOMC announcement within the last seven days of the month. $FF4$ is the change in the three-month ahead federal funds futures within 30-minutes of an FOMC announcement. NS is the first principal component of the instrument set $\{MP1, MP2, ED2/SF3, ED3/SF4, ED4/SF5\}$ which is the 30-minute change in these futures around an FOMC announcement. BRW is a Fama-MacBeth regression of the daily change in one- to 30-year constant maturity Treasury yields. NS data/BRW method is a Fama-MacBeth regression of the NS data. BRW data/NS method is the first principal component of the BRW data. The sample is January 1995 to September 2024.

2.6 PREDICTABILITY Because commonly used monetary shock series have been shown to be predictable and hence not entirely exogenous, we include in our discussion of shock construction predictability tests standard in the literature. Karnaukh and Vokata (2022), Sastry (2021), and Bauer and Swanson (2023) have shown that the NS shocks series is predictable by observables in the form of economic news, and Bu et al. (2021) confirm that the BRW shocks series is not. We find that shocks constructed from federal funds futures are the most likely to be predictable by economic news.

Standard tests assess if economic news predicts monetary shocks ε^i_t. Let T index months and t higher frequencies. Following the literature, ϵ^i_t is aggregated to a monthly frequency by summation, $\epsilon^i_T = \sum_t \epsilon^i_t$ and all news indicators pre-date the FOMC announcement in a given month.

$$\varepsilon^i_T = \alpha + \beta news^k_T + e_T \tag{9}$$

$$\text{news variable } k = \Big\{ \quad \text{Blue-Chip GDP revisions, Non-farm payrolls, ADS index, Brave et. al Index}$$

$$\text{shock } i = \Big\{ \quad MP1,\ FF4,\ NS,\ BRW,\ NS - interchange,\ BRW - interchange$$

Figure (6) shows the predictability coefficients $\hat{\beta}$ estimated from equation (9) for various measures of economic news along with their 95% confidence intervals. A monetary shock series is predicted by pre-existing economic news and is therefore not entirely exogenous to underlying economic conditions

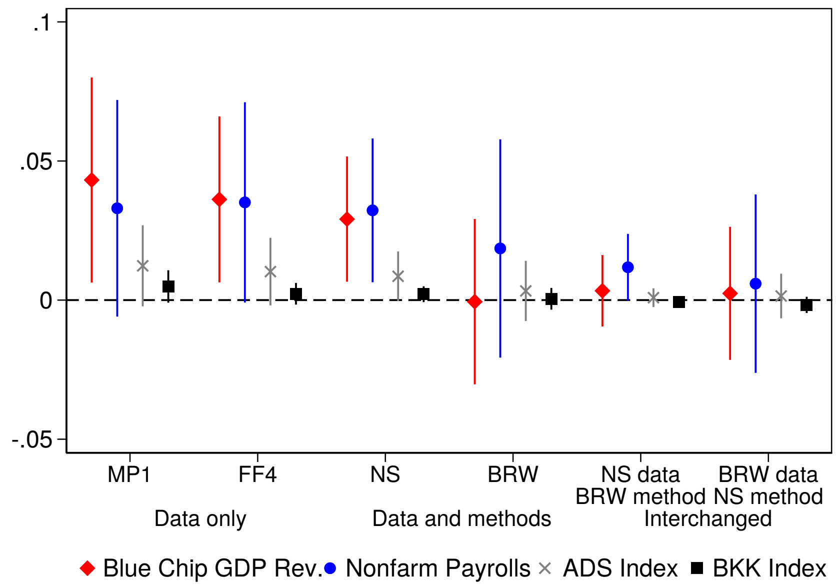


Figure 6: Predictability coefficients with 95% confidence intervals.

Estimate of $\hat{\beta}$ in equation (9) $\varepsilon_t^i = \alpha + \beta news_T^k + e_T$ are obtained via OLS with robust standard errors that are similar when bootstrapped. The sample is from January 1995 to September 2024 and excludes the second quarter of 2020. See Appendix Figure (A.17) for results over additional subsamples and with different controls. For the specification using the Blue Chip GDP revisions, we follow Bauer and Swanson (2023) and exclude observations where the FOMC announcement is in the first three business days of the month from 1995 to December 2000 and the first two business days thereafter to ensure that the Blue Chip Survey was completed prior to the FOMC announcement. Blue Chip GDP revisions are the monthly revision of one-quarter ahead GDP growth forecasts. The specification using non-farm payrolls assures that the FOMC meeting is after the FOMC release which is typically the first Friday of every month. Non-farm payrolls are the monthly change in the nonfarm payrolls release. The ADS Index is the Aruoba et al. (2009) business conditions index. The BKK index is the Brave et al. (2019) Big Data index. $MP1$ is the 30-minute change around an FOMC announcement in the current month's federal funds future if the FOMC announcement is in the first 23 days of the month with an adjustment or the next month's federal funds future if the FOMC announcement is within the last seven days of the month. $FF4$ is the change in the three-month ahead federal funds futures within 30-minutes of an FOMC announcement. NS is the first principal component of the instrument set $\{MP1, MP2, ED2/SF3, ED3/SF4, ED4/SF5\}$ which is the 30-minute change in these futures around an FOMC announcement. BRW is a Fama-MacBeth regression of the daily change in one- to 30-year constant maturity Treasury yields. NS data/BRW method is a Fama-MacBeth regression of the NS data. BRW data/NS method is the first principal component of the BRW data.

when confidence intervals do not encompass zero. Figure (6) shows that the NS shock series appears to suffer the most from predictability. The underlying instrument set can account for this finding, particularly the eurodollar/SOFR futures that are only used in the construction of shock series based on the NS data. Karnaukh and Vokata (2022) find that eurodollar futures tend to be more predictable than short-term fed funds futures, which could help explain why the $MP1$ and $FF4$ shock series are less likely to be predictable than the NS shock series. In fact, only those shock series constructed from short-term futures—$MP1$, $FF4$, NS, and the NS data interchanged shock series—have any statistically significant predictability coefficients.

Finally, figure (6) confirms that shock series constructed from long-term interest rates—the BRW shock series and its interchanged counterpart constructed from the NS principal component method—are unpredictable according to several standard tests in the literature. Because the interchanged shock series with the BRW data is also unpredictable, including long-term rates in shock construction may help assure that high-frequency series are indeed controlling for all available pre-existing information. However, the shocks constructed only from fed funds futures—the $MP1$ and $FF4$ shock series—are only marginally predictable suggesting that predictability is most strongly associated with series constructed from the NS data.

See Appendix figure (A.17) for additional results over different sub-samples.

3 MONETARY TRANSMISSION

After discussing the construction of high-frequency monetary shock series and some of their basic properties, we now explore how data and methods affect estimates of the transmission of monetary policy. We find that differences in monetary shock series are more likely to affect monetary transmission estimates from specifications that rely on forecast revisions than those from local projections or VARs. The BRW shocks series constructed from longer-term rates and the Fama-MacBeth method delivers transmission estimates that are the same sign as theoretical predictions in all specifications studied. By contrast, the shocks constructed from futures with maturities of one year or less tend have opposite-signed transmission estimates in the forecast revision specification and conventionally-signed responses in the local projections or VAR specifications. Among these shocks constructed from futures with maturities of one year or less, transmission estimates using the $MP1$ shock series are the closest to having the same sign across all specifications. This supports the findings of Paul (2020) that the $MP1$ shock series can potentially reduce bias from either the so-called “Fed information effect" or forward guidance without appealing to the add-on techniques of Miranda-Agrippino and Ricco (2021), Bauer and Swanson (2023, 2022), Jarocinski and Karadi (2020), Nunes et al. (2023), Zhu (2023), and others.

3.1 FORECAST REVISION SPECIFICATION

The monetary transmission specification of Campbell et al. (2012) and Nakamura and Steinsson (2018) estimate the response of monthly Blue Chip GDP forecast revisions to high-frequency monetary shocks. Let T index months and t higher frequencies. Following the literature, ϵ_t^i is aggregated to a monthly frequency by summation, $\epsilon_T^i = \sum_t \epsilon_t^i$.

$$\text{Blue Chip GDP Revisions}_T = \alpha + \beta \varepsilon_T^i + e_T \tag{10}$$

Equation (10) can be estimated via OLS because the dependent and independent variables are not simultaneously determined. If the change in actual GDP were used instead of the change in expected GDP, this would not be the case. Because quarterly GDP statistics are the accumulation of economic output over three months, it is impossible to disentangle the output produced before an FOMC announcement—and hence pre-determined at the time of the announcement—from the output produced after the announcement. By contrast a monthly series of GDP forecast revisions side-steps simultaneous determination by subtracting forecasts made before the announcement from those made after. The resulting forecast revision brackets the FOMC announcement and can estimate the effect of policy on perceptions about economy activity. In fact, researchers exclude monetary shock observations in the first several business days of the month to ensure that the Blue Chip survey was completed prior to an FOMC announcement (see Appendix B for more details).

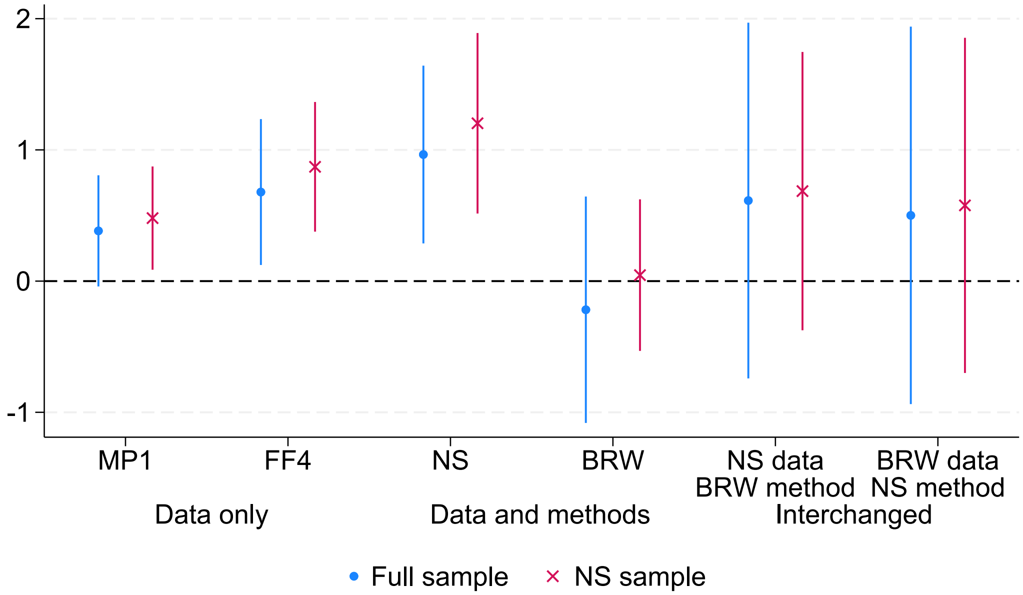


Figure 7: Forecast revision coefficients and 95% confidence intervals

$\hat{\beta}$ in eq. (10) Blue Chip GDP Revisions$_T = \alpha + \beta\varepsilon^i_T + e_T$ is estimated via OLS. Robust standard errors are similar when bootstrapped. The full sample is from January 1995 to September 2024 and the NS sample is from January 1995 to August 2015. Following Bauer and Swanson (2023), we exclude observations where the FOMC announcement is in the first three business days of the month from 1995 to December 2000 and the first two business days thereafter to ensure that the Blue Chip Survey was completed prior to the FOMC announcement. See Appendix Figure (B.18) for results over additional subsamples and with different controls. $MP1$ is the 30-minute change around an FOMC announcement in the current month's federal funds future if the FOMC announcement is in the first 23 days of the month with an adjustment or the next month's federal funds future if the FOMC announcement is within the last seven days of the month. $FF4$ is the change in the three-month ahead federal funds futures within 30-minutes of an FOMC announcement. NS is the first principal component of the instrument set $\{MP1, MP2, ED2/SF3, ED3/SF4, ED4/SF5\}$ which is the 30-minute change in these futures around an FOMC announcement. BRW is a Fama-MacBeth regression of the daily change in one- to 30-year constant maturity Treasury yields. NS data/BRW method is a Fama-MacBeth regression of the NS data. BRW data/NS method is the first principal component of the BRW data.

The coefficient $\hat{\beta}$ from equation (10) estimates monetary transmission and is shown in figure (7) along with 95% confidence intervals for the six high-frequency shocks studied in this paper. Although New Keynesian theory predicts that the response of GDP to a contractionary monetary shock should be significant and negative, figure (7) show that this is not the case for all shock series. Estimates of monetary transmission are positive and significant for the standard shocks based on short-term interest rate futures—the $MP1$, $FF4$, and NS shock series. Campbell et al. (2012) and Nakamura and Steinsson (2018) account for these opposite-signed responses as an information mismatch between the central bank and private agents. They argue that this so-called "Fed information" effect can upwardly bias estimates and account for opposite-signed responses arise via the more informed central bank using announcements to signal information to private agents about the underlying economy. Bauer and Swanson (2023) find a similar upward bias and argue it arises from the central bank and private agents responding to economic news.

The BRW and the interchanged shock series do not produce statistically significant responses suggesting that the opposite-signed response is only found in a subset of shock series. Bu et al. (2021) attribute the lack of opposite-signed response in their shock series to a combination of longer-term rates and methods. As BRW explain, if there is a differential effect of the Fed Information effect on short- and long-term rates—as shown by Hansen et al. (2019)—, adding long-term rates to the construction of monetary shock series can offset the information effect found in short-term rates. However, any information effect in short-term rates is unlikely to be offset in principal component analysis because the procedure extracts linear combinations of the underlying instruments and hence will preserve any information effect in the underlying data. Although Miranda-Agrippino and Rey (2020) and Stavrakeva and Tang (2019) find evidence of information effects in factors constructed from longer-term rates, as long as there is a differential responsiveness of short- and long-term rates, a Fama-MacBeth regression will not necessarily inherit an information effect detected in a subset of rates.

Even though the BRW shock series is the only series of the four main shocks that does not result in a positive and significant opposite-signed response, we note that the $MP1$ shock series of Kuttner (2001) is only on the margin of significance and is only statistically significant in the original NS sample from 1995 to 2015. Appendix figure (B.18) confirms the findings of marginal significance across samples and controls. For researchers concerned that an opposite-signed response in a shock series indicates contamination from Central Bank information signaling, we argue that the $MP1$ shock series may be an alternative to the NS shock series. Although additional procedures to the NS shock series can purge these information effects, $MP1$ offers the advantage of simple construction from raw data.[12]

3.2 Daily Local Projections

Although the information mismatch between central banks and private agents can account for opposite-signed responses of monetary transmission estimates, Jacobson et al. (2022) present the information mismatch between economic modelers and private agents as a complementary explanation. When response variables are observed at a lower frequency than explanatory variables—as is the case with most macroeconomic response variables—temporal aggregation bias can affect transmission estimates. Jacobson et al. (2022) show that time aggregated data can lead to earlier arriving response coefficients being magnified relative to their later arriving counterparts. When using the daily inflation series from the Billion Prices Project [Cavallo and Rigobon (2016)] as a response variable instead of the monthly official CPI, Jacobson et al. (2022) find that initial positive response coefficients are indeed magnified relative to later arriving negative coefficients. After all, the opposite-signed positive response is quite temporary, if detected at all, when the data frequencies of explanatory and re-

[12] Three examples of rigorous procedures to purge monetary shocks from contamination are works by Miranda-Agrippino and Ricco (2021), Jarocinski and Karadi (2020), and Bauer and Swanson (2022). First, Miranda-Agrippino and Ricco (2021) prescribe projecting monetary shock series onto their lags and Federal Reserve Green Book forecasts to control for the fact that shock series and forecasts are correlated. Secondly, Jarocinski and Karadi (2020) exploit the co-movement of stock prices and interest rates to disentangle information shocks from pure monetary shocks. Finally, Bauer and Swanson (2022) prescribe orthogonalizing monetary shock series relative to economic and financial series that are predated and correlated with the monetary shock series.

sponse variables are better matched. Additionally, a specification with matched data frequencies does not require researchers to discard FOMC announcements that occur early in the month as is necessary for identification when data from the Blue Chip survey are used as a response variable.

After showing that the daily inflation series decently approximates the official CPI, Jacobson et al. (2022) compute local projections and find conventionally-signed responses with only a short-lived initial adverse response. Their local projection for day $t+h$ is the following,

$$\pi_{t+h} = \alpha_{(h)} + \beta_{(h)}\varepsilon_t^i + \Gamma_{(h)} z_t + e_t^{(h)}, \quad e_t^{(h)} \sim \mathcal{N}(0, \sigma_{(h)}) \tag{11}$$

Where π_{t+h} is daily inflation at day $t+h$ calculated as the 30-day percentage change, z_t is the vector of controls which are the 30 lags of daily inflation, and ε_t^i is one of the six monetary shock series studied in this paper. Estimates are obtained from the Canova and Ferroni (2022) toolbox using instrumental variables with robust heteroskedasticity and autocorrelation consistent (HAC) standard errors reported at 90 percent error bands.

Figure (8) shows the estimated impulse response functions $\hat{\beta}_{(h)}$ of the daily inflation index to a one-standard deviation contractionary monetary shock for each of the six high-frequency series constructed in this paper. The impulse responses to all four constructed monetary shock series estimate statistically significant conventionally-signed responses. If there is an opposite-signed response, it is short-lived and ambiguous. In the daily local projections specification with matched frequencies of explanatory and response variables, neither data nor methods seem to imply much difference in the sign of the estimates. This finding contrasts with that of the forecast revision specification in section 3.1, where both data and methods drove differences in estimates of monetary transmission.

Panels (8a) and (8b) repeat the main exercise of Jacobson et al. (2022) and show that the responses of daily inflation to the *NS* and *BRW* shock series are both conventionally-signed. Even though the transmission estimates of the forecast revision specification in section 3.1 are positive and significant for the *NS* shock series, the local projection estimates are negative—and hence conventionally-signed—for a majority of the 60-day response horizon shown. The only positive—and hence opposite-signed response—is short-lived lasting about 10 days before turning negative. About 30 days after the initial impulse, the response is negative and significant. In fact, the estimated response coefficients with a negative sign are the only estimates that are statistically significant. When using the *BRW* shock series, the impulse responses are unambiguously negative about 60-days after a contractionary monetary shock. Unlike the *NS* shocks series, there are almost no estimated opposite-signed impulse response coefficients from the *BRW* shock series. The positive responses of the *BRW* shocks series are consistent with those of the forecast revision specification in section 3.1.

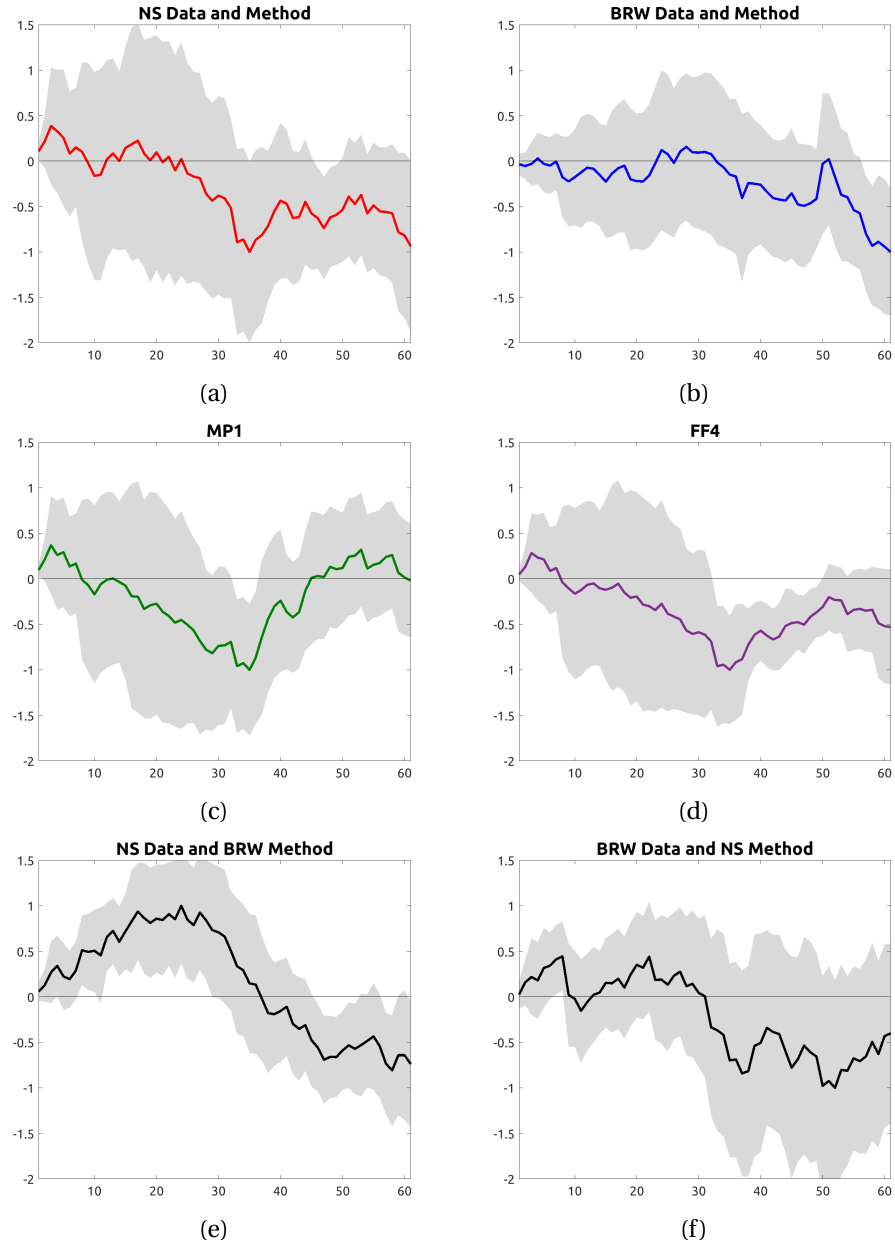


Figure 8: Impulse response functions of local projections to a 1 percentage point monetary shock, x-axis is days and y-axis is percentage points.

Estimates of $\hat{\beta}_{(h)}$ in equation (11) $\pi_{t+h} = \alpha_{(h)} + \beta_{(h)}\varepsilon^i_t + \Gamma_{(h)} z_t + e^{(h)}_t, \quad e^{(h)}_t \sim \mathcal{N}(0, \sigma_{(h)})$ are obtained via the Canova and Ferroni (2022) toolbox with robust heteroskedasticity and autocorrelation consistent (HAC) standard errors reported at 90 percent error bands. The daily inflation series π_t is the 30-day percentage change of the Billion Prices Project daily price index which is publicly available from July 2008 to August 2015 via Cavallo and Rigobon (2016). All monetary shock series shown are calculated over the January 1995 to August 2015 sub-sample instead of the full 1995 to 2024 sample. $MP1$ is the 30-minute change around an FOMC announcement in the current month's federal funds future if the FOMC announcement is in the first 23 days of the month with an adjustment or the next month's federal funds future if the FOMC announcement is within the last seven days of the month. $FF4$ is the change in the three-month ahead federal funds futures within 30-minutes of an FOMC announcement. NS is the first principal component of the instrument set $\{MP1, MP2, ED2, ED3, ED4\}$ which is the 30-minute change in these futures around an FOMC announcement. BRW is a Fama-MacBeth regression of the daily change in one- to 30-year constant maturity Treasury yields. NS data/BRW method is a Fama-MacBeth regression of the NS data. BRW data/NS method is the first principal component of the BRW data.

Turning to the interchanged shock series, the NS data with the BRW method shown in panel (8e) is the only series among the six studied in this paper that has a significant opposite-signed response. These shocks are the smallest in magnitude so any large swing in inflation will be ascribed to a relatively tiny impulse and result in a statistically significant response coefficient. For this reason, the shock series constructed from the NS data with the BRW method likely estimates a larger initial positive impulse response than the NS shock series constructed from its standard principal component analysis method shown in panel (8a).

Because shock series constructed from short-term rates shown in panels (8a), (8c)-(8e) all detect an initial positive impulse response, it may be tempting to ascribe opposite-signed responses to short-term rates. However, the point estimates of the impulse responses of the interchanged shock series constructed from the BRW data with the NS method shown in panel (8f) are similar to those constructed with the standard NS data and method shown in panel (8a). Methods must therefore also play a role in the similarity of coefficients observed in panels (8a),(8c)-(8d), and (8f). In the case of the interchanged shock series with the BRW data and the NS method shown in panel (8f), the error bands are wider resulting in no statistically significant response from zero. Because the distribution of the interchanged series is larger than that of the NS series over the 2008 to 2015 period, it is likely that the additional variation leads to less precise estimates.

Overall, differences in estimates of monetary transmission from local projections with matched frequencies of explanatory and response variables matter less than in the forecast revision specification with mismatched frequencies. Both data and methods account for this finding as the point estimates are quite similar for 1) the NS shock series relying on short-term futures and principal component analysis, 2) the $MP1$ and $FF4$ shock series relying on short-term futures, and 3) the long-term BRW data in the principal component analysis.

3.3 VECTOR AUTOREGRESSION

In addition to specifications relying on forecast revisions or local projections, the effect of monetary policy on the macroeconomy is frequently estimated via a structural vector autoregression framework at a monthly frequency by using high-frequency monetary policy shocks as external instruments. Relative to the previous two specifications studied, the VAR specification has disadvantages and advantages. Unlike the daily local projection specification, VAR specifications typically have mismatched data frequencies in the form of high-frequency shocks and low-frequency response variables. On the other hand, the VAR specification has the advantage of allowing for feedback between multiple macroeconomic variables as co-movements of variables like inflation and output are well documented but absent from the specifications in sections 3.1 and 3.2.

We use the VAR specification of Bauer and Swanson (2022) which is a variant of Gertler and Karadi (2015). The external instrument imposes a second moment restriction to identify shocks, more specifically it replaces one column of the rotation matrix with predicted values from a regression of a reduced form VAR innovation on the external instrument.[13] We focus on the VAR with external instruments as it is the dominant specification in empirical macroeconomics as noted by Miranda-Agrippino and Ricco

[13] See Stock and Watson (2018) for additional documentation of VARs with external instruments.

(2023). Bauer and Swanson (2022) provide additional comparisons of the impulse responses of the NS shock and their orthogonalized variant in several VAR specifications including one where the shock series is used an internal instrument or in local projections.

Identification via an external instrument hinges on a high-frequency monetary policy shock series ε_t^i satisfying relevance and exogeneity conditions to be an adequate external instrument for ε_t^{mp} the unobservable true monetary shocks.

$$E[\varepsilon_t^{mp}\varepsilon_t^i] \neq 0 \qquad \text{and} \qquad E[\varepsilon_t^i \varepsilon_t^{\cancel{mp}}] = 0$$

Where ε_t is any serially uncorrelated structural shocks driving the economy and $\varepsilon^{\cancel{mp}}$ is a subset of these shocks unrelated to monetary policy.

Since the true value of ε_t^{mp} is unobserved, both conditions ultimately must be justified logically. All high-frequency monetary shock series studied in this paper should satisfy the relevance condition as they capture monetary news conveyed by FOMC announcements by construction. The exclusion condition should also be satisfied because of the tight windows around FOMC announcements should prevent non-monetary news from moving markets. Section 2.6 calls into question the exclusionary restriction by showing that several commonly used monetary shock series—those of $MP1$, $FF4$, and NS—may be contaminated by observables and hence predictable. However, other shock series like those of BRW and $MP1$ have been shown to be unpredictable, suggesting there are alternatives for concerned researchers. Otherwise, we point researchers interested in relying on the $FF4$ or NS shocks to the orthogonalization procedure of Bauer and Swanson (2022). Similarly, researchers concerned about an information effect contaminating the exogeneity of the $FF4$ or NS shock series should explore the add-on procedures of Miranda-Agrippino and Ricco (2021), Jarocinski and Karadi (2020), Nunes et al. (2023), and Zhu (2023) that isolate pure shocks from their information counterparts. However, we note that the $MP1$ and BRW shock series show no or marginal evidence of predictability or adversely-signed responses in the previous sections and may allow researchers to side-step these additional procedures.

The specification for a VAR with external instruments is given as:

$$Y_T = \alpha + B(L)Y_{T-1} + s_1 Y_T^{2Y} + \tilde{u}_T \tag{12}$$

Where Y_T is a vector containing four monthly economic variables from January 1973 to December 2019: the log of the consumer price index (CPI), the log of industrial production (IP), the Gilchrist and Zakrajšek (2012) excess bond premium, and the two-year zero-coupon Treasury yield at a monthly frequency. Appendix D details the sources of these series, which we match the exact vintage used by Bauer and Swanson (2022)(https://www.michaeldbauer.com/files/FOMC_Bauer_Swanson.xlsx). We also note that the two-year Treasury yield is the daily change observed at the end of the month as in the previously mentioned excel spreadsheet used by Bauer and Swanson (2022). The excess bond premium controls for financial factors and the two-year Treasury is a measure of the stance of monetary policy. Although the original Gertler and Karadi (2015) specification uses the one-year Treasury, the two-year has the advantage of being less constrained at the ELB and is used by Bauer and Swanson (2022), our main comparison.

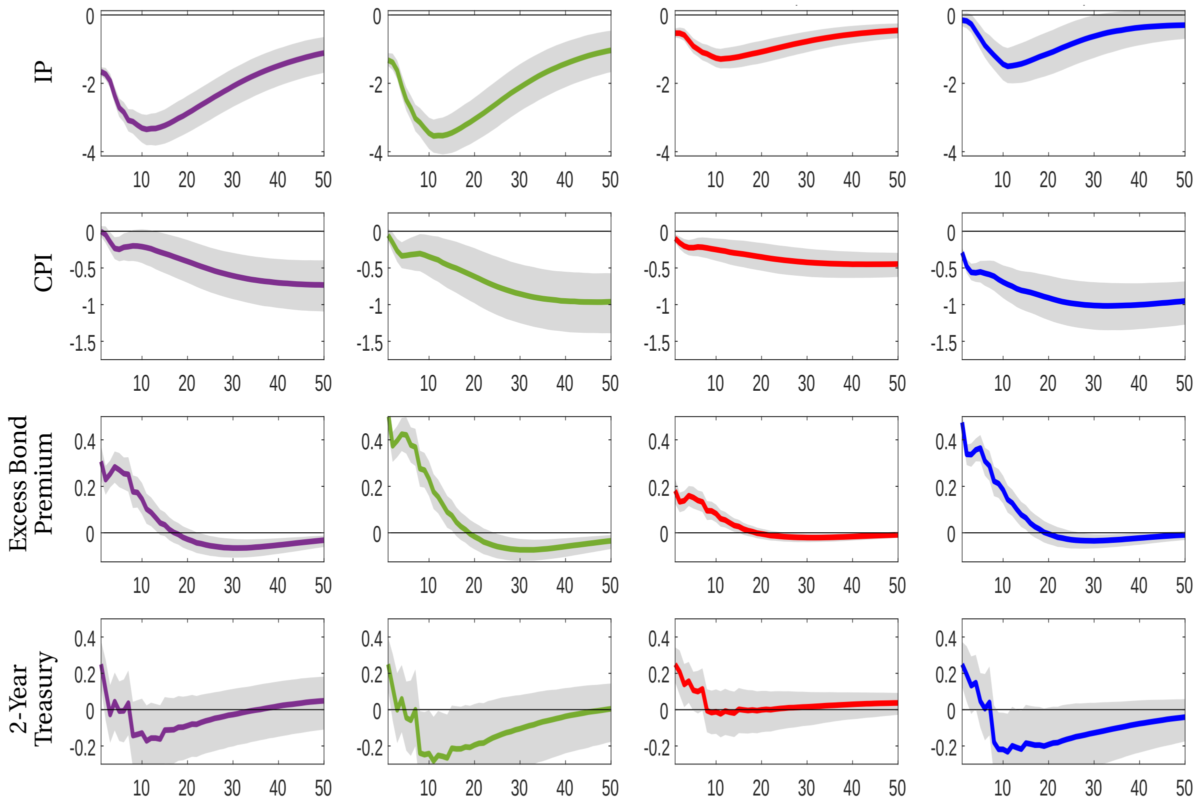
Next, $B(L)$ is the matrix polynomial in the lag operator. Although Bauer and Swanson (2022) follow Gertler and Karadi (2015) and Ramey (2016) in using 12 lags, we shorten to 8 lags due to the sample size of our high-frequency shocks. Bauer and Swanson (2022) construct a version of the NS shock series from 1988 to 2019 while we begin our sample in 1995 which is as close to the 1994 introduction of explicit policy statements as our intraday data allows without resorting to sources we cannot replicate from intraday data on actual trades. Appendix C confirms that shortening the lags does not substantially change the qualitative estimates of monetary policy transmission, but does result in slightly different point estimates. As noted by Ramey (2016), these types of specifications are highly sensitive to the underlying data sample and may therefore differ from the original Gertler and Karadi (2015) estimates which are from 1991 to 2012.

Finally, ϵ_t^i is the instrument for $s_1 Y_T^{2y}$ estimated via two-stage least squares and $\tilde{u}_T$ is the residual. The sample of the external instrument ε_t^i does not have to be the same as that of the economic data. In fact, the sample used for our six shock series is from January 1995 to December 2019 and the sample for the economic data is from January 1973 to February 2020. Furthermore, following the literature ϵ_t^i is aggregated to a monthly frequency by summation, $\epsilon_T^i = \sum_t \epsilon_t^i$. We do not make any further adjustments for the timing of shocks within the month as Ramey (2016) and Miranda-Agrippino and Ricco (2021) find that the adjustments proposed by Gertler and Karadi (2015) can induce serial correlation.[14] Appendix C confirms that we obtain similar results using our constructed monetary policy shocks to those constructed by Bauer and Swanson (2022) using the data available from the author's website.[15]

Figure (9) plots impulse responses from equation (12) obtained via the Canova and Ferroni (2022) toolbox with 68 percent error bands and 20,000 draws. For the four main shock series studied in this paper, the impulse responses to a 25 basis point monetary shock are qualitatively in line with macroeconomic theory and similar in sign and shape. The response of the two-year Treasury shown in the bottom row of each panel rises on impact and is normalized so that its initial response is 25 basis points. After initially rising, the two-year Treasury decreases and returns to zero about 10 months after the initial impulse. The excess bond premium displayed in the third row rises on impact to about 0.2 to 0.4 percentage point in all series shown and then declines towards zero.

The impulse responses of both industrial production and CPI shown in rows one and two of figure (9), respectively, to a contractionary monetary shock are significantly negative—as standard New Keynesian theory predicts. We find no evidence of an opposite-signed responses in CPI or industrial production as was found in the forecast revision specification in section 3.1 or elsewhere in the literature. Differences in point estimates among the four shock series are only in magnitude rather than in sign. The responses of industrial production shown in the first row are the largest for the $MP1$ and $FF4$ shock series shown in panels (9a) and (9b), respectively. The responses of CPI shown in the second row have similar interpretation to the responses for industrial production. All CPI responses are statistically significant and negative with those of the $MP1$ and $FF4$ shocks in panels (9a) and (9b), respectively, being the largest in magnitude. However, the response of CPI to the BRW shock series in panel (9d) has an initial response

[14] See footnote 10.
[15] See https://www.michaeldbauer.com/files/FOMC_Bauer_Swanson.xlsx.



(a) $MP1$ Shock (b) $FF4$ Shock (c) NS Shock (d) BRW Shock

Figure 9: Impulse responses to a 25 basis point monetary shock, x-axis is months and y-axis is percentage points.

Impulse responses are estimates from equation (12) $Y_T = \alpha + B(L)Y_{T-1} + s_1 Y_T^{2Y} + \tilde{u}_T$ obtained via the Canova and Ferroni (2022) Bayesian VAR toolbox with 68 percent error bands, 20,000 draws, and 8 lags. The sample of monetary shock series is from January 1995 to December 2019 while the sample of economic data is from January 1973 to February 2020. $MP1$ is the 30-minute change around an FOMC announcement in the current month's federal funds future if the FOMC announcement is in the first 23 days of the month with an adjustment or the next month's federal funds future if the FOMC announcement is within the last seven days of the month. $FF4$ is the change in the three-month ahead federal funds futures within 30-minutes of an FOMC announcement. NS is the first principal component of the instrument set $\{MP1, MP2, ED2/SF3, ED3/SF4, ED4/SF5\}$ which is the 30-minute change in these futures around an FOMC announcement. BRW is a Fama-MacBeth regression of the daily change in one- to 30-year constant maturity Treasury yields. IP is the industrial production index, CPI is the consumer price index, excess bond premium is from Gilchrist and Zakrajšek (2012), and the two-year Treasury is the end of the month daily change in the zero-coupon yield. All sources of series are detailed in Appendix D.

that is largest in magnitude the CPI.

The differences between the NS and BRW shock series are relatively minor with the exception of the response of the excess bond premium, which can be explained by BRW's shock construction including the longer-end of the yield curve. Inference with respect to other variables (CPI, industrial production and two-year Treasury) would not be substantially different between the BRW and NS series. Conversely, the $MP1$ and $FF4$ shock series show much larger responses of the CPI.

Both the similarity of impulse responses and the conventionally-signed estimates in figure (9) could suggest that differences in monetary shocks series are negligible when estimating monetary transmission in a VAR with external instruments. However, figure (10) shows that the impulse responses of the interchanged shock series are quite different than their counterparts shown in figure (9) as the inter-

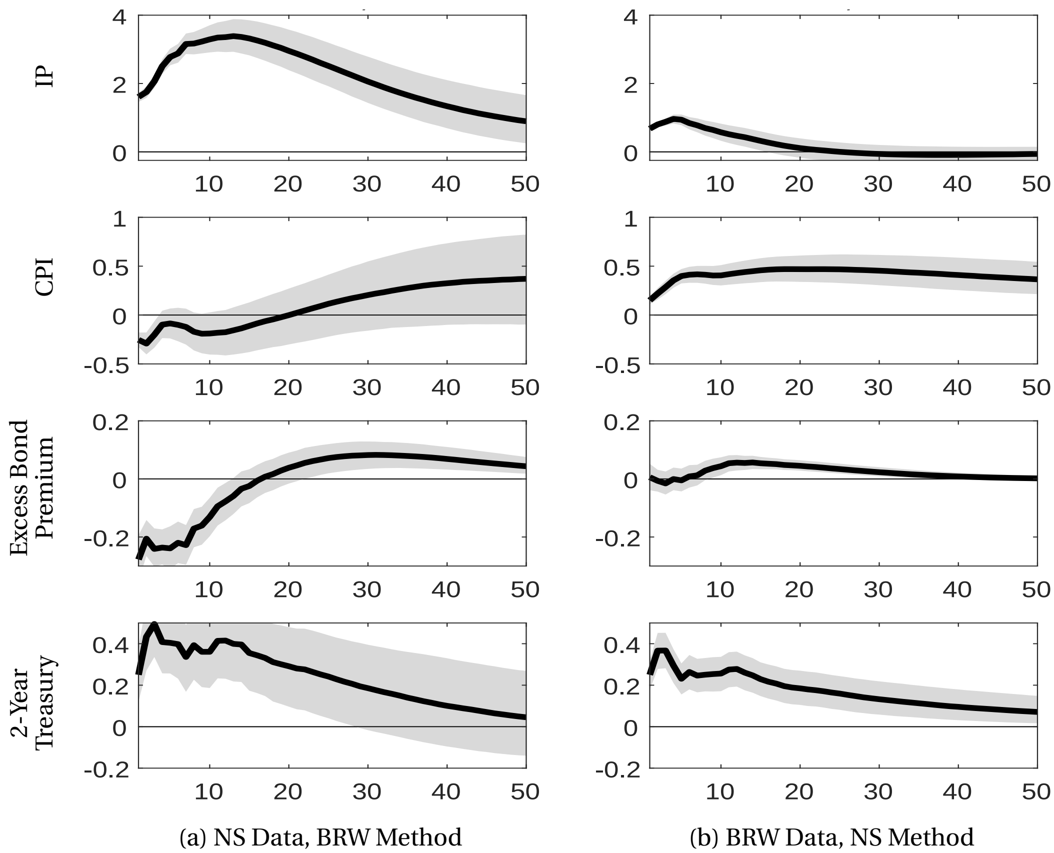


Figure 10: Impulse response to a 25 basis point monetary shock, x-axis is months and y-axis is percentage points.

Impulse responses are estimates from equation (12) $Y_T = \alpha + B(L)Y_{T-1} + s_1 Y_T^{2Y} + \tilde{u}_T$ obtained via the Canova and Ferroni (2022) Bayesian VAR toolbox with 68 percent error bands, 20,000 draws, and 8 lags. The sample of monetary shock series is from January 1995 to December 2019 while the sample of economic data is from January 1973 to February 2020. NS data/BRW method is a Fama-MacBeth regression of the NS data, the instrument set $\{MP1, MP2, ED2/SF3, ED3/SF4, ED4/SF5\}$ which is the 30-minute change in these futures around an FOMC announcement. BRW data/NS method is the first principal component of the BRW data, the daily change in one- to 30-year constant maturity Treasury yields. IP is the industrial production index, CPI is the consumer price index, excess bond premium is from Gilchrist and Zakrajšek (2012), and the two-year Treasury is the end of the month daily change in the zero-coupon yield. All sources of series are detailed in Appendix D.

changed shock series often estimate opposite-signed responses. Interchanging data and methods in this circumstance will drastically change the inference. Together, these findings suggest that even though differences in monetary shock series can affect VAR estimates, the effects of these differences range from quantitatively small when comparing the four main shock series studied to qualitatively large when examining combinations of data and methods. An econometrician must proceed cautiously as inference is not robust to all modern constructions of monetary policy shock series. Appendix table (3) displays the first-stage F-statistics.

Although section 2 documents differences in several commonly used monetary policy shocks, we find that the effect of these differences on estimates of monetary transmission can be small depending on the specification used. Specifications like the daily local projections and VAR with external instruments in sections 3.2 and 3.3, respectively, are more similar in terms of signs and magnitudes of estimates than the forecast revision specification in section 3.1.

4 CONCLUSION

Because monetary policy simultaneously affects and responds to economic conditions, identifying exogenous monetary instruments is an ongoing challenge for researchers. Since at least Kuttner (2001), high-frequency environments have proven useful for overcoming these challenges by extracting unanticipated market surprises that control for all available information prior to an FOMC announcement. To construct monetary shock series, researchers separate monetary news from their non-monetary counterparts by calculating the change in asset prices minutes after an FOMC announcement relative to the prices observed just before.

Although various high-frequency monetary shock series rely on similar narrow time windows around the same monetary policy announcements, we document that their signs and magnitudes are quite different for the United States. Furthermore, these differences are starkest when the federal funds rate is at its effective lower bound and the Federal Reserve has typically deployed an expansive toolkit. Because underlying data and statistical methods can differ in shock construction, we ask what drives differences in monetary shock series. We find that data on long-term rates can contribute to differences, but methods are also important. Because the Federal Reserve's 21st century monetary policy toolkit can affect short- and long-term rates, long-term rates can capture additional information. However, long-term rates may be, on average, relatively unresponsive to monetary policy. Therefore, methods like the Bu et al. (2021) Fama-MacBeth regression that rely on the differential responsiveness of short and long-term rates are more effective at extracting additional information from long-term rates.

After constructing commonly used monetary shock series from raw data to highlight the choices faced by researchers, we analyze if differences in shock series matter for inference. We find that estimates of monetary transmission from local projections and VARs are more similar across shock series than their counterparts estimated via forecast revisions. In fact, some of the shock series with the simplest data and methods—the Bu et al. (2021) BRW and Kuttner (2001) $MP1$ shock series—are the most likely to deliver estimates of monetary transmission that are consistent with predictions from New Keynesian models across several different specifications.

REFERENCES

Acosta, Miguel, “The Perceived Causes of Monetary Policy Surprises,” 2023. Working Paper.

_ **, Connor M. Brennan, and Margaret M. Jacobson**, “Constructing high-frequency monetary policy surprises from SOFR futures,” *Economics Letters*, 2024, *242*, 111873.

Altavilla, Carlo, Luca Brugnolini, Refet S. Gürkaynak, Roberto Motto, and Giuseppe Ragusa, “Measuring euro area monetary policy,” *Journal of Monetary Economics*, 2019, *108*, 162–179.

Andrade, Philippe and Filippo Ferroni, “Delphic and Odyssean Monetary Policy Shocks: Evidence from the Euro Area,” *Journal of Monetary Economics*, 2021, *117*, 816–832.

Aruoba, Boragan and Thomas Drechsel, “Identifying Monetary Policy Shocks: A Natural Language Approach,” 2023. Working Paper.

Aruoba, S. Boragan, Francis X. Diebold, and Chiara Scotti, “Real-Time Measurement of Business Conditions,” *Journal of Business and Economic Statistics*, 2009, *27* (4), 417–427.

Barakchian, S. Mahdi and Christopher Crowe, “Monetary policy matters: Evidence from new shocks data,” *Journal of Monetary Economics*, 2013, *60* (8), 950–966.

Bauer, Michael D. and Eric T. Swanson, “A Reassessment of Monetary Policy Surprises and High-Frequency Identification,” in “NBER Macroeconomics Annual 2022, volume 37,” University of Chicago Press, 2022.

_ **and** _ , “An Alternative Explanation for the "Fed Information Effect",” *American Economic Review*, March 2023, *113* (3), 664–700.

Boehm, Christoph E. and T. Niklas Kroner, “Monetary Policy without Moving Interest Rates: The Fed Non-Yield Shock,” 2023. Working Paper.

Braun, Robin, Silvia Miranda-Agrippino, and Tuli Saha, “Measuring monetary policy in the UK: The UK monetary policy event-study database,” *Journal of Monetary Economics*, 2024, p. 103645.

Brave, Scott A., Andrew Butters, and David Kelley, “A New “Big Data" Index of U.S. Economic Activity,” 2019. Economic Perspectives, Federal Reserve Bank of Chicago.

Bu, Chunya, John Rogers, and Wenbin Wu, “A unified measure of Fed monetary policy shocks,” *Journal of Monetary Economics*, 2021, *118*, 331–349.

Bundick, Brent and A. Lee Smith, “The Dynamic Effect of Forward Guidance Shocks,” *Review of Economics and Statistics*, 2020, *102* (5), 946–965.

Caldara, Dario and Edward Herbst, “Monetary Policy, Real Activity, and Credit Spreads: Evidence from Bayesian Proxy SVARs,” *American Economic Journal: Macroeconomics*, 2019, *11* (1), 157–192.

Campbell, Jeffery R., Charles L. Evans, Jonas D. M. Fisher, and Alejandro Justiniano, "Macroeconomic Effects of Federal Reserve Forward Guidance," *Brookings Papers on Economic Activity*, 2012, pp. 1–54.

Canova, Fabio and Filippo Ferroni, "A hitchhiker's guide to empirical macro models," 2022. Working Paper.

Carlstrom, Charles T. and Margaret M. Jacobson, "Thresholds or Dates in Monetary Policy Communications," 2013. Federal Reserve Bank of Cleveland Economic Trends.

Cavallo, Alberto and Roberto Rigobon, "The Billion Prices Project: Using Online Data for Measurement and Research," *Journal of Economic Perspectives*, 2016, *31* (1).

Christiano, Lawrence J., Martin Eichenbaum, and Charles Evans, "The Effects of Monetary Policy Shocks: Evidence from the Flow of Funds," *The Review of Economics and Statistics*, 1996, *78* (1), 16–34.

_ , _ , and Charles L. Evans, "Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy," *Journal of Political Economy*, 2005, *113* (1), 1–45.

Cieslak, Anna and Andreas Schrimpf, "Non-monetary News in Central Bank Communication," *Journal of International Economics*, 2019, *118*, 293–315.

Ettmeier, Stephanie and Alexander Kriwoluzky, "Same, but different? Testing monetary policy shock measures," *Economics Letters*, 2019, *184*, 108640.

Fama, Eugene F. and James D. MacBeth, "Risk, Return, and Equilibrium: Empirical Tests," *Journal of Political Economy*, 1973, *81* (3), 607–636.

Gertler, Mark and Peter Karadi, "Monetary Policy Surprises, Credit Costs, and Economic Activity," *AEJ: Macroeconomics*, 2015, *7*, 44–76.

Gilchrist, Simon and Egon Zakrajšek, "Credit Spreads and Business Cycle Fluctuations," *American Economic Review*, June 2012, *102* (4), 1692–1720.

Gürkaynak, Refet, Burçin Kısacıkoğlu, and Sang Seok Lee, "Exchange Rate and Inflation under Weak Monetary Policy: Turkey Verifies Theory," 2024. Working Paper.

Gürkaynak, Refet S., Brian P. Sack, and Eric T. Swanson, "Do Actions Speak Louder than Words? The Response of Asset Prices to Monetary Policy Actions and Statements," *International Journal of Central Banking*, 2005, *1*, 55–93.

Gürkaynak, Refet S, Brian P Sack, and Eric T Swanson, "Market-Based Measures of Monetary Policy Expectations," *Journal of Business & Economic Statistics*, 2007, *25* (2), 201–212.

Hansen, Stephen, Michael McMahon, and Matthew Tong, "The long-run information effect of central bank communication," *Journal of Monetary Economics*, 2019, *108*, 185–202.

Hanson, Samuel G. and Jeremy C. Stein, "Monetary Policy and Long-Term Real Rates," *Journal of Financial Economics*, 2015, *115*, 429–448.

Jacobson, Margaret M., Christian Matthes, and Todd B. Walker, "Temporal Aggregation Bias and Monetary Policy Transmission," 2022. Working Paper.

Jarocinski, Marek and Peter Karadi, "Deconstructing Monetary Policy Surprises: The Role of Information Shocks," *AEJ:Macroeconomics*, 2020, *12* (2).

Jarociński, Marek, "Estimating the Fed's unconventional policy shocks," *Journal of Monetary Economics*, 2024, *144*, 103548.

Karnaukh, Nina and Petra Vokata, "Growth forecasts and news about monetary policy," *Journal of Financial Economics*, 2022, *146* (1), 55–70.

Kuttner, Kenneth N., "Monetary Policy Surprises and Interest Rates: Evidence from the Fed Funds Futures Market," *Journal of Monetary Economics*, 2001, *47*, 523–544.

Lewis, Daniel J., "Announcement-Specific Decompositions of Unconventional Monetary Policy Shocks and Their Effects," *The Review of Economics and Statistics*, 03 2023, pp. 1–46.

McKay, Alisdair and Christian K. Wolf, "What Can Time-Series Regressions Tell US About Policy Counterfactuals?," *Econometrica*, 2023, *91*, 1695–1725.

Miranda-Agrippino, Silvia and Giovanni Ricco, "The Transmission of Monetary Policy Shocks," *American Economic Journal: Macroeconomics*, July 2021, *13* (3), 74–107.

_ **and** _ , "Identification with External Instruments in Structural VARs," *Journal of Monetary Economics*, 2023, *135* (C), 1–19.

_ **and Hélène Rey**, "The Global Financial Cycle after Lehman," *AEA Papers and Proceedings*, May 2020, *110*, 523–28.

Nakamura, Emi and Jón Steinsson, "High-Frequency Identification of Monetary Non-Neutrality: The Information Effect," *Quarterly Journal of Economics*, 2018, *133*, 1283–1330.

Nunes, Ricardo, Ali Ozdagli, and Jenny Tang, "Interest Rate Surprises: A Tale of Two Shocks," 2023. Discussion Papers 2320, Centre for Macroeconomics (CFM).

Paul, Pascal, "The Time-Varying Effect of Monetary Policy on Asset Prices," *The Review of Economics and Statistics*, 10 2020, *102* (4), 690–704.

Piazzesi, Monika and Eric T. Swanson, "Futures prices as risk-adjusted forecasts of monetary policy," *Journal of Monetary Economics*, 2008, *55* (4), 677–691.

Ramey, V.A., "Chapter 2 - Macroeconomic Shocks and Their Propagation," in John B. Taylor and Harald Uhlig, eds., *Handbook of Macroeconomics*, Vol. 2, Elsevier, 2016, pp. 71–162.

Rigobon, Roberto, "Identification Through Heteroskedasticity," *The Review of Economics and Statistics*, 11 2003, *85* (4), 777–792.

Romer, Christina D. and David H. Romer, "Does Monetary Policy Matter? A New Test in the Spirit of Friedman and Schwartz," in Olivier J. Blanchard and Stanley Fischer, eds., *NBER Macroeconomics Annual 1989*, Cambridge, MA: MIT Press, 1989, pp. 121–170.

_ **and** _ , "A New Measure of Monetary Shocks: Derivation and Implications," *American Economic Review*, 2004, *94* (4), 1055–1084.

Rudebusch, Glenn D., "Do Measures of Monetary Policy in a Var Make Sense?," *International Economic Review*, 1998, *39* (4), 907–931.

Sastry, Karthik A., "Disagreement About Monetary Policy," 2021. working paper.

Sims, Christopher A., "Comment on Glenn Rudebusch's "Do Measures of Monetary Policy in a Var Make Sense?"," *International Economic Review*, 1998, *39* (4), 933–941.

Stavrakeva, Vania and Jenny Tang, "The Dollar During the Great Recession: US Monetary Policy Signaling and the Flight to Safety," 2019. Working Paper.

Stock, James and Mark Watson, "Identification and Estimation of Dynamic Causal Effects in Macroeconomics Using External Instruments," *Economic Journal*, 2018, *128* (610), 917–948.

Swanson, Eric and Vishuddhi Jayawickrema, "Speeches by the Fed Chair Are More Important than FOMC Announcements: An Improved High-Frequency Measure of U.S. Monetary Policy Shocks," 2023. Working Paper, UC Irvine.

Swanson, Eric T., "Measuring the effects of federal reserve forward guidance and asset purchases on financial markets," *Journal of Monetary Economics*, 2021, *118*, 32–35.

_ , "The Macroeconomic Effects of the Federal Reserve's Conventional and Unconventional Monetary Policies," 2023. Working Paper 31603.

_ **and John C. Williams**, "Measuring the Effect of the Zero Lower Bound on Medium- and Longer-Term Interest Rates," *American Economic Review*, October 2014, *104* (10), 3154–85.

Vissing-Jorgensen, Annette and Arvind Krishnamurthy, "The Effects of Quantitative Easing on Interest Rates: Channels and Implications for Policy," 2011. Brookings Paper on Economic Activity.

Wieland, Johannes F. and Mu-Jeung Yang, "Financial Dampening," *Journal of Money, Credit and Banking*, 2020, *52* (1), 79–113.

Zhu, Linyan, "Let the Market Speak: Using Interest Rates to Identify the Fed Information Effect," 2023. Working Paper.

A Appendix Shock Construction

A.1 Futures Contracts Details The federal funds futures contract unit is \$4,167 × contract index with a tick size of one-quarter of one basis point (0.0025), or \$10.4175 (0.0025 × \$4,167) for the nearest month's contract and one-half of one basis point (0.005), or \$20.835 per contract for all other months. Contracts are monthly listed for 60 consecutive months and are traded Sunday through Friday from 6:00 pm to 5:00 pm EST. The effective federal funds rate is calculated as a volume-weighted median of overnight federal funds transactions and is reported by the Federal Reserve Bank of New York the next business day by 9 A.M. Eastern Time in the FR 2420 Report of Selected Money Market Rates. Expiring contracts are cash settled against the average daily federal funds overnight rate for the delivery month, rounded to the nearest one-tenth of one basis point with final settlement occurring on the first business day following the last trading day.

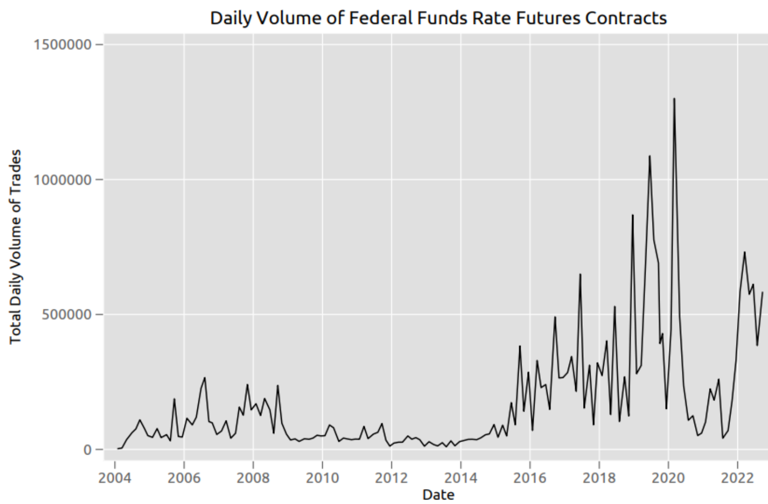


Figure A.11: Total daily number of trades of federal funds futures contracts. Source: CME Group Inc.

The pricing of eurodollar futures follows the same convention as the fed funds futures: 100-index, with a contract unit of \$2,500 × contract index. Tick size was one-quarter of one basis point (0.0025 = \$6.25 per contract) in the nearest expiring contract month and one-half of one basis point (0.005 = \$12.50 per contract) in all other contract months. Contracts were quarterly listed, maturing during the months of March, June, September, or December, plus four serial months and a spot month, extending out ten years. Contracts were settled in cash on the 2nd London bank business day prior to the 3rd Wednesday of the contract month, and here we follow the timing convention of Nakamura and Steinsson (2018) in that new quarters begin on the 15th day of the month of the preceding quarter (e.g., 2023:Q1 would begin on December 15, 2022). Convergence to a final settlement price was forced by "randomly" polling twelve banks actively participating in the LIBOR market during the last 90 minutes of trade and at close. Of course our use of quotation marks in "randomly" refers to the price fixing that had taken place in this market. Highest and lowest price quotes were dropped and the arithmetic average of the remaining quotes determined final settlement.

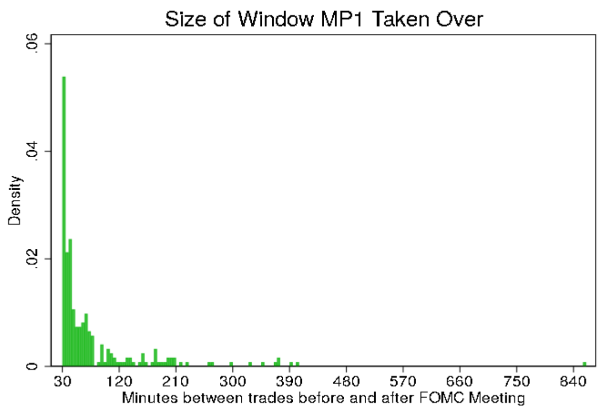
A.2 APPENDIX: WINDOWS FOR SOURCING INTRADAY TRADES The $MP1$, $FF4$, and NS shock series are all constructed from intraday futures data observed minutes before a FOMC announcement and minutes after. However, due to the availability of trades, the minutes "before" and "after" may not be as uniform as researchers would like.

Following Nakamura and Steinsson (2018) and Gürkaynak et al. (2007), researchers construct intraday shocks by selecting trades of federal funds or eurodollar futures 10 minutes before an FOMC announcement and 20 minutes after. However, there are not always trades at these exact times. Typically, trades that take place less than 10 minutes before an announcement or 20 minutes after are not considered. Trades that take place more than 10 minutes before an announcement are considered and researchers select the closest possible trade since 4:00 P.M. on the preceding day—the time when after-hours trading officially begins. Similarly, if there is no trade exactly 20 minutes after an FOMC announcement the closest trade is taken, up to noon on the subsequent day. If no suitable trades before or after the monetary policy announcement exist within these conditions, the change is set to 0.

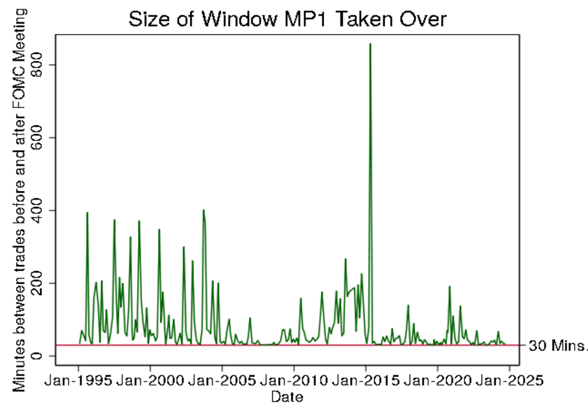
Figures (A.12) and (A.13) show the size of the time windows around FOMC announcements for each of the five futures in the NS instrument set and the $FF4$ series.

Figure (A.12) shows that trades in federal funds futures markets are often not available in exact 30-minute windows around FOMC announcements. While a large share of available intraday trades are within an hour of an announcement, it is not uncommon for intraday windows to be several hours long. Moreover, wider windows are particularly prevalent pre-2005 and during ELB periods. Figure (A.13) reveals a similar, although less extreme, phenomenon in the availability of trades in eurodollar futures.

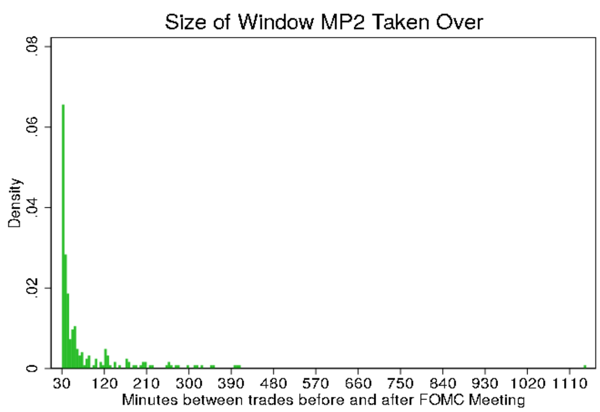
Overall, we note that the lack of uniformity in window sizes does not seem to affect shock construction. If we set windows to be one or two hours, and hence increase the uniformity, shock series are still tightly correlated to their counterparts constructed from 30-minute windows.



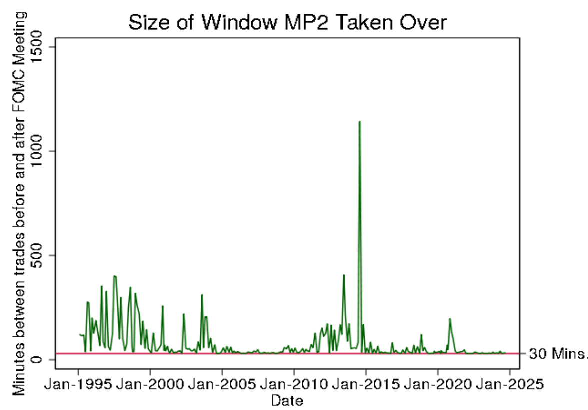
(a) Histogram of time over which $MP1$ is sourced.



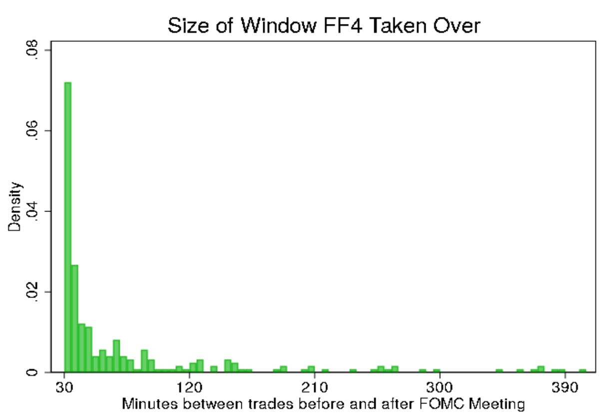
(b) Time over which $MP1$ is sourced, over time.



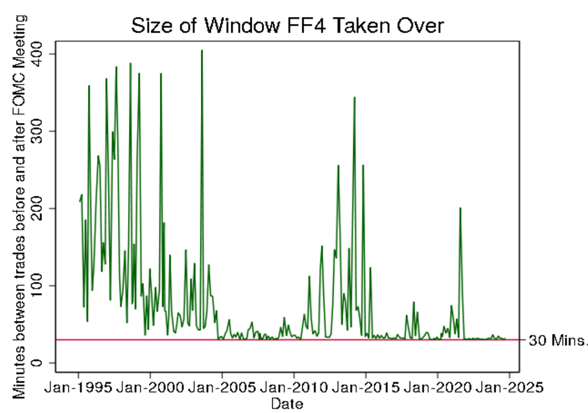
(c) Histogram of time over which $MP1$ is sourced.



(d) Time over which $FF4$ is sourced, over time.

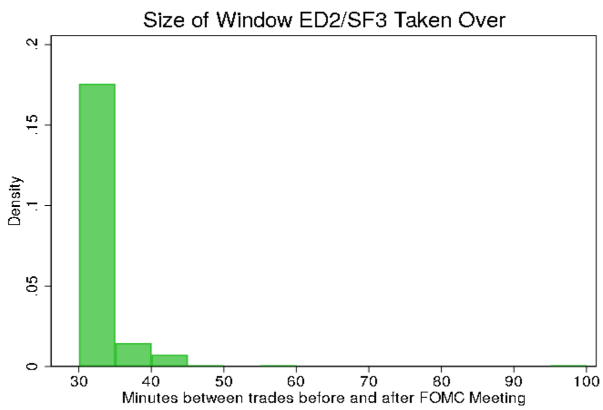


(e) Histogram of time over which $FF4$ is sourced.

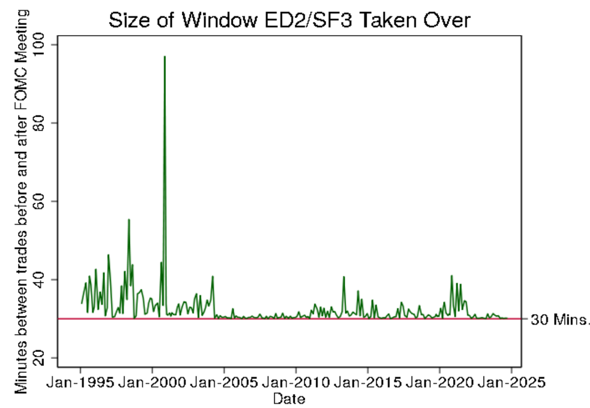


(f) Time over which $FF4$ is sourced, over time.

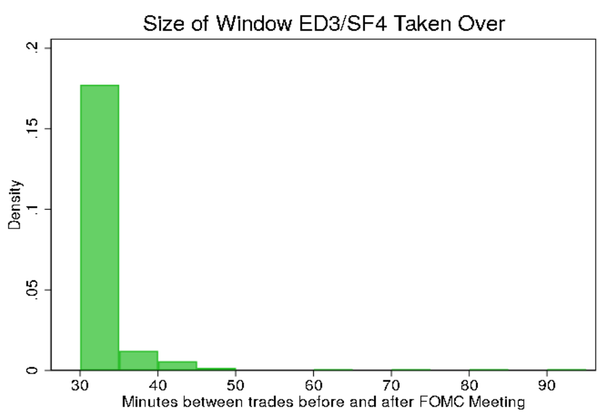
Figure A.12: Time windows around FOMC announcements for federal funds rate futures.



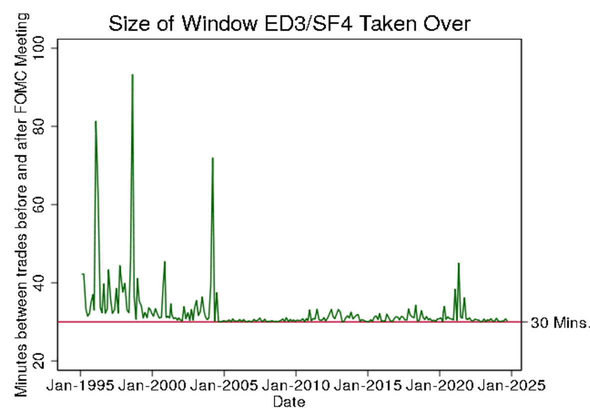
(a) Histogram of time over which $ED2/SF3$ is sourced.



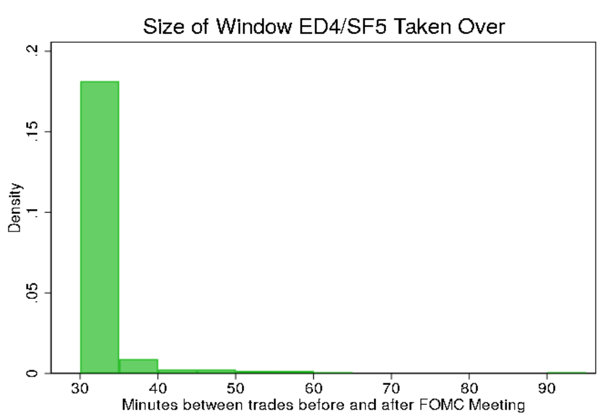
(b) Time over which $ED2/SF3$ is sourced, over time.



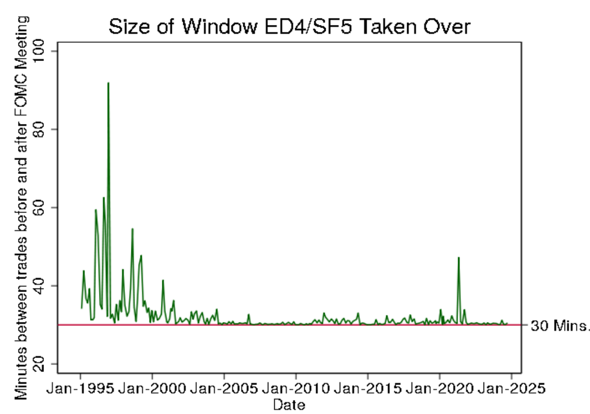
(c) Histogram of time over which $ED3/SF4$ is sourced.



(d) Time over which $ED3/SF4$ is sourced, over time.



(e) Histogram of time over which $ED4/SF5$ is sourced.

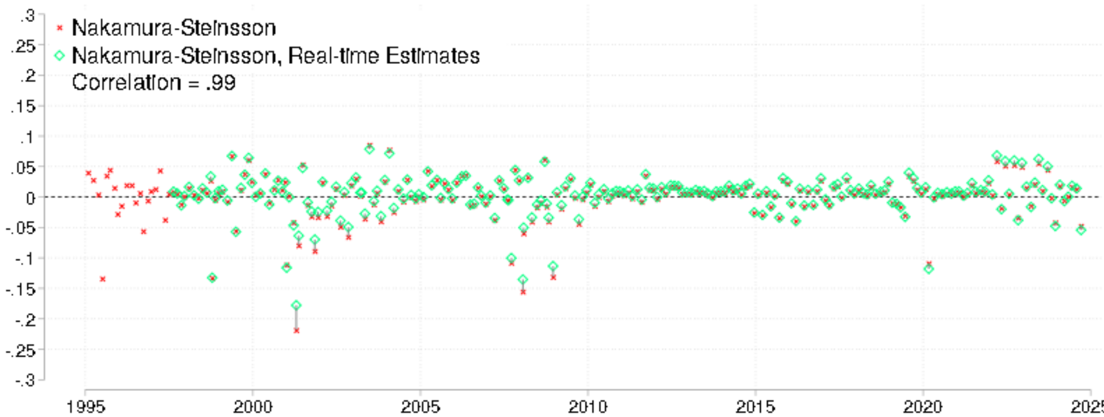


(f) Time over which $ED4/SF5$ is sourced, over time.

Figure A.13: Time windows around FOMC announcements for eurodollar futures. SOFR futures replace eurodollar futures starting in January 2022.

A.3 APPENDIX: REAL TIME ESTIMATES The $MP1$ and $FF4$ shock series are based on changes in raw data, with $MP1$ having a small scalar multiple adjustment based on the days remaining in the month of a meeting. In contrast, the Nakamura and Steinsson (2018) and Bu et al. (2021) shock series utilize statistical procedures (PCA and Fama-MacBeth regression, respectively), which raise concerns of discrepancies in shock estimates compared to real-time versions.

We compare these shocks to their so-called "real-time" counterparts—that is, shocks for which the n^{th} monetary policy announcement's shock is calculated using data for only the first n monetary policy announcements. We begin these real-time estimates at the 30th meeting in our sample so that the statistical procedures have sufficient observations. Figure (A.14) shows that, overall, there is not much difference between the real-time shock estimates and estimates taken over the whole sample. Both shocks have a correlation close to one with their real-time counterpart. Some real-time observations, particularly for the BRW shock series near the onset of the Great Financial Crisis, can substantially differ, but these are not many. Overall, these give us reassurance that it does not much matter if a researcher uses shocks constructed as real-time estimates or shocks constructed using the entire sample.



(a) Nakamura and Steinsson (2018) shock series

(b) Bu et al. (2021) shock series

Figure A.14: Real-time versions of Nakamura and Steinsson (2018) and Bu et al. (2021) series.

Monetary shock series are calculated from January 1995 to September 2024. Real-time estimates calculate the shocks from the first 30 FOMC announcements and then update the estimates recursively. From the 31st estimate onward, each shock observation only contains information that was available at the time of the FOMC announcement. NS is the first principal component of the instrument set $\{MP1, MP2, ED2/SF3, ED3/SF4, ED4/SF5\}$ which is the 30-minute change in these futures around an FOMC announcement. BRW is a Fama-MacBeth regression of the daily change in one- to 30-year constant maturity Treasury yields.

A.4 APPENDIX: NAKAMURA AND STEINSSON (2018) SHOCK SERIES WITH TREASURY YIELDS IN THE INSTRUMENT SET Figure (A.15) shows the original NS shock series along with a version that is augmented to include one-, five-, ten-, and 30-year Treasury yields in the instrument set. Including the long-term rates has little effect on the resulting series because monetary policy is unresponsive to longer-term rates on average.

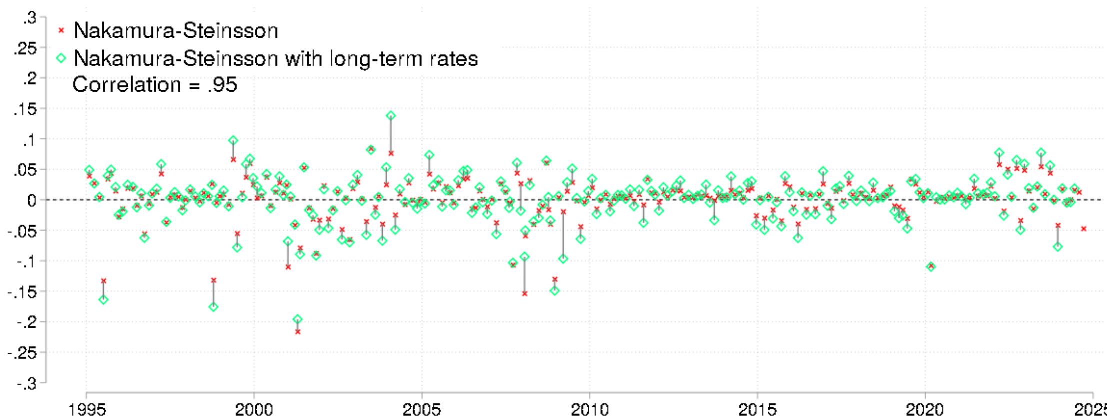


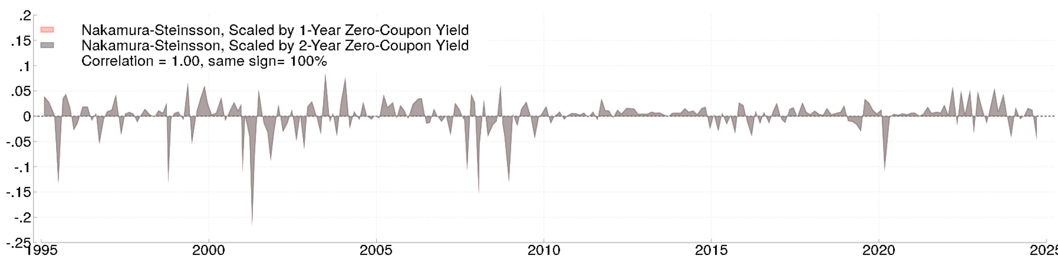
Figure A.15: Nakamura and Steinsson (2018) series with and without long-term rates .

Monetary shock series are calculated from January 1995 to September 2024. NS is the first principal component of the instrument set $\{MP1, MP2, ED2/SF3, ED3/SF4, ED4/SF5\}$ which is the 30-minute change in these futures around an FOMC announcement. NS with long-term rates augments the original instrument set with one-, five-, ten-, and 30-year Treasury yields.

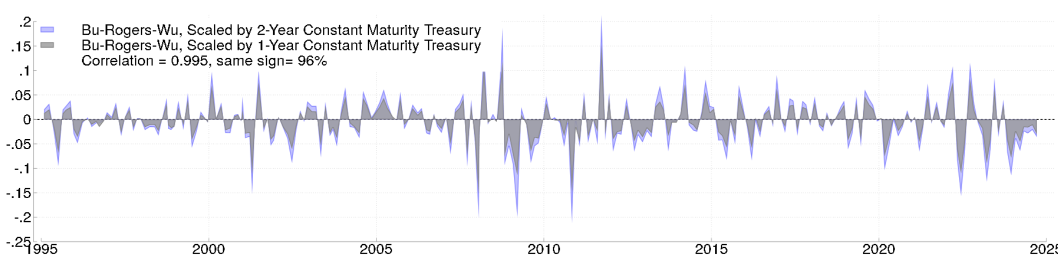
A.5 APPENDIX: SCALINGS OF SHOCKS The methodologies of both the Bu et al. (2021) and Nakamura and Steinsson (2018) monetary policy shocks require scaling for interpretation. Both shocks scale to Treasury yields: the Nakamura and Steinsson (2018) shock scales to the one-year zero-coupon Treasury yield while the Bu et al. (2021) shock scales to the two-year constant maturity Treasury yield. To test if the choice of scaling matters, we use different maturities.

Figure (A.16a) shows that using the change in the two-year zero-coupon Treasury yield instead of the one-year makes little difference for the Nakamura and Steinsson (2018) shock series: both versions of the series share the same sign 100% of the time and their correlation coefficient is a perfect 1.00. This nearly perfect correlation stems from the final step of the shock construction where one scales the first principle component by the coefficient estimate of the scaling variable on the first principle component.

Figure (A.16b) similarly shows that scaling makes little difference for the Bu et al. (2021) shock series. The correlation coefficient between the shock series constructed from the original two-year constant maturity scaling and its counterpart constructed from the one-year is 0.96. When there is some difference in estimates, it is because the scaling variable used in the Bu et al. (2021) Fama-MacBeth regression is used in both the beginning and end of shock construction. While the choice of scaling at the end is simply a means to convert a shock series to interpretable units in the same manner as in the construction of the Nakamura and Steinsson (2018) shock series, the choice of scaling at the beginning could be less innocuous. In the first step of the Fama-MacBeth regression, the choice of scaling variable is also a choice of normalization for which to assess average responsiveness. However, as figure (A.16b) demonstrates, this choice ultimately makes little difference in the constructed monetary shock series.



(a) Nakamura and Steinsson (2018) shock series



(b) Bu et al. (2021) shock series

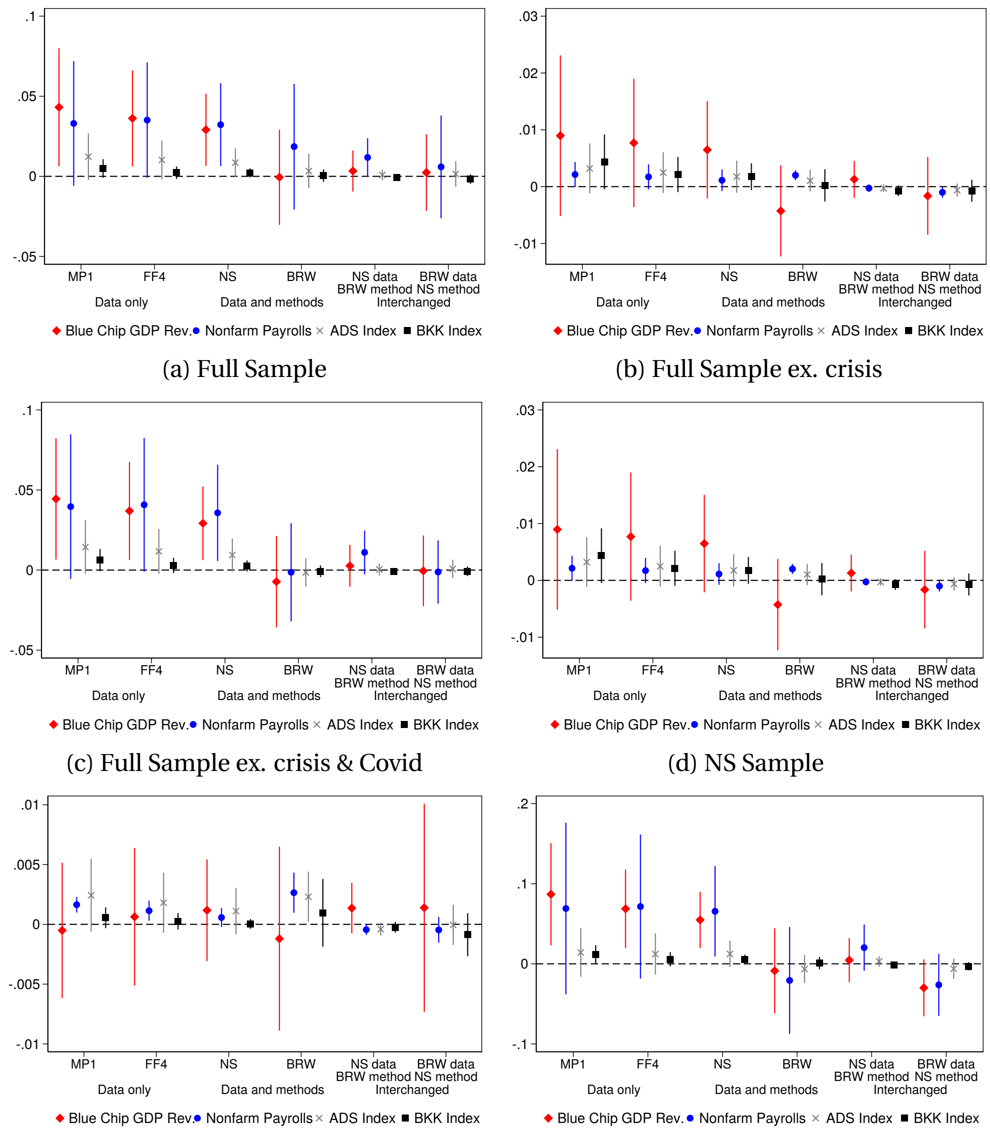
Figure A.16: Monetary shock series under different scaling assumptions.

Monetary shock series are calculated from January 1995 to September 2024. NS is the first principal component of the instrument set $\{MP1, MP2, ED2/SF3, ED3/SF4, ED4/SF5\}$ which is the 30-minute change in these futures around an FOMC announcement. BRW is a Fama-MacBeth regression of the daily change in one- to 30-year constant maturity Treasury yields.

A.6 APPENDIX: PREDICTABILITY REGRESSIONS Because high-frequency monetary policy shock series should be exogenous, it is clearly desirable that the series are not significantly associated with observable macroeconomic news. Following the literature, we test if the six series studied in this paper are predictable by economic news. More specifically, we use as measures of economic news the monthly releases of one quarter-ahead Blue Chip Economic Indicators output growth revisions, the business conditions index of Aruoba et al. (2009) (ADS Index), the Chicago Fed Big Data Business Cycle Indicator of Brave et al. (2019), or the monthly change in nonfarm payrolls. See Appendix D for sources of these series.

The predictability regressions are estimated via OLS with Huber-White robust standard errors, where the dependent variable is the monetary shock series being tested and the independent variable is the macroeconomic news that may be a predictor of the shock. Monetary shock series are aggregated to a monthly frequency and months without a monetary policy announcement are dropped from the sample.

Following the literature, we assure that news pre-dates FOMC announcements. The Blue Chip one quarter-ahead output growth revisions and the nonfarm payrolls releases are not released on the first of the month, so for specifications using either as an independent variable must exclude months in which there a monetary policy announcement before the release of the independent variable. For specifications where the independent variable is Blue Chip one quarter-ahead output growth revisions, we exclude months before December 1, 2000 in which a monetary policy announcement is within the first four business days of the month and we drop months after December 1, 2000 for which a monetary policy announcement is within the first three business days of the month. For specifications where the independent variable is the monthly change in nonfarm payrolls, we exclude months in which a monetary policy announcement occurs within the first seven days of the month and within the first business week of the month.



(a) Full Sample

(b) Full Sample ex. crisis

(c) Full Sample ex. crisis & Covid

(d) NS Sample

(e) ELB episodes

(f) Non-ELB episodes

Figure A.17: Predictability regressions

Estimate of $\hat{\beta}$ in eq. (9) $\varepsilon^i_T = \alpha + \beta news^k_T + e_T$ are OLS. Panel (a) is the full sample from January 1995 to September 2024. Panel (b) is the full sample ex-crisis which excludes the first three months of 2009. Panel (c) is the full sample ex crisis and Covid which excludes the first three months of 2009 and the second quarter of 2020. Panel (d) is the NS sample from January 1995 to August 2015. Panel (e) is the ELB sample defined as December 16, 2008 to December 16, 2015 and March 15, 2020 to March 16, 2022. Panel (f) is the non-ELB sample defined as all dates except those in panel (e). For the specification using the Blue Chip GDP revisions, we follow Bauer and Swanson (2023) and exclude observations where the FOMC announcement is in the first three business days of the month from 1995 to December 2000 and the first two business days thereafter to ensure that the Blue Chip Survey was completed prior to the FOMC announcement. Blue Chip GDP revisions are the monthly revision of one-quarter ahead GDP growth forecasts. The specification using non-farm payrolls assures that the FOMC meeting is after the FOMC release which is often the first Friday of every month. Non-farm payrolls are the monthly change in the non-farm payrolls release. The ADS Index is the Aruoba et al. (2009) business conditions index. The BKK index is the Brave et al. (2019) Big Data index. $MP1$ is the 30-minute change around an FOMC announcement in the current month's federal funds future if the FOMC announcement is in the first 23 days of the month with an adjustment or the next month's federal funds future if the FOMC announcement is within the last seven days of the month. $FF4$ is the change in the three-month ahead federal funds futures within 30-minutes of an FOMC announcement. NS is the first principal component of the instrument set $\{MP1, MP2, ED2/SF3, ED3/SF4, ED4/SF5\}$ which is the 30-minute change in these futures around an FOMC announcement. BRW is a Fama-MacBeth regression of the daily change in one- to 30-year constant maturity Treasury yields. NS data/BRW method is a Fama-MacBeth regression of the NS data. BRW data/NS method is the first principal component of the BRW data.

B APPENDIX: FORECAST REVISION SPECIFICATION

This section describes the data construction for the forecast revision specifications used to estimated monetary policy transmission. This specification is estimated via OLS with Huber-White robust standard errors. The dependent variable is monthly GDP revisions for the year-ahead. More specifically, for a given month we take the average of the revisions for the one-, two-, and three-quarter ahead forecasts. The independent variable is the respective monetary policy shock being tested, excluding shocks occurring in either the first two (after December 2000) or three (before December 2000) business days of the month, as this is when the Blue Chip survey is still being collected. The sample is from January 1995 to September 2024.

THE INDEPENDENT VARIABLE: MONETARY POLICY SHOCK each of the six shock series studied are aggregated to a monthly frequency by summing values across the month. There are particular steps necessary to take before in aggregation that must be taken to ensure that the aggregated monetary policy shocks of a month precede any Blue Chip output growth revision.

We drop meetings occurring before that month's survey collection of Blue Chip is finished. Before December 2000, this was the fourth business day of the month but thereafter was the third business day of the month. This step has several sub-steps. Before December 1, 2000, we also drop any meetings within the first three business days of the month while after December 1, 2000 we drop any meetings within the first two business days of the month. Before December 1, 2000, this means that we drop monetary policy announcements that occur before the fourth day of the month or meetings that are either on the fifth or fourth day of the month and either a Monday, Tuesday, or Wednesday. After December 1, 2000 this means that we drop all meetings that occur before the third day of the month as well as meetings that are either on the third or fourth day of the month and on a Monday or a Tuesday. We then do a monthly sum of monetary policy shocks by month, excluding months during which there are no applicable FOMC meetings.

THE DEPENDENT VARIABLE: GDP FORECAST REVISIONS The dependent variable is the median GDP forecast revisions for the year ahead from the current month from the Blue Chip Economic Indicators. The Blue Chip releases GDP forecasts from the previous month within the first week of the current month. For example, the forecasts for October would be released within the first week of November.

Year-ahead forecast revisions are calculated as the average change in the one, two, and three quarter-ahead median GDP forecasts for the current month. For example, the year-ahead output growth forecast revision for December 2007 is obtained by subtracting the GDP forecasts for 2008Q1, 2008Q2, and 2008Q3 from the November 2007 edition of the Blue Chip Economic Indicators from those from the December 2007 edition of the Blue Chip Economic Indicators.

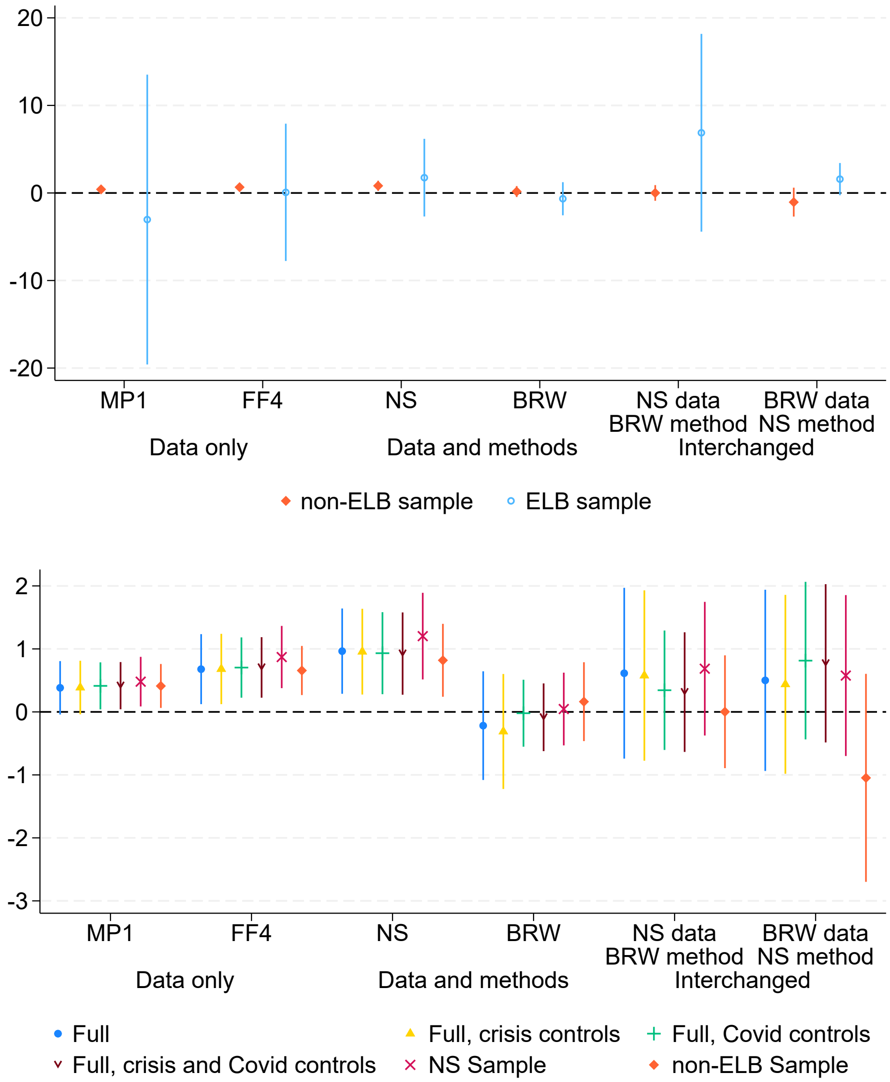


Figure B.18: Forecast revision coefficients and 95% confidence intervals

Estimates of $\hat{\beta}$ in eq. (10) Blue Chip GDP revisions$_T = \beta \varepsilon^i_T + e_T$ are obtained via OLS. The robust standard errors are similar when bootstrapped. The full sample is from January 1995 to September 2024. Crisis controls are indicator variables for the first three months of 2009 and Covid controls are for the second quarter of 2020. The NS sample is from January 1995 to August 2015. The ELB is defined as December 16, 2008 to December 16, 2015 and March 15, 2020 to March 16, 2022. Following Bauer and Swanson (2023), we exclude observations where the FOMC announcement is in the first three business days of the month from 1995 to December 2000 and the first two business days thereafter to ensure that the Blue Chip Survey was completed prior to the FOMC announcement. $MP1$ is the 30-minute change around an FOMC announcement in the current month's federal funds future if the FOMC announcement is in the first 23 days of the month with an adjustment or the next month's federal funds future if the FOMC announcement is within the last seven days of the month. $FF4$ is the change in the three-month ahead federal funds futures within 30-minutes of an FOMC announcement. NS is the first principal component of the instrument set $\{MP1, MP2, ED2/SF3, ED3/SF4, ED4/SF5\}$ which is the 30-minute change in these futures around an FOMC announcement. BRW is a Fama-MacBeth regression of the daily change in one- to 30-year constant maturity Treasury yields. NS data/BRW method is a Fama-MacBeth regression of the NS data. BRW data/NS method is the first principal component of the BRW data.

C APPENDIX: VAR

Using the Canova and Ferroni (2022) toolbox, we estimate the VAR specification of Bauer and Swanson (2022) using each of the six monetary shock series studied in this paper. The monthly VAR has four economic variables: two-year zero-coupon Treasury yields, industrial production (IP), the consumer price index (CPI), and the Gilchrist and Zakrajšek (2012) excess bond premium, in that order. The two-year zero-coupon Treasury yield and Gilchrist and Zakrajšek (2012) excess bond premium are both divided by 100, and the log of taken of industrial production and CPI. The two-year zero-coupon Treasury yield is aggregated from a daily to a monthly frequency by using the last observation for each month. Data series and their sources are described in more detail in Appendix D. Appendix figure (C.19) plots the impulse response functions for the four economic variables to a 25 basis point NS shock.

First, we reproduce Bauer and Swanson's (2022) results with data from their website (https://www.michaeldbauer.com/files/FOMC_Bauer_Swanson.xlsx). Panel (C.19b) in the middle shows that our replication is a close match to their results shown in panel (C.19a) on the left. Differences in error bands arise due to slight variation in methodology. While we use the Bayesian VAR toolbox of Canova and Ferroni (2022), they use frequentist 90 percent bootstrapped standard errors. However, these differences in error bands do not materially alter the implications of the estimates.

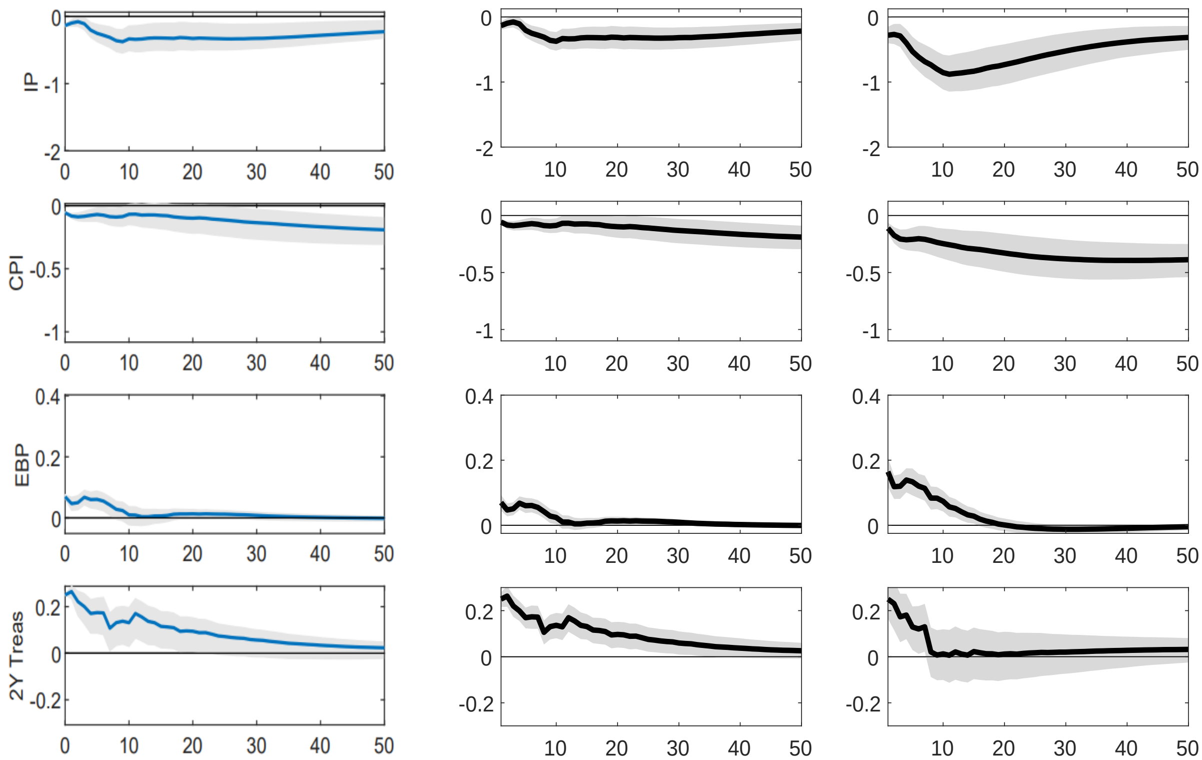
Second, we compare estimates from Bauer and Swanson (2022) to those from our construction of the NS shock series in a specification with 8 lags instead of 12. Bauer and Swanson's (2022) version of the NS shock series is from February 1988 to December 2019 while ours is from January 1995 to September 2024. Following Swanson and Jayawickrema (2023), they obtain a longer sample by constructing the NS shock series using the first principal component of the (*ED1/SF2*, *ED2/SF3*, *ED3/SF3*, *ED4/SF4*) instrument set scaled by a 1 percentage point change in the *ED4* rate instead of the (*MP1*, *MP2*, *ED2/SF3*, *ED3/SF4*, *ED4/SF5*) instrument set scaled by the daily change in the one-year zero-coupon Treasury.[16] With our relative shorter sample for monetary shock series as an external instrument, we found that using 12 lags sacrifices too many degrees of freedom for error bands to be informative. We instead use 8 lags as a remedy and our results are shown in panel (C.19c). While there are quantitative differences in the magnitudes of the responses, such as impulse responses that are larger, the results are still quite similar to those of Bauer and Swanson (2022) shown on the left in panel (C.19a). Therefore, we proceed to implement our various monetary policy shocks as external instruments starting in 1995 in VARs with 8 lags. The increase in magnitudes of impulse responses as the sample shortens can be attributed to the prevalence of zero observations in the monetary shock series—after all, in most years there are four months without a monetary policy announcements. As the sample shortens, the zeros are more prominent and give rise to larger magnitudes.

[16] Starting the sample earlier than 1994 requires relatively more judgement on defining FOMC announcement dates and times as the Federal Reserve only began officially releasing FOMC statements in 1994.

Series name	F-stat	Robust F-stat
$MP1$	0.77	0.54
$FF4$	0.78	0.31
NS	1.89	1.24
BRW	0.91	0.83
NS data, BRW method	0.6	0.46
BRW data, NS method	2.51	4.1

Table 3: First-stage F-statistics.

Estimates from equation (12) $Y_T = \alpha + B(L)Y_{T-1} + s_1 Y_T^{2Y} + \tilde{u}_T$ obtained via the Canova and Ferroni (2022) Bayesian VAR toolbox with 68 percent error bands, 20,000 draws, and 8 lags. The sample of monetary shock series is from January 1995 to December 2019 while the sample of economic data is from January 1973 to February 2020. $MP1$ is the 30-minute change around an FOMC announcement in the current month's federal funds future if the FOMC announcement is in the first 23 days of the month with an adjustment or the next month's federal funds future if the FOMC announcement is within the last seven days of the month. $FF4$ is the change in the three-month ahead federal funds futures within 30-minutes of an FOMC announcement. NS is the first principal component of the instrument set $\{MP1, MP2, ED2/SF3, ED3/SF4, ED4/SF5\}$ which is the 30-minute change in these futures around an FOMC announcement. BRW is a Fama-MacBeth regression of the daily change in one- to 30-year constant maturity Treasury yields. NS data/BRW method is a Fama-MacBeth regression of the NS data. BRW data/NS method is the first principal component of the BRW data. IP is the industrial production index, CPI is the consumer price index, excess bond premium is from Gilchrist and Zakrajšek (2012), and the two-year Treasury is the end of the month daily change in the zero-coupon yield. All sources of series are detailed in Appendix D.



(a) Bauer and Swanson (2022)

(b) Replication using data from Bauer and Swanson (2022)

(c) Replication using 8 instead of 12 lags

Figure C.19: Impulse responses to a 25 basis point NS shock series, x-axis is months and y-axis is percentage points.

Panel (a) is figure (3) in Bauer and Swanson (2022). Estimates in panels (b) and (c) are from equation (12) $Y_T = \alpha + B(L)Y_{T-1} + s_1 Y_T^{2Y} + \tilde{u}_T$ obtained via the Canova and Ferroni (2022) Bayesian VAR toolbox with 68 percent error bands and 20,000 draws. IP is the industrial production index, CPI is the consumer price index, excess bond premium is from Gilchrist and Zakrajšek (2012), and the 2-year Treasury is the end of the month daily change in the zero-coupon yield. All sources of series are detailed in Appendix D.

D Appendix: Data

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

ADS INDEX is a daily business conditions index from Aruoba et al. (2009) and available for download from the Federal Reserve Bank of Philadelphia (https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/ads).

BLUE CHIP GDP FORECAST REVISIONS are the monthly forecast revision of the median GDP forecast. They are obtained from Haver Analytics' Blue Chip Economic Indicators (http://www.haver.com/our_data.html).

BKK INDEX is a daily coincident index from Brave et al. (2019) that provides a summary statistic for the state of the economy. It is available for download from Indiana University Kelley School of Business (https://www.ibrc.indiana.edu/bbki/).

CONSTANT MATURITY TREASURY YIELDS are daily market yields on U.S. Treasuries obtain via the H.15 Selected Interest Rate Release from the Federal Reserve Board.

DAILY CPI The Billion Prices Project publicly available daily CPI can be obtained via Cavallo and Rigobon (2016) for July 2008 through August 2015 (https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi%3A10.7910%2FDVN%2F6RQCRS). This is series `indexCPI` for `country==USA` in spreadsheet `pricestats_bpp_arg_usa.csv` in folder `all_files_in_csv_format.zip`. 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. The index is not seasonally adjusted constructed from webscraped prices of multichannel retailers that sell both online and offline.

EURDOLLAR FUTURES are available at an intraday tick frequency from 1995 to March 2023 via the CME Group Inc. DataMine (https://datamine.cmegroup.com/) at the Federal Reserve Board.

EXCESS BOND PREMIUM is a monthly credit spread index from Gilchrist and Zakrajšek (2012) and is available from the Federal Reserve Board (https://www.federalreserve.gov/econres/notes/feds-notes/ebp_csv.csv.)

FEDERAL FUNDS FUTURES are available at an intraday tick frequency from 1995 to present via the CME Group Inc. DataMine at the Federal Reserve Board (https://datamine.cmegroup.com/).

FOMC ANNOUNCEMENT DATES AND TIMES the dates of FOMC announcements for 1995-2024 are obtained directly from the Federal Reserve's public website (https://www.federalreserve.gov/monetarypolicy/fomccalendars.htm). For selecting the exact times of the announcements, we first use the release time as printed on the FOMC's public press release or otherwise on the Federal Reserve's public website. This is possible for the meetings of 8/7/2007, 5/9/2010, and from 2016 to 2024. Whenever it is not possible to use release time from the Federal Reserve's public website, we next take release times as recorded in the data of Gürkaynak et al. (2005), which covers meetings from 1995-2004. Finally, we consider the time of the first article on Bloomberg regarding the FOMC announcement, which mainly covers meetings from 2005 to 2015. We drop all notational meetings including August 27, 2000, October 4, 2019, March 11, 2008, and August 10, 2007. Following much of the literature, we drop the meetings after 9/11. We drop the March 15, 2020 unscheduled meeting as it occurred on a Sunday and it is difficult to source trades.

INDUSTRIAL PRODUCTION is the seasonally adjusted monthly Industrial Production Index from the Federal Reserve Board (`ALFRED: INDPRO_20200616`).

CONSUMER PRICE INDEX is the seasonally adjusted monthly Consumer Price Index from the Bureau of Labor Statistics (`FRED: CPIAUCSL_20210208`).

NONFARM PAYROLLS, ALL EMPLOYEES is the monthly total nonfarm payrolls release from the Bureau of Labor Statistic's Current Employment Statistics Establishment Survey (`FRED: PAYEMS`).

ZERO-COUPON TREASURY YIELDS are continuously compounded zero-coupon daily yields (mnemonic: `SVENYXX`) obtained from the Federal Reserve Board (https://www.federalreserve.gov/data/yield-curve-tables/feds200628_1.html or as a csv file).