Disentangling Monetary Policy, Central Bank Information, and Fed Response to News Shocks

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This version: February 3, 2025
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Abstract

The paper separately identifies three components of high-frequency surprises around FOMC and non-FOMC Fed announcements: a monetary policy shock, a component related to the different views of the market and the Fed about the economy (central bank information shock, CBI, Jarociński and Karadi 2020), and a component related to the market misperception of the Fed policy rule (Fed response to news shock, FRN, Bauer and Swanson 2023b). It achieves identification by utilizing (i) the high-frequency co-movement of interest rate and stock price surprises, (ii) the predictability of surprises by public news, and (iii) the heteroskedasticity between FOMC and non-FOMC announcements. It estimates the dynamic impacts of these shocks in a daily local projection and in a monthly Bayesian VAR model and confirms the robust presence of the central bank information shock. It finds that the FRN shock plays some role in the daily data, but its impact is marginal in the monthly data. The monetary policy shock, purged from the impact of both CBI and FRN, generates impulse responses consistent with theoretical predictions.

1. Introduction

Tracking the macroeconomic impact of identified monetary policy (MP) shocks is invaluable to assess the transmission of monetary policy and to distinguish between competing macroeconomic models (Christiano et al. 2005; Gagliardone and Gertler 2023). An informative and popular proxy of such shocks are high-frequency interest-rate surprises around the announcements of the Federal Reserve (Fed) (Kuttner 2001; Gürkaynak et al. 2005b; Gertler and Karadi 2015a). However, this proxy can be contaminated with contemporaneously changing market perception about the economic outlook due to Fed communication, a view that is often referred to as the central bank information effect (CBI, Romer and Romer 2000; Jarociński and Karadi 2020). And a further source of contamination can come from contemporaneously changing market perception about the systematic policy rule (Miranda-Agrippino and Ricco 2021; Hack et al. 2024). The latter channel has recently been forcefully advocated as the 'Fed response to news (FRN)' effect by Bauer and Swanson (2023b,a). This view argues that the Fed's unexpectedly aggressive systematic policy response coupled with omitted fresh public economic news can be mismeasured as central bank information effect, even though Fed news is actually only about policy. In this paper, we propose a new approach to separately identify MP, CBI and FRN shocks and we contrast their contributions to the economy.

Our analysis confirms the robust presence of the central bank information shocks, even when the FRN effect is carefully controlled for. Furthermore, even though FRN shocks play a significant role in some specifications – in daily local projections, and monthly VARs using surprises around FOMC events – their impact in our baseline monthly VAR with both FOMC and non-FOMC events is marginal. This can be the result of the stimulative impact of favorable fresh public news and the adverse impact of tighter policy rule offsetting each other. Monetary policy shocks cleaned from the impact of both CBI and FRN shocks generate a downturn in activity, a reduction in the price level and a deterioration of financial conditions, in line with theoretical predictions.

High-frequency changes in interest-rate futures prices around Fed announcements offer a popular proxy for monetary policy shocks (Kuttner 2001; Gürkaynak et al. 2005b; Gertler and Karadi 2015b). Financial market prices incorporate available information about the state of the economy and the systematic policy rule before the event. With a sufficiently narrow window that excludes other systematic news, the surprise, therefore, can be expected to include only the impact of Fed communication. However, the surprise will not be a pure measure of monetary policy shocks, i.e. a temporary deviation from a systematic policy rule, if market participants are imperfectly informed about the economy or the systematic policy. In either of these cases, the surprise will be contaminated by the systematic response of monetary policy to the state of the economy.

The CBI view focuses on Fed communication about the economic outlook. It argues that such communication moves private expectations either because the Fed has private information; uses different economic models to process the public information available in the market (Melosi 2017; Nakamura and Steinsson 2018; Jarociński and Karadi 2020; Miranda-Agrippino and Ricco 2020); or because Fed communication coordinates private expectations (Morris and Shin 2002). A CBI shock has two components, an underlying economic shock (e.g. a recent improvement in the health of the financial sector) and the central bank communication about it, which latter induces a sudden move in market perceptions. Jarociński and Karadi (2020) used high-frequency co-movement of interest rates and stock prices around FOMC statements to separately identify monetary policy (negative comovement) and CBI shocks (positive comovement). The idea behind the identification is that updates in private expectations about the economy due to a Fed communication needs to show up in high-frequency repricing of share prices: depreciation in case of a policy tightening shock; and appreciation in case of a good news about the economy. The approach showed that a favourable CBI shock indeed causes a temporary boom in activity and prices in line with the view that the Fed announcement reveals an ongoing underlying boom that the policy partially counteracts and offsets within a couple of years. Correspondingly, the interest rate surprise cleaned from the impact of the CBI shock leads to a more pronounced downturn in activity and decline in prices than its uncleaned counterpart.

The FRN view (Bauer and Swanson 2023b,a) offers an alternative source of contamination of the monetary policy surprise. It also has two components. First, it argues that standard specifications that rely on monthly data, as those used in survey-expectation-revision equations by Campbell et al. (2012); Nakamura and Steinsson (2018), or in VARs used by Gertler and Karadi (2015a) and Jarociński and Karadi (2020) omit some publicly available information that are informative about concurrent economic shocks. Second, it argues that since the early 1990s the market has systematically underestimated the aggressiveness of systematic monetary policy, and shows that publicly available news indeed forecast a significant portion of the high-frequency interest rate surprises. Overall, the view argues that interest rate surprises caused by an unexpectedly aggressive response to fresh public news (FRN shocks) could be mistakenly identified as CBI shocks. To control for the impact of FRN shocks, the view suggests to purge high-frequency interest-rate surprises from the component that is predicted by fresh public news. A monetary policy shock thus identified generates an amplified economic downturn in a monthly VAR setting. Furthermore, the interest-rate surprise component predicted by fresh public news, predicts a similar temporary boom as the CBI shock.

Which view is more relevant in the data? And how should one best disentangle monetary policy surprises and estimate its components? This paper sets out to address these questions.

The first contribution of the paper is to extend the sample of Fed events from FOMC statements used by previous research, to non-FOMC events, including Fed chair speeches, publication of minutes, etc., which have been shown to raise the relevance of the high-frequency interest-rate surprises (Swanson and Jayawickrema 2023; Swanson 2023).

Its second contribution is to propose a methodology to separately identify a monetary policy shock, a central bank information shock and a Fed response to news shock. To achieve this, it combines the predictability of interest rate surprises with fresh public news with the high-frequency co-movement of interest rates and stock prices. The starting point in the identification is the requirement in the FRN view: an FRN shock needs to co-move with the component of the interest rate surprises that are explained by fresh public news. The key contribution of this paper is to point out a further identifying restriction inherent in the FRN view. In particular, a tighter than expected systematic policy necessarily leads to a stock price *depreciation* on impact. The argument is similar to an adverse monetary policy shock: the tighter than expected interest rate policy generates a temporary downturn - reducing the near-term cash flow of shares - and an increase in the discount rate. This restriction also helps to distinguish it from the CBI shock, which requires a *positive* comovement between interest rates and stock prices: good news about the economy leads to both a stock price appreciation and an accompanying tightening of systematic policy to offset its effects. Lastly, the monetary policy shock is identified as a shock that both co-moves with the interest rate surprises that are unexplained by fresh public news and generates a negative high-frequency comovement between interest rates and stock prices.

The third contribution of the paper is to improve the precision of the estimates by utilizing the differences in the relative strengths of the three channels in FOMC versus non-FOMC events. In particular, it combines sign restrictions with a heteroskedasticity-based identification (Rigobon 2003). It shows that the forecastability of the interest rate surprises is weaker at non-FOMC events than at FOMC events, indicating the FRN shocks are weaker during the former than during the latter. Furthermore, it shows that the negative relation between interest rate surprises is stronger during FOMC events than during non-FOMC events, suggesting that CBI shocks, which generate the positive comovement, are more prevalent in the non-FOMC subsample. This heteroskedasticity provides extra information that sharpens the inference.

We first assess the impact of the identified shocks on daily financial variables, such as stock prices, breakeven inflation, corporate bond spreads, and the VIX through local projections over a 60-day horizon. We find that central bank information shocks are a robust feature of the data even when FRN shocks are taken into account. A favorable CBI shock leads to increases in stock prices and breakeven rates and significant decreases in corporate bonds spreads and the VIX. We also find that FRN shocks exert a significant impact on financial prices. However, the responses to hawkish FRN shocks are *contractionary*, leading to significant declines in breakeven inflation rates and stock prices and increases in corporate bond spreads and the VIX. This implies that the impact of monetary policy tightening dominates the effect of favorable fresh public news. This partly supports the FRN view: revisions in market perception about systematic policy indeed affect high-frequency surprises. However, it is inconsistent with a key conclusion of the FRN view, which argues that FRN shocks *attenuate* the estimated medium-term effects of monetary policy if not properly controlled for. On the contrary, FRN shocks exert a qualitatively similar influence on financial variable as monetary policy shocks, albeit monetary policy shocks die out somewhat faster.

Second, we implement the identification in a Bayesian VAR framework with monthly data between 1988:01-2024:09. The VAR includes the 1-year Treasury rate as a monetary policy indicator; a monthly interpolation (Stock and Watson 2010) of real GDP and the GDP deflator, as indicators for activity and prices; and the S&P 500 stock market index and the excess bond premium (Favara et al. 2016) as indicators for the financial conditions. The identification utilizes three high-frequency variables: the interest rate surprises (i) explained and (ii) unexplained by fresh public news and (iii) surprise in the S&P500 index, all in a 30 minute window around Fed announcements. They are measured in over 600 Fed communication events including FOMC statements, Fed-chair speeches, publication of minutes. We show robustness to restricting the event sample to FOMC statements to foster comparability with previous research.

We establish several results. First, we show that central bank information effects are a robust feature of the data. Even when we allow for the presence of Fed response to news effects, the identified CBI shocks cause a significant temporary boom in monthly data in all our specifications. Second, in our baseline monthly VAR specification with a wide range of Fed events, Fed response to news shocks have only marginal impact on monthly fluctuations. One could obtain somewhat less sharp, but similarly valid results relying on simpler methods that ignore the presence of FRN effects (Jarociński and Karadi 2020). Considering only FOMC statements would be insufficiently informative to precisely estimate the effects of the three shocks. Third, we find that monetary policy shocks purged from the impact of both CBI and FRN effects generate a temporary downturn in activity and prices and are accompanied by a temporary deterioration of financial conditions, in line with theoretical predictions.

Related literature Our paper contributes to the strand of empirical research that measures the causal impact of monetary policy on the economy through identifying temporary deviations from systematic policy - monetary policy shocks (Romer and Romer 2004; Christiano et al. 2005; Uhlig 2005; Arias et al. 2019). It builds on the insight of Gertler and Karadi (2015a), who use high-frequency financial market surprises around FOMC announcements (Kuttner 2001; Gürkaynak et al. 2005b) as instruments in a structural vector autoregression. Accurate high-frequency identification requires refinements if there is imperfect information about systematic policy or the state of the economy, which market participants learn about from policy announcements. Researchers have used different approaches to clean monetary policy shocks from these confounding factors. One strand cleans the surprises from the Fed's private information Barakchian and Crowe (2013); Gertler and Karadi (2015b); from a combination of the Fed's private information and public information Miranda-Agrippino and Ricco (2021); or only from public information Bauer and Swanson (2023b,a). Another strand of the literature achieves identification by looking at the co-movement with a wider set of high-frequency financial variables, including stock prices, (Cieślak and Schrimpf 2018; Jarociński and Karadi 2020) or text-based indicators (Acosta 2023). The literature has consistently found that confounding factors cause a significant bias, and controlling for them leads to monetary policy effects that are stronger and consistently in line with theoretical predictions. The paper's contribution is to provide a new measure of monetary policy shocks that cleans them from a wide set of confounding factors.

The paper also contributes to the debate on the existence of the central bank information effect: whether Fed communication about the economic outlook drives private expectations and the macroeconomy. Proponents argue that the Fed's efforts in macroeconomic data processing and analysis provide it relevant private information that private agents find useful (Romer and Romer 2000; Melosi 2017; Nakamura and Steinsson 2018). Those challenging the channel argue that the market efficiently aggregates information about the state of the economy, to which the Fed cannot usefully contribute; if the Fed has private information about anything, it is the nature of its systematic policy (Faust et al. 2004). Our paper revisits the debate and seriously considers whether the Fed response to news channel proposed recently by Bauer and Swanson (2023b,a) and outlined above is a valid alternative to the central bank information effect based on high-frequency identification Jarociński and Karadi (2020); Miranda-Agrippino and Ricco (2021).

The paper extends the set of Fed communication events from FOMC announcements to include also press conferences, chair speeches, and publication of meeting minutes. Our paper shows that extending the set of events is not only important for improving the relevance of high-frequency surprises as shown by Swanson and Jayawickrema (2023) as a response to a critique of Ramey (2016); but also helps to cleanly assess the overall importance of different communication channels. Our paper shows that while on a narrow set of FOMC meeting announcements, Fed response to news channel is relevant, its contribution becomes marginal in the broad sample of Fed communication events.

Our paper also contributes to the event-study literature that analyzes the impact of Fed communication on financial market prices. Within this literature, (Brooks et al. 2018) has recently pointed out that the high-frequency interest-rate surprises pass-through to Treasury yields gradually, a puzzling fact they called the post-FOMC drift. We contribute to this literature by pointing out that the drift is related to information shocks inherent in the surprise (primarily central bank information shocks, but also Fed response to news shocks), while the response to pure monetary policy shocks do not show any significant drift.

The paper is structured as follows. Section 2 presents a theoretical framework with a precise decomposition of monetary policy surprises into a monetary policy, a Fed response to news and a central bank information shocks, and use the framework to derive the necessary restrictions for the identification of the three shocks. Section 3 presents the data, the construction of Fed event windows and reproduces the Bauer and Swanson (2023b,a) regressions. Section 4 presents the dynamic effects of the shocks on financial and macroeconomic variables within a local projection event study and a Bayesian VAR framework. Section 5 show the robustness of the results and Section 6 concludes.

2. Theoretical framework

This section outlines a simple theoretical framework which simultaneously accounts for both Fed policy rule misperception by the public, giving rise to the Fed response to news effect, and heteregeneous views on the state of the economy by the Fed and the public, giving rise to the Fed information effect.

2.1. Fed Policy Rule and Market Perceptions

Federal Reserve sets its policy rate, i as a function of the state of the economy, represented by x (for instance, the output gap). We assume the following policy rule:

$$i = \alpha_F x_F + \varepsilon \tag{1}$$

where α_F is the Fed's response coefficient, x_F is the Fed's view of the economy, and ε represents a monetary policy shock. The market's expectation of the policy rate, denoted $E_M(i)$, is:

$$E_M(i) = \alpha_M x_M \tag{2}$$

where α_M is the market's perception of the Fed's reaction function coefficient, and x_M is the market's view of the economy.

The monetary policy surprise (MPS) is defined as the difference between the actual policy rate and the expected policy rate:

$$\text{MPS} = i - E_M(i)$$

2.2. Decomposing the Monetary Policy Surprise

After subtracting (2) from (1) and rearranging the terms, the monetary policy surprise can be unpacked into three distinct components:

$$\underbrace{i - E^M(i)}_{MPS} = \underbrace{\alpha^F(x^F - x^M)}_{\Rightarrow CBI} + \underbrace{(\alpha^F - \alpha^M)x^M}_{\Rightarrow FRN} + \underbrace{\varepsilon}_{MP\text{ (shock)}}$$

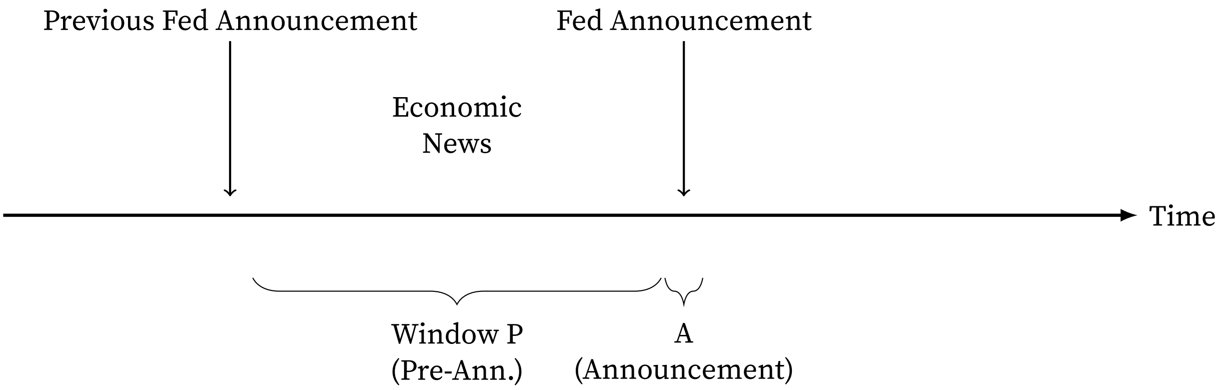
These three terms correspond to the following shocks:

a. **Monetary policy shock (MP)**: ε, the exogenous component of monetary policy, independent of the state of the economy
b. **Fed response to news effect (FRN)**: arises from the Fed and the market having different views on the Fed's reaction function, $(\alpha^F - \alpha^M)x^M \neq 0$
c. **Central bank information effect (CBI)**: arises from the Fed and the market having different views on the state of the economy, $\alpha_F(x_F - x_M) \neq 0$

2.3. Timing of Events and Their Effects

Figure 1 illustrates the stylized timeline of events. The Fed Announcement Window (Window A) is a narrow time window during which the Fed communication dominates all other news about the economy. Think of a commonly used window starting 10 minutes before the start of the Fed communication and ending 20 minutes after its end. The Pre-Announcement Window (Window P) precedes the Fed Announcement Window and is dominated by other economic news.

FIGURE 1. Stylized timeline



Consistently with Bauer and Swanson (2023b), we assume that market misperceives the Fed reaction coefficient to be lower than it actually is, i.e. $\alpha_M < \alpha_F$.

Without loss of generality, consider shocks that result in *positive* realizations of the monetary policy surprise (MPS). The three shocks we consider have the following consequences.

a. **MP shock:** The Fed announces higher policy rates for reasons exogenous to the state of the economy. As a result, stock prices fall immediately and the economic activity declines in the medium term.
b. **FRN effect:** News arriving in the Pre-Announcement window suggests that the economy is strong ($x_M = x_F > 0$), but on the announcement day, the Fed responds more aggressively than expected ($\alpha_F > \alpha_M$). As a result, stock prices fall immediately, but in the medium term the economy strengthens.
    - Stock prices fall due to the tighter systematic monetary policy. The positive news about the economy were already incorporated in the stock prices ahead of the Fed announcement, so the only news in the Fed Announcement Window is about the stronger-than-expected monetary policy response.
    - In the medium run economic activity increases, consistently with the positive economic news in the Pre-Announcement window. The tighter than expected policy do not fully offset this effect.
c. **CBI effect:** The Fed announces that the economy is stronger than the market had anticipated ($x_F > x_M$), leading to a larger-than-expected rate hike. As a result, stock prices rise immediately, and the economy strengthens in the medium run.
    - Stock prices rise, as positive dividend news dominate negative discount rate news for reasonable calibrations of the Fed reaction function.
    - In the medium run economic activity increases, consistently with the positive economic news in the Fed announcement.

2.4. Key predictions of the framework

2.4.1. High-Frequency Response of Stock Prices Distinguishes the FRN from CBI

The first prediction of this framework is that the high-frequency response of stock prices can help distinguish between CBI and FRN effects. When a CBI shock occurs, the announcement provides good news about the economy, leading to a simultaneous increase in both interest rates and stock prices. In contrast, an FRN shock implies tighter-than-expected monetary policy without new information about the economy, resulting in a drop in stock prices.

In summary:

- **CBI effect**: Stock prices increase due to the positive economic outlook.
- **FRN effect**: Stock prices decrease due to the unexpectedly tight policy stance.

This distinction allows us to identify the nature of surprises in Fed announcements and their impact on the economy, based on high-frequency data on stock prices and interest rates.

2.4.2. FRN and CBI imply a similar attenuation bias in the econometric estimates of monetary policy effects

The second prediction of this framework is that econometric estimates that use high-frequency interest rate surprises (MPS) as an instrument for monetary policy shocks suffer from an attenuation bias. Both FRN and CBI effects predict episodes where positive MPS is followed by strong economic activity (or negative MPS by weaker economic activity). The presence of these episodes attenuates the estimates of the effects of monetary policy, if the FRN and CBI effects are not properly controlled for.

3. Data

This section explains our data on high-frequency market reactions to Fed communication (high-frequency surprises). First, we replicate and extend the Gürkaynak et al. (2005a) dataset of high-frequency surprises, adding also surprises around more types of Fed communication, such as Fed chair speeches and minutes releases, following Swanson and Jayawickrema (2023). Second, we run the Bauer and Swanson (2023b) predictive regressions with these high-frequency surprises.

3.1. Data sources

We take high-frequency financial market data from three sources: TickData, Datascope Tick History and Pi Trading.[1] The main variables of interest are Eurodollar/SOFR

[1] We have access to Datascope Tick History database with real-time updates, but the dataset starts only in 1996. Therefore, we combine it with data from TickData (access to time series till 2019) and Pi Trading, which both go back to before 1988, when we start our analysis. We combine the datasets in a way to maximize coverage from a single source. Surprises calculated from different sources using overlapping samples are almost identical.

futures[2] and the S&P500 futures. The first four futures tenors, ED1, ED2, ED3, ED4, come from TickData (until 2019), and Datascope Tick History (from 2019). Eurodollar futures were replaced by SOFR futures in January 2023. S&P 500 futures, SP500FUT, from TickData (until 2008), from 2008 onwards we use E-mini S&P 500 futures from Datascope Tick History.[3] Relying on S&P 500 futures, as opposed to the actual stock index, has the advantage that the futures market is active while the New York Stock Exchange is closed. We also show robustness using the S&P 500 stock index, SP500, obtained from Pi Trading.

We construct the interest rate surprise, MPS, as the first principal component of the ED1, ED2, ED3 and ED4 surprises computed over Fed event windows defined below.

3.2. Events, samples

We construct event windows in two steps. First, we collect the timestamps of Fed events and define the time windows that bracket those events. Second, we collect the timestamps of the potential *interfering events* and adjust the Fed event windows to remove the overlap with the interfering events.

Fed event windows. We collect the timestamps of FOMC announcements, post-FOMC press conferences, Fed chair speeches and congressional testimonies,[4] and the release of the FOMC meeting minutes. From 1997 onward, the source is the Bloomberg Economic Calendar. Before 1997 we took the times of FOMC announcements from Bauer and Swanson (2023a) and the times of Fed chair speeches and testimonies from Board of Governors of the Federal Reserve System and Greenspan (2019). We obtain 1691 timestamps between January 1988 and September 2024. We dropped 8 timestamps that point to overlapping events and 66 timestamps for which the high-frequency variables of interest were missing, leaving us with 1617 timestamps. Table 1 reports the count of events of each type. The 358 FOMC announcements include FOMC press releases (from 1994 onward) as well as timestamps of the first post-FOMC open market operations collected by Bauer and Swanson (2023a) (before 1994). The second column reports the assumed duration of each type of event. We define windows around the events that start 10 minutes before the start of the event and end 20 minutes after the end of the event.

[2] Eurodollar futures were based on the London Interbank Offered Rate (LIBOR). LIBOR was assembled using rates on unsecured interbank transactions. The rate and derivatives based on it was phased out between 2021-2023. It was gradually replaced by the Secured Overnight Financing Rate (SOFR), a rate based on transactions in the U.S. Treasury repurchase (repo) market.

[3] E-mini S&P500 futures became the most liquid market due to its smaller contract size. The dataset contains also Fed funds futures and Treasury futures which we only use in the robustness exercises and report in more detail in the Appendix.

[4] In some cases (10 out of 369), we know that the text of the congressional testimony was released ahead of the actual testimony. We treat the release of the text of the congressional testimony as a separate event.

TABLE 1. Fed events, January 1988 - September 2024: counts, window lengths, median absolute ED3 surprises

Event type	Count	Duration (min)	Med(|ED3|)	#|ED3| > 3bp
FOMC announcement	358	0	0.020	155
Post-FOMC press conference	79	60	0.015	26
Release of FOMC meeting minutes	217	30	0.010	36
Fed Chair speech	584	90	0.010	126
Fed Chair congressional testimony	369	180	0.015	131
Release of testimony text	10	30	0.003	2

Interfering events. Asset prices in Fed windows might be affected by some other *interfering events* that occur simultaneously. Therefore, we adjust the Fed event windows for the interfering event windows. Kerssenfischer and Schmeling (2024) systematically study which types of events move financial markets the most, and we choose interfering events based on their results. In particular, we use the set of 18 types of interfering events consisting of ECB monetary policy decisions and press conferences, major US data releases and Treasury auction results.[5] We create windows around these interfering events that start 10 minutes before and end 20 minutes after the interfering event. We then eliminate from Fed event windows any overlap with the interfering event windows. If an interfering event occurs in the middle of a longer Fed window and this procedure would leave us with two windows, we leave only the longer of the two windows. 263 windows (16%) are affected by the adjustment.

In the last step, we compute the changes of the main interest rates and of the S&P500 stock index in the Fed windows. The fourth column of Table 1 reports the median absolute change of ED3 (the third Eurodollar future).

We have verified that we are able to closely replicate the dataset of Gürkaynak et al. (2005b) using our procedures and data sources. We compare the 2019 version of that well-known dataset with the surprises that we obtain in the FOMC announcement windows. The correlations on an event-by-event basis are at least 94% for all variables.

We define big events as those during which the ED3 moves by at least 3 basis points (the same threshold is used by Bauer and Swanson 2023b). Given these data we create the following subsamples:

a. Baseline: FOMC announcements and "big" non-FOMC events, 679 observations
b. FOMC announcements, 358 observations
c. "Big" non-FOMC events, 321 observations

When estimating the impact of the shocks on other variables we drop all Fed events that happen in March 2020, in order to prevent the unusual Covid-related fluctuations from having an outsized impact on the results. We explain our decision in Appendix C.

[5]These are all the US events that enter their Figure 1, including US Employment report, US ISM PMI Manufacturing, US Auction Result Notes, US Jobless Claims, US CPI and Earnings, US Chicago PMI, US Auction Result Bond, US University of Michigan Surveys, US Conference Board Leading Indicator, US Retail Sales, US Durable Goods, US ISM PMI Non-Manufacturing, US GDP, US Auction Announcement Bill, US PPI, US Existing Home Sales, US New Home Sales.

3.3. Bauer-Swanson regressions

In this section we replicate Bauer-Swanson regressions of the monetary policy surprises (MPS) on observable economic variables and decompose MPS into a fitted value and the residual.

$$MPS_t = \beta y_t + \varepsilon_t, \tag{3}$$

where MPS is an interest rate surprise and y_t is a vector of variables known to the market participants before the Fed event window. Bauer and Swanson use a different vector y_t in the alternative papers (Bauer and Swanson 2023b,a; Swanson 2024). In order to be conservative, we take as y_t the union of all readily available regressors from their three recent papers.

TABLE 2. Explanatory variables of the Bauer-Swanson regressions

Acronym	Definition	Used in[a]
s_unemplrate	Unemployment rate surprise	AER, IMF
s_nfp	Non-farm payrolls surprise	AER, MA, IMF
s_rgdp	Real GDP surprise	AER, IMF
s_corecpi	Core CPI surprise	AER, IMF
m_corecpi	Core CPI median forecast	AER
dcorecpi6m	6-month change in Core CPI	AER
cycle_bbk	BBK Index	AER
l1l90logsp500	Δ log SP500 (3m)	AER, MA, IMF
l1l90pc2	Δ yield curve slope (3m)	AER, MA
l1l90logbcomsp	Δ log commodity price (3m)	AER, MA, IMF
isk1m	Treasury yield skewness (1m)	MA
employ_yoy	Employment growth (12m)	MA
l1l90sveny02	Δ 2-year Treasury (3m)	IMF
l1l90sveny10	Δ 10-year Treasury (3m)	IMF
l1l90baa10y	Δ Baa spread (3m)	IMF
d3mwuxia	Δ Shadow fed funds rate (3m)	IMF
l1l30anfci	Δ Chicago Fed NFCI (1m)	IMF

[a] AER denotes Bauer and Swanson (2023b), MA denotes Bauer and Swanson (2023a) and IMF denotes Swanson (2024).

TABLE 3. Bauer-Swanson regressions

	Baseline	FOMC	Non-FOMC
(Intercept)	-0.0111	-0.0211**	0.0015
	(0.0082)	(0.0100)	(0.0134)
s_unemplrate	0.0166	0.0136	0.0103
	(0.0169)	(0.0205)	(0.0297)
s_nfp	0.0159	0.0174	0.0312
	(0.0118)	(0.0136)	(0.0408)
s_rgdp	0.0097*	0.0045	0.0126
	(0.0054)	(0.0070)	(0.0083)
s_corecpi	0.0180	0.0274	0.0041
	(0.0261)	(0.0326)	(0.0418)
m_corecpi	-0.0259	-0.0108	-0.0332
	(0.0353)	(0.0427)	(0.0592)
dcorecpi6m	-0.0071	-0.0021	-0.0150*
	(0.0044)	(0.0051)	(0.0078)
cycle_bbk	-0.0004	-0.0009	0.0005
	(0.0013)	(0.0016)	(0.0024)
l1l90logsp500	0.0922*	0.1273**	0.0460
	(0.0495)	(0.0646)	(0.0752)
l1l90pc2	-0.1772	-0.1881	-0.0135
	(0.1642)	(0.2143)	(0.2500)
l1l90logbcomsp	0.1138***	0.1637***	0.0534
	(0.0394)	(0.0533)	(0.0591)
isk1m	0.0300***	0.0355***	0.0329
	(0.0115)	(0.0135)	(0.0203)
employ_yoy	0.4248*	0.4713*	0.1301
	(0.2205)	(0.2447)	(0.4384)
l1l90sveny02	-0.0482	-0.0601	0.0084
	(0.0492)	(0.0643)	(0.0748)
l1l90sveny10	0.0652	0.0684	0.0078
	(0.0624)	(0.0813)	(0.0950)
l1l90baa10y	-0.0059	-0.0098	0.0184
	(0.0110)	(0.0142)	(0.0180)
d3mwuxia	-0.0043	0.0217**	-0.0166
	(0.0079)	(0.0106)	(0.0120)
l1l30anfci	0.0500***	0.0359*	0.0298
	(0.0133)	(0.0212)	(0.0196)
N	679	358	321
R-squared	0.070	0.191	0.053
Adj.R-squared	0.047	0.150	0.000

Table 3 shows that on FOMC meeting days, which was used as a baseline sample in Bauer and Swanson (2023b,a), the regressors indeed predict a sizable fraction, around 19% of the surprises - similarly to the results emphasized by Bauer and Swanson. However, when we extend the events to other type of Fed events, the explanatory power of the same set of regressors declines substantially. The R-squared drops to single digits in the Non-FOMC sample and in the combined sample.

4. Dynamic effects

This section constructs the three shocks and tracks their effects in daily (yield curve, stock prices, TIPS/breakeven rates, spreads) and monthly data (activity, prices, financial variables).

4.1. Identification: sign and magnitude restrictions

After decomposing MPS as: MPS = FIT + RES, we specify the following sign and magnitude restrictions relating these variables to the underlying economic shocks.

a. Monetary policy shock (MP) is associated with a negative co-movement between the unexplained component of the interest rate surprise (RES) and the stock price surprise (SP500)
b. Fed response to news shock (FRN) is associated with a negative co-movement between the predicted component of the interest rate surprise (FIT) and the stock price surprise (SP500)
c. Central bank information shock (CBI) is associated with a positive co-movement between the interest rate surprise (MPS) and the stock price surprise (SP500)
d. "Good proxy" restriction: in the variance decomposition of the fitted value of the Bauer-Swanson regression (FIT), the FRN shock dominates the MP shock
e. "Good proxy" restriction: in the variance decomposition of the residual of the Bauer-Swanson regression (RES), the MP shock dominates the FRN shock

These restrictions can be represented as follows:

$$\begin{pmatrix} RES \\ FIT \\ SP500 \end{pmatrix} = \begin{pmatrix} + & c_{12} & c_{13} \\ c_{21} & + & c_{23} \\ - & - & + \end{pmatrix} \begin{pmatrix} MP \\ FRN \\ CBI \end{pmatrix} \tag{4}$$

where - denotes a negative sign restriction, + denotes a positive sign restriction, and

$$c_{13} + c_{23} > 0, \qquad \text{Assumption 3} \tag{5}$$

$$|c_{12}| < c_{11}, \qquad \text{Assumption 4} \tag{6}$$

$$|c_{21}| < c_{22}, \qquad \text{Assumption 5.} \tag{7}$$

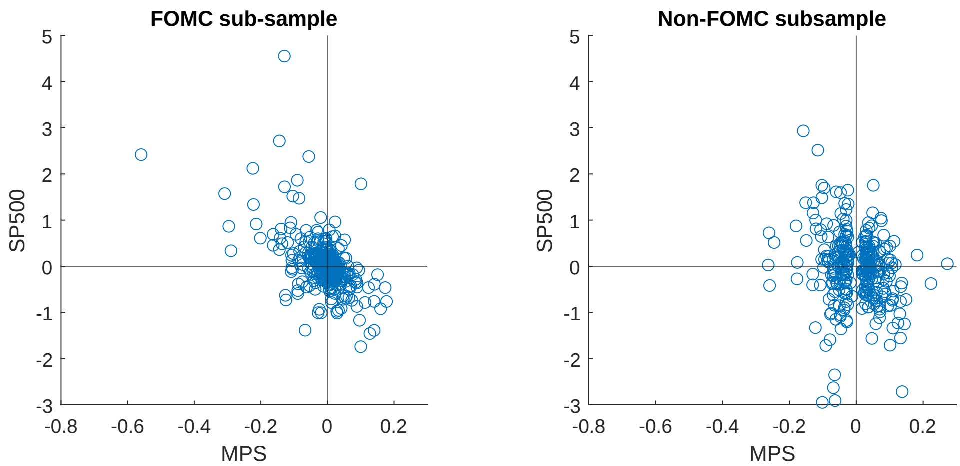
In a nutshell, the sign restrictions reflect the theoretical analysis in section 2 while the magnitude restrictions state that if RES is a good proxy for MP and FIT a good proxy for FRN, then c_{12} and c_{21} will be small.

4.2. Sharpening the inference through heteroskedasticity-based identification

Sign and magnitude restrictions on their own are consistent with many different decompositions, but we can sharpen the inference by bringing in the additional information contained in the heteroskedasticity between the FOMC and non-FOMC events.

Two observations suggest that the mix of shocks in the FOMC and non-FOMC events is significantly different. First, Table 3 shows that the R-squared of the Bauer-Swanson regressions is much higher in the FOMC subsample than in the non-FOMC subsample. This suggests that the FRN shocks, proxied by the fitted values of Bauer-Swanson regressions, are more prevalent in the FOMC subsample. Second, the negative relation between interest rate surprises and stock price surprises is stronger in the FOMC subsample, while in the non-FOMC subsample there are more cases of a positive co-movement. See Figure 2. This suggests that the CBI shocks, which generate the positive co-movement, are more prevalent in the non-FOMC subsample.

FIGURE 2. Scatter plots of interest rate and stock price surprises in FOMC and Non-FOMC subsamples



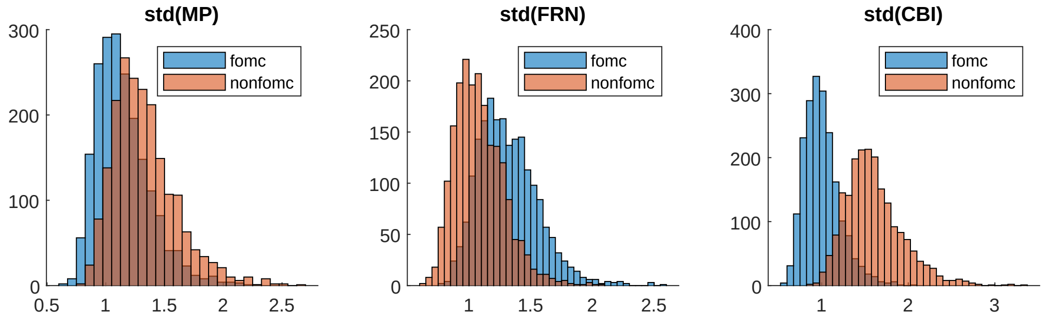
To reflect the information contained in the heteroskedasticity of our data we estimate the following model generalizing equation (4):

$$y_t = C' u_t, \qquad u_{nt} \sim \mathcal{N}(0, \sigma^2_{ns}), \qquad s \in \{\text{FOMC, Non-FOMC}\} \tag{8}$$

where t indexes the Fed events, $y_t = (RES_t, FIT_t, SP500_t)$ are the residual and fitted value of the Bauer-Swanson regression and the stock price surprise observed at event t, $u_t = (MP_t, FRN_t, CBI_t)$ are orthogonal MP, FRN and CBI shocks occurring at event t and C collects the effects of the shocks u_t on the observable quantities y_t. The key feature of the model is that shock n ($n \in \{\text{MP,FRN,CBI}\}$) has a different variance on the FOMC and on Non-FOMC events. The fact that C is identified in the presence of such heteroskedasticity is known since Rigobon (2003), (see also, e.g., Lanne et al. 2010; Brunnermeier et al. 2021). We estimate model (8) with Bayesian methods, using a Gibbs sampler described in detail in the Appendix. When sampling C and u_t, $t = 1, \ldots T$ we impose the sign and magnitude restrictions stated in Section 4.1. In practice, only very few draws from the Gibbs sampler violate these restrictions.

Figure 3 reports the posterior distributions of the shock standard deviations across

FIGURE 3. Shock standard deviations in the heteroskedastic model



regimes. It confirms the observations that the FRN shocks are larger in the FOMC subsample and the CBI shocks are larger in the Non-FOMC subsample.

TABLE 4. Variance decompositions in the estimated heteroskedastic model (8).

	RES	FIT	SP500
MP	**0.71**	**0.18**	**0.34**
	(0.13)	(0.10)	(0.14)
FRN	**0.15**	**0.82**	**0.18**
	(0.10)	(0.10)	(0.09)
CBI	**0.14**	**0.01**	**0.48**
	(0.10)	(0.01)	(0.14)

Posterior mean, standard deviation in parentheses.

The estimated C implies that 71% of the variance of the Bauer-Swanson residuals reflect monetary policy shocks, 15% reflect FRN shocks and 14% CBI shocks. Bauer-Swanson fitted values are mainly reflecting the FRN shocks (82% of the variance), with some contamination by monetary policy shocks (18%) and very little role for the CBI shocks.

4.3. Event study: Impact of shocks in daily data

Figure 4 reports local projections of daily financial variables on the raw interest rate surprise (MPS), and the posterior median MP, FRN and CBI shocks constructed in the previous section. More in detail, we run the regressions of $y_{t+h} - y_{t-1} = \alpha + \beta_h u_t + \varepsilon_t^h$, where y is a response variable, u is a shock, t is the day of the Fed event, h is the horizon, in days. β_h captures the effect of the shock at horizon h. We have also run specifications with additional lagged controls and obtained very similar results. All shocks are reported with the sign that leads to a positive interest rate surprise. These correspond to a contractionary MP shock, and favorable FRN and CBI shocks, the latter two associated with good news about the economy.

Two results stand out. First, the impact of the favourable FRN shock is contractionary. Similarly to the MP shock, it leads to a depreciation of the stock prices (logsp500), a decline in the breakeven inflation rates (bkeven02, bkeven10), and a worsening of financial conditions, as reflected in the increase in the corporate bond spreads (bofaml us bbb oas) and VIX (vixcls). These results align well with the narrative that at a daily frequency, the favorable public news is mostly incorporated in asset prices by the Fed announcement date, and the surprise associated with the more aggressive systematic response to this news amounts to a contractionary policy shock. Notably, the interest rate response to the FRN shock (sveny02,sveny10) is somewhat more gradual and persistent than the response to the MP shock and leads to more pronounced impact on the breakeven inflation rates. This is in line with changes in systematic policy, which leads to more persistent changes in policy and a larger cumulative impact. However, for most variables the contractionary effect of the tight monetary policy dominates the stimulative effect of favorable public news also in the longer run (up to 60 business days). This finding does not align well with the narrative of the FRN shock proposed by Bauer and Swanson. Most notably, the FRN shocks do not attenuate the estimated effects of monetary policy at these horizons. As a result, controlling for the FRN component is insufficient to clean the instrument from the attenuation biases: controlling for the CBI channel is more important. This conclusion aligns with the findings from the VAR analysis presented in the following subsection.

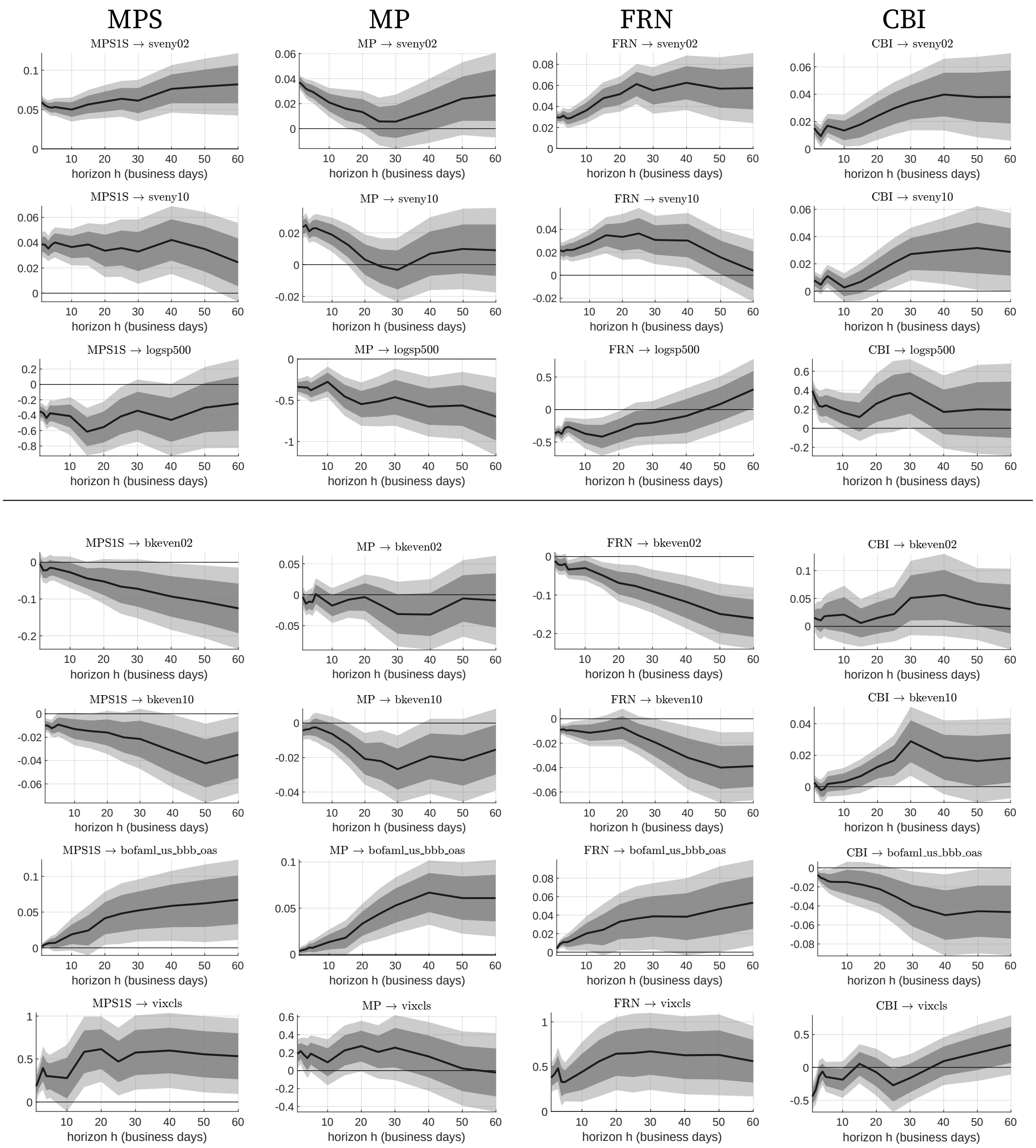
Second, the effects of the CBI shock are different from the other two shocks. Financial conditions improve and long-term breakeven rates increase. Most notably, the the long-term interest rates show a significantly different dynamics – with implications to the post-FOMC drift documented by Brooks et al. (2018). The figure suggests that the post-FOMC drift in Treasury yields is primarily driven by CBI shocks, with FRN shocks also contributing to a lesser extent. In contrast, monetary policy shocks that have been adjusted to exclude the effects of CBI and FRN do not produce any such drift in the 10-year Treasury rate.

4.4. Macroeconomic effects: monthly VAR

We now turn to assessing the dynamic effects of the three shocks in a monthly Bayesian VAR framework. Our baseline VAR includes eight variables: three shocks identified in the high-frequency and five low-frequency macroeconomic variables. The low-frequency variables include the monthly 1-year Treasury rate as a monetary policy indicator (gs1); the logarithm of the monthly average S&P500 stock price index (logsp500); monthly interpolations of the GDP (us gdp) and the GDP deflator (us gdpdef) as indicators of real activity and the price level; and, finally, the Gilchrist and Zakrajsek (2012) external bond premium (ebp) as an indicator of financial conditions.

The VAR has 12 lags. The sample is monthly, from January 1988 to September 2024. The estimation is Bayesian with a standard specification of the Minnesota prior (with the "overall tightness coefficient" of 0.2). The posterior simulation accounts for the uncertainty about the shock identification, i.e. we repeatedly draw the shocks from their posterior distribution implied by model (8) and then we draw the VAR parameters conditionally on the draw of the shocks. We report the results based on 2,000 draws

FIGURE 4. Daily local projections, $y_{t+h} - y_{t-1} = \alpha + \beta_h u_t + \varepsilon_t^h$



Note. Point estimates of the response (β_h), with heteroskedasticity robust 68% and 90% bands.

from the posterior.

FIGURE 5. Dynamic effects of MP, FRN and CBI shocks in a monthly VAR. Heteroskedasticity-based identification.

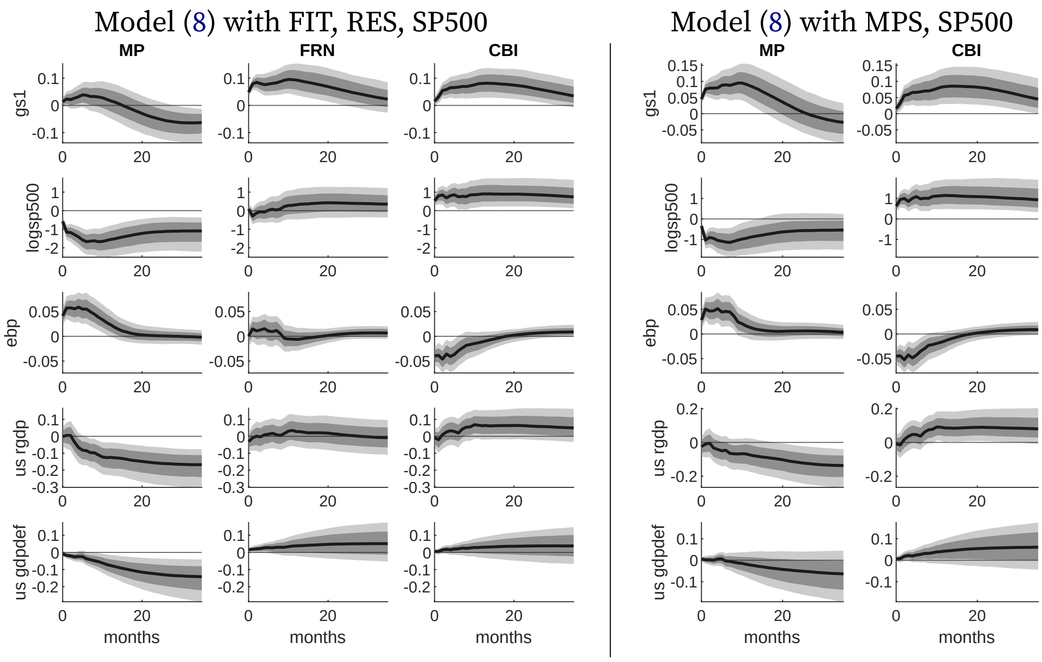


Figure 5 presents the impulse responses to the monetary policy (MP), Fed response to news (FRN) and central bank information (CBI) shocks identified as outlined in Sections 4.1 and 4.2. The results make two observations clear. First, the Fed response to news shock while significantly tightens the monetary policy indicator for a few months, leads to no significant response in either activity, prices or financial conditions in the following months. Second, central bank information shocks exert a significant positive dynamic impact on the macroeconomy (Jarociński and Karadi 2020) even after we control for the potential presence of the Fed response to news channel. The central bank information shock is significantly different from the impact of the monetary policy shock, so ignoring its presence leads to biased estimates. A monetary policy tightening caused by a monetary policy shock, in line with theoretical predictions, depreciates stock prices and leads to a worsening financial conditions, and causes a persistent downturn. In contrast, a tightening caused by a favorable central bank information shock appreciates stock valuations and improves financial conditions and cause a temporary upturn in activity and prices that persistently tight monetary policy offsets in one or two years.

In the right panel of Figure 5 we report what happens when we estimate (8) for only two variables, MPS and SP500. Figure 2 reports the data into which we fit the model. The estimation yields one shock accounting for the negative co-movement between MPS and SP500, and the other one accounting for their positive co-movement. We label these shocks as MP and CBI respectively. The right panel shows that the effects of the MP shock are quite similar in this case, with the main differences being that the

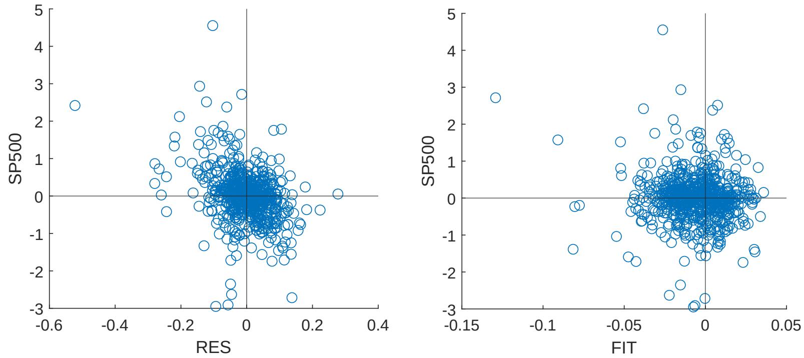


FIGURE 6. Scatter plots of the comovement of the BS residuals (RES) and fitted values (FIT) with the S&P500 surprises

response of the 1-year Treasury yield is somewhat more persistent and the decline of the GDP deflator somewhat less significant.

5. Robustness

In this section, we characterize the robustness of our results. First, we overview some challenges of an FRN-only approach (Bauer and Swanson 2023a,b), which disregards the presence of the central bank information effect. Second, we show robustness when we disregard information inherent in the heteroskedasticity of the shocks and impose only sign and magnitude-restrictions. And third, we show robustness when we restrict attention to FOMC events.

5.1. Challenges with an FRN-only approach

Bauer and Swanson (2023a,b) disregards the existence of the central bank information effect and do not utilize information inherent in high-frequency stock-price surprises. In this section, we assess the robustness of our results in case we follow their approach.

Figure 6 shows the co-movement of the Bauer-Swanson regression[6] residuals (RES) and fitted values (FIT) with the high-frequency stock market surprises (SP500) in our baseline 1988-2024 sample. Notably, events regularly show a *positive* co-movement between interest rates and stock prices, and appear in the North-East or the South-West quadrants. Such co-movement is inconsistent with either monetary policy shocks or Fed response to news shocks, as both would imply an updated policy perception on impact and should lead to a negative interest-rate-stock-price co-movement. As we show next, events with positive co-movement are not the result of noise or measurement error either, because extra information inherent in the high-frequency stock-price surprises have significant impact on the evolution of the macroeconomy.

In order to assess the macroeconomic implications of an FRN-only approach, we implement a “pure” Bauer-Swanson’s approach, illustrated in Figure 7. In this

[6] see Section 3.3.

approach we assume that Bauer-Swanson residual is a perfectly measured monetary policy shock, the Bauer-Swanson fitted value is a perfectly measured FRN shock, and we abstract from the possibility of a CBI shock. To track the effects of these shocks on the macroeconomy we order the residual first, the fitted value second and the S&P500 surprise third. Then we identify the VAR recursively. To justify this approach, note that first, since the residuals and the fitted values are orthogonal, their ordering does not matter, we only put the residual first to have the monetary policy effects in the first column as the preceding figures. Second, the inclusion of the S&P500 surprise as the third variable does not affect the estimated effects of MP and FRN shocks.

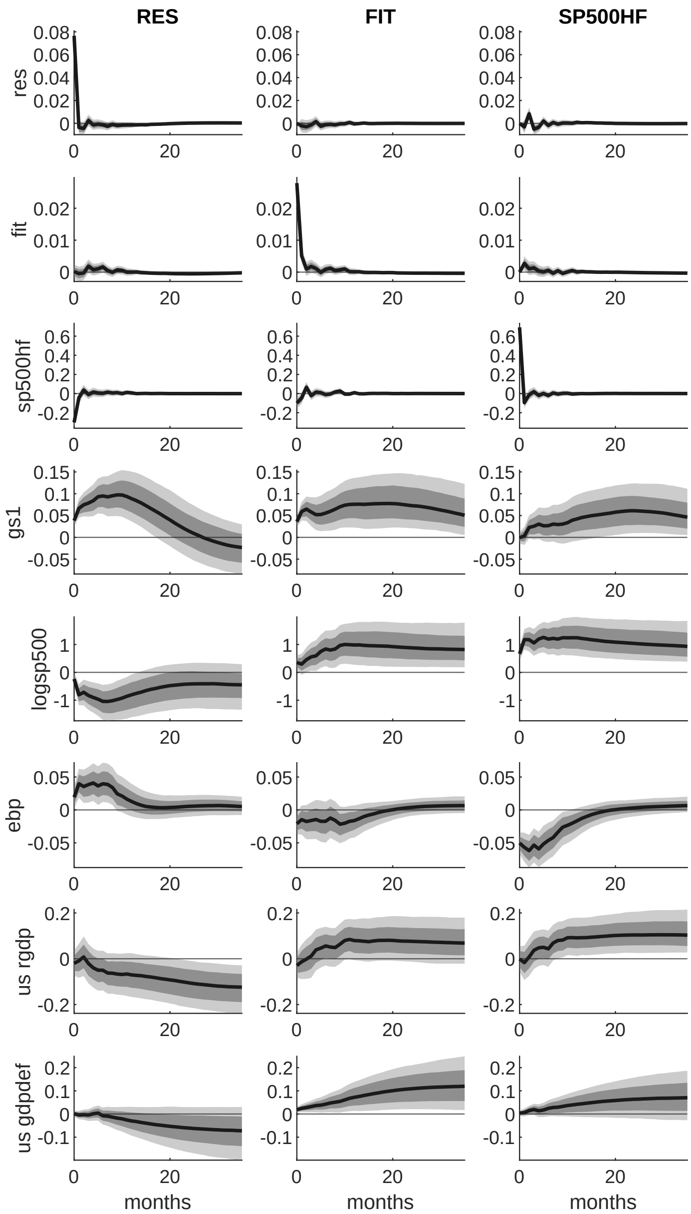
The results in Figure 7 are consistent with Bauer and Swanson (2023a) but at the same time raise a question about the comprehensiveness of their approach.

They are consistent, because, as they point out, controlling for the FRN effect captured by FIT reduces the attenuation bias in the interest rate surprises. The effects of RES shocks on the economy are significantly contractionary and consistent with theoretical predictions. The effects of FRN shocks are expansionary, indicating that they capture the attenuation bias.

However, the results in the third column suggest that something important is missing in the Bauer and Swanson story. By including the S&P500 surprise after RES and FIT we remove all stock price surprise variation explained by the interest rate surprises (both "predictable" and "unpredictable" in-sample), leaving only the unexplained residual variation. One might think that the primary information in Fed communications is about interest rates and that stock price reaction reflect only this information, plus some noise. However, the results in Figure 7 challenge this view. It shows that stock-price movements not explained by interest-rate news are followed by highly significant responses of the key macroeconomic and financial variables: persistent increases in Treasury yields and stock prices, a decrease in the excess bond premium, and gradual rises in real GDP and its deflator. The lesson is that the high-frequency stock price response to Fed communication helps understand the consequences of the communication over and above the interest rate surprise.

To identify monetary policy shocks, how important is it to control for both central bank information and Fed response to news effects? Figure 8 compares impulse responses to monetary policy shocks under different identification schemes. Our baseline methodology (Section 4.4) controls for both CBI and FRN effects, the FRN-only approach follows Bauer and Swanson (2023a), the CBI-only approach is based on Jarociński and Karadi (2020), with sharper inference using the heteroskedasticity of shocks between FOMC and non-FOMC events, and the fourth, naive approach uses only the high-frequency interest rate surprise as instrument. The impulse responses are broadly similar, but both the FRN-only and the CBI-only approaches eliminate some attenuation bias relative to the naive approach and imply a quantitatively larger impact on activity, prices and financial conditions with a somewhat smaller interest rate shock. Controlling for both channels lead to an even stronger effect (including a

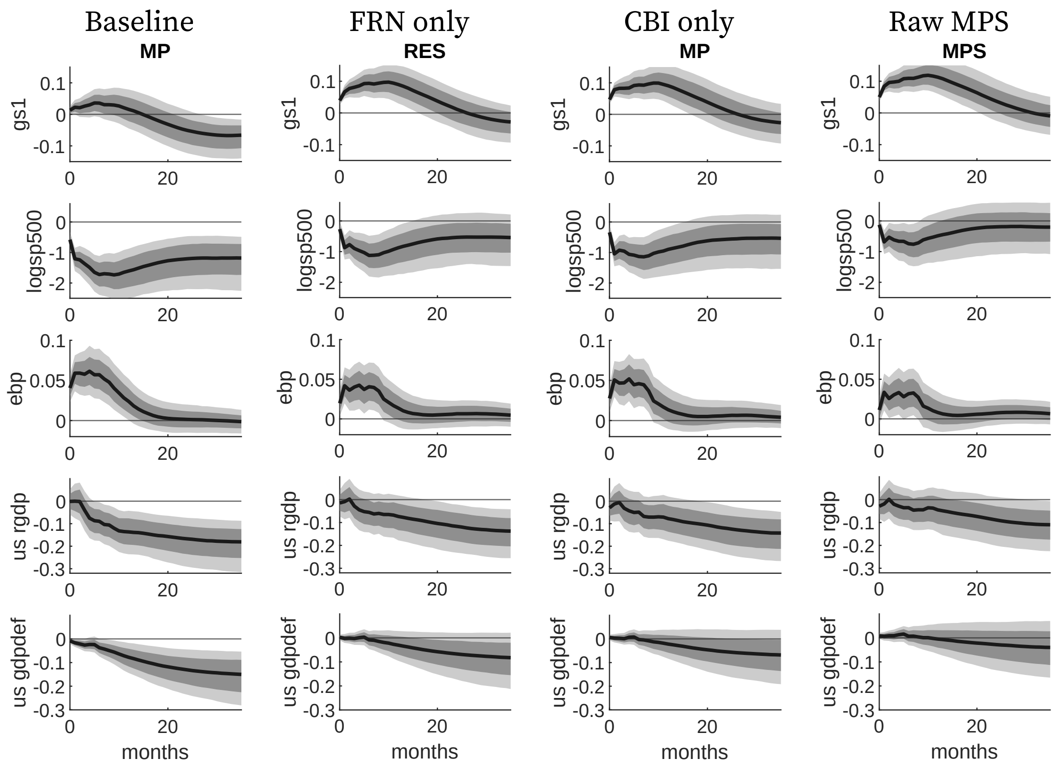
FIGURE 7. The “pure” Bauer-Swanson approach: dynamic effects of Bauer-Swanson residuals, fitted values, and S&P500 surprises in a monthly VAR. Baseline sample.



Notes. The two shades of grey show 68% and 90% posterior bands. The black solid line shows the median impulse response. The VAR is monthly 1988:01-2024:09. Baseline set of Fed events (both FOMC and Non-FOMC).

significant impact on the price level that the other methods fail to deliver) at an even smaller interest rate shock. This result indicates that controlling for both channels is important to arrive at unbiased estimates.

FIGURE 8. Impulse responses to monetary policy shocks across different identification schemes. Baseline sample.



Notes. Impulse responses to monetary policy shocks under the baseline (Section 4.4), under the FRN-only approach (Section 5.1), under a CBI-only approach (Section 5.1) and using the raw monetary policy surprise. The shaded areas show robust 68% and 90% bands. The black solid line shows the median impulse response. The VAR is monthly 1988:01-2024:09. Baseline set of Fed events (both FOMC and Non-FOMC).

5.2. Event study and SVAR results with only sign and magnitude restrictions

In this section, we conduct our baseline exercises with only sign and magnitude restrictions outlined in Section 4.1, without bringing in the information contained in the heteroskedasticity of the data. The set of possible identifications consistent with the sign and magnitude restrictions alone includes many different cases (Wolf 2022). To give an example, Table 5 reports the variance decomposition for the median target identification (Fry and Pagan 2011). Compared with the heteroskedasticity-informed identification, the Fed response to news (FRN) shock plays an even smaller role in explaining the Bauer-Swanson residual (RES) and the monetary policy shock (MP) plays an even smaller role in explaining the Bauer-Swanson fitted value (FIT). Like in the heteroskedasticity-informed case, the interest rate surprises are affected by the CBI shock. Unlike in the heteroskedasticity-informed case, where the CBI shock affects mainly the REs, in the median rotation central bank information (CBI) shock also explains a nontrivial fraction of FIT: the CBI accounts for 21% of the variance of RES and for 19% of the variance of FIT.

TABLE 5. Variance decompositions in the median rotation.

Baseline (FOMC and Non-FOMC events)

	res	fit	sp500hf
MP contrib.	0.81	0.02	0.47
FRN contrib.	0.01	0.74	0.27
CBI contrib.	0.18	0.23	0.27

FOMC only

	res	fit	sp500hf
MP contrib.	0.86	0.02	0.49
FRN contrib.	0.00	0.80	0.35
CBI contrib.	0.14	0.18	0.16

Note. Each column sums up to one.

We report the dynamic effects of the median shocks in a daily local projection in the Appendix Figure A2. The results are overall similar to the results reported in Figure 4.

We next study the effects of sign-restriction identified shocks in a monthly VAR. The VAR includes the same low-frequency variables as before, but a different set of high-frequency variables. The high-frequency variables are now the residual (res) and fitted value (fit) of the Bauer-Swanson regressions described in Section 3.3, and surprises in the S&P500 stock market index calculated over our baseline Fed events sample including both FOMC and non-FOMC events. The high-frequency variables are aggregated to the monthly frequency by adding up. In this VAR we identify three shocks using the sign and magnitude restrictions from Section 4.1.

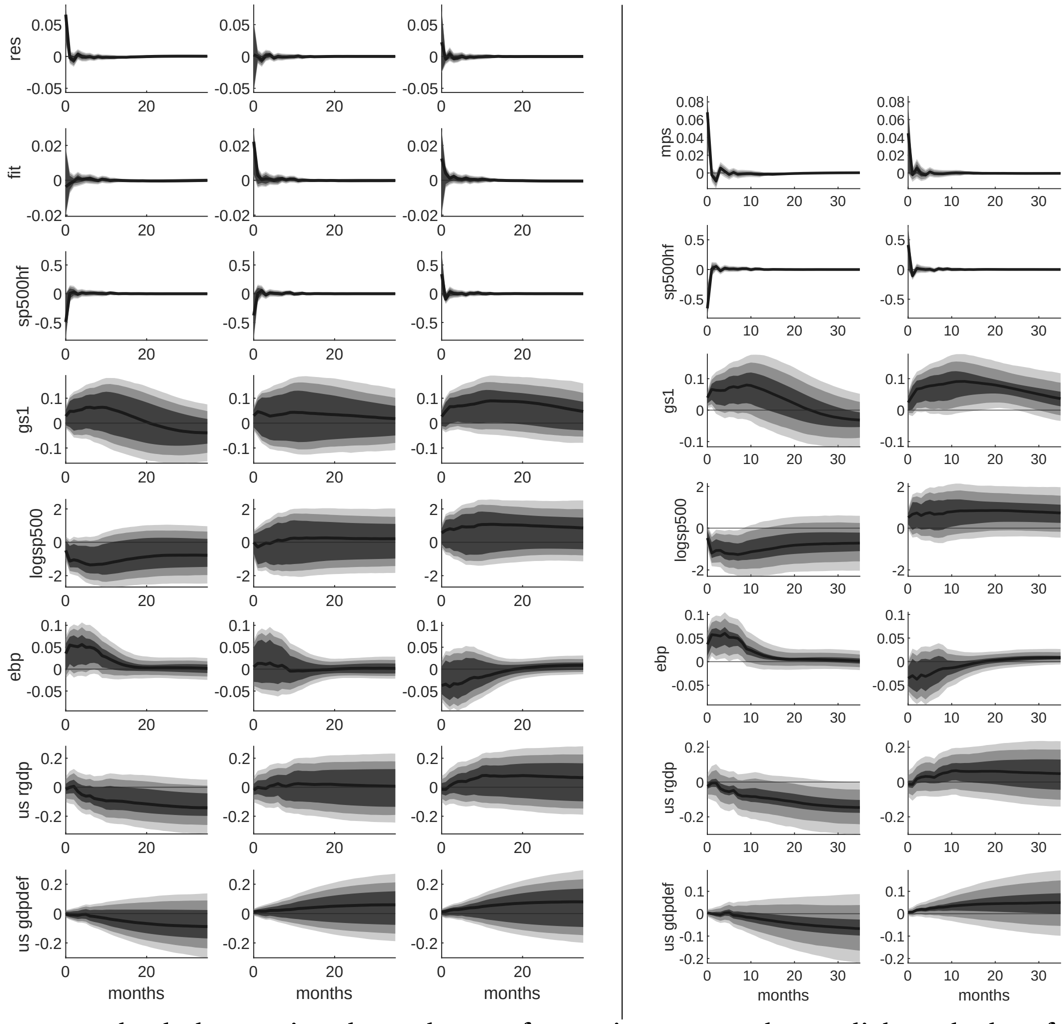
Figure 9 reports the full range of impulse responses identified by our sign restrictions, obtained with the methodology of Giacomini and Kitagawa (2021). The dark regions show the full set of posterior means consistent with sign restrictions, while the shades of grey show robust 68% and 90% posterior bands. Monetary policy shocks are contractionary for virtually all rotations consistent with the sign restrictions. For CBI and FRN shocks the sets of posterior means overlap to a larger extent and include zeros, so it is harder to draw strong conclusions about their relative roles.

According to the posterior median impulse response, one specific rotation, plotted with the solid line, the CBI shock is more expansionary than the FRN shock, i.e. it generates a more severe attenuation bias when not accounted for. The impulse responses of the median FRN shock are close to zero, implying that its attenuation bias is close to zero, in line with our baseline result.

FIGURE 9. Dynamic effects of MP, FRN and CBI shocks identified by sign and magnitude restrictions only. Monthly VAR with the robust bands of Giacomini and Kitagawa (2021). Baseline sample.

Section 4.1 identification | JK identification

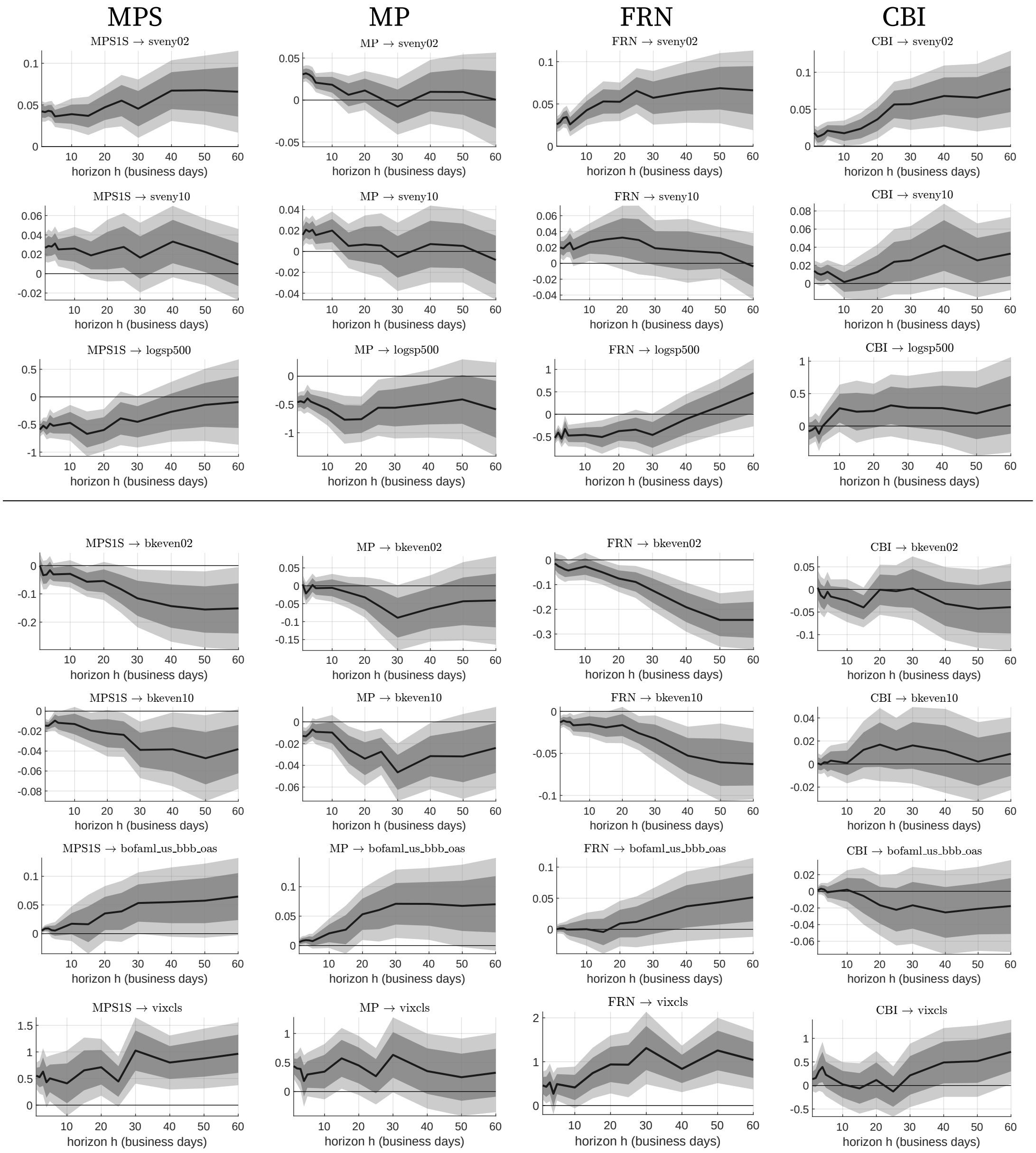
MP | FRN | CBI | MP | CBI



Notes. The darkest region shows the set of posterior means. The two lighter shades of grey show robust 68% and 90% bands. The black solid line shows the median impulse response. The VAR is monthly 1988:01-2024:09. Baseline set of Fed events (both FOMC and Non-FOMC).

5.3. Event study and SVAR results with only FOMC statements

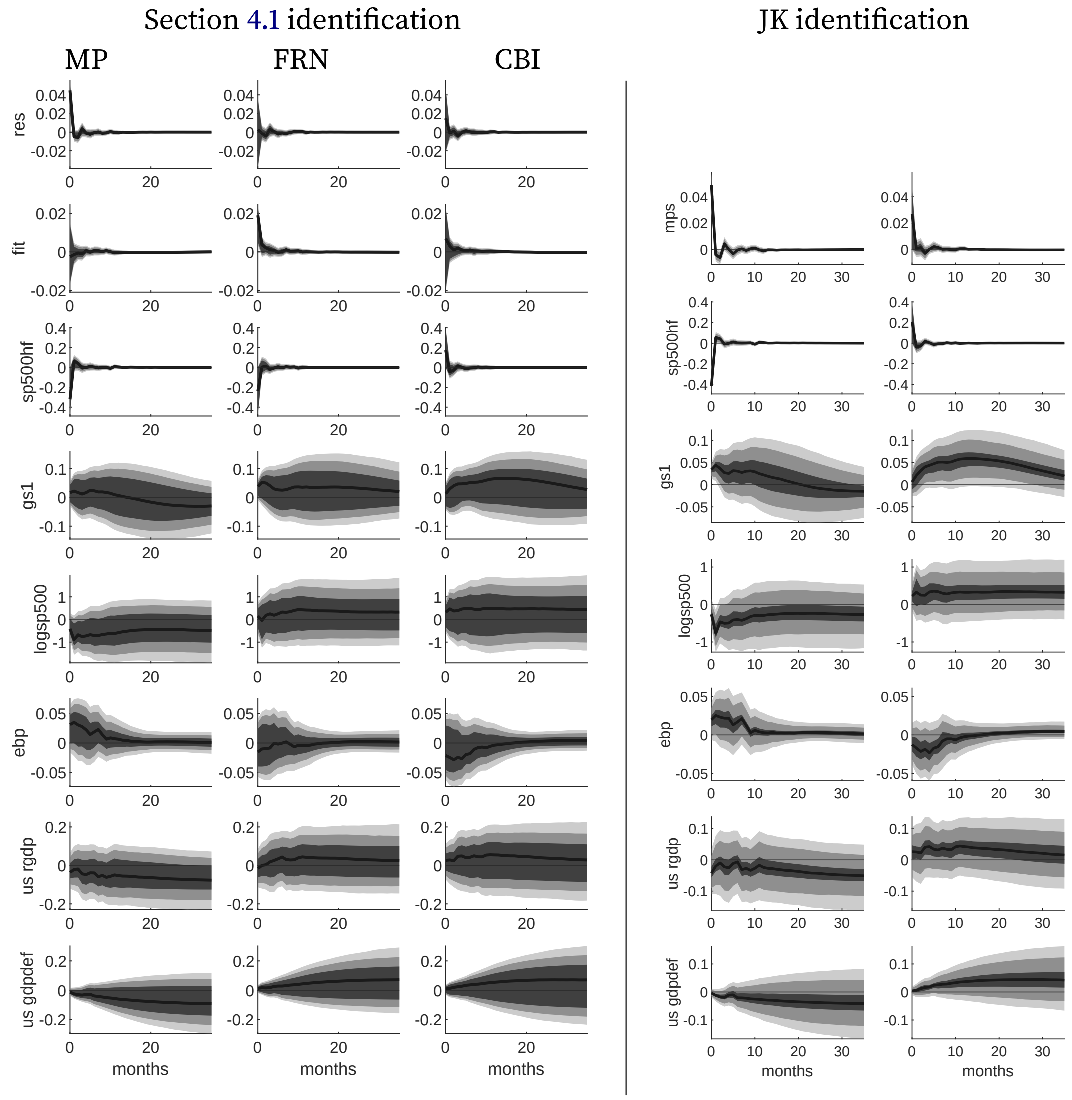
FIGURE 10. Daily local projections, FOMC sample, sign and magnitude restrictions, median target shock



Note. Point estimates of the response, with heteroskedasticity robust 68% and 90% bands.

Figure 11 repeats the VAR exercise presented above restricting the set of the Fed events to FOMC announcements only. This facilitates comparison with the previous literature, including Bauer and Swanson (2023b), which predominantly used this restricted sample. The results show, first, that the Fed response to news shock leads to an appreciation of stock prices, an improvement of financial conditions, and an upturn in activity and prices, albeit none significantly differently from zero. These findings are consistent with the conclusion of Bauer and Swanson (2023b), who suggests that tighter than expected policy response to fresh public news at FOMC meeting dates can bias

FIGURE 11. Dynamic effects of MP, FRN and CBI shocks in a monthly VAR. FOMC sample.



the estimates of monetary policy shocks in monthly VARs if not properly controlled for. Second, however, the results assign a similarly relevant role to the Fed information shocks, which lead to a similar stock price appreciation, and improvement in financial conditions and an upturn in activity and prices. This is inconsistent with the message of Bauer and Swanson (2023b), who proposed the FRN channel as substitute to the CBI effect. The results, instead, show that CBI shocks are likely as important as FRN shocks, but the limited variation generated by the restricted number of FOMC events is insufficient to reliably differentiate between the two channels.

6. Conclusion

This paper extends the sample of FOMC statements with non-FOMC Fed announcements, and develops a methodology to separately identify monetary policy (MP) shocks, central bank information (CBI) shocks, and Fed response to news (FRN) shocks. To achieve this, it uses (i) the high-frequency co-movement of interest rates and stock prices, (ii) the predictability of surprises by fresh public news, and (iii) the heteroskedasticity between FOMC and non-FOMC events. Our findings confirm the significant presence of CBI effects and argues that insufficiently controlling for them would lead to biased monetary policy shock estimates. The Fed response to news channel is significant in daily local projections, but in our baseline monthly VAR specification it has a marginal impact. Monetary policy shocks, when purged of CBI and FRN effects, generate macroeconomic responses consistent with theoretical expectations, including a temporary downturn in economic activity and prices and a deterioration in financial conditions.

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Appendix A. Construction of high-frequency surprises

TABLE A1. Correlations of selected surprises in the GSS dataset (2019 version) and in our dataset

Variable	GSS identifier	JK identifier	Correlation	N.obs.
Fourth Fed funds future	FF4	FF4	0.959	195
Fed funds rate after the next FOMC	MP1	MP1	0.988	197
Front Eurodollar future	ED1	ED1	0.972	285
First Back Eurodollar future	ED2	ED2	0.975	285
Second back Eurodollar future	ED3	ED3	0.967	285
Third back Eurodollar future	ED4	ED4	0.941	285
2-year Treasury yield	ONRUN2	TFUT02	0.958	242
5-year Treasury yield	ONRUN5	TFUT05	0.981	242
10-year Treasury yield	ONRUN10	TFUT10	0.966	242
30-year Treasury yield	ONRUN30	TFUT30	0.941	242
S&P500 (spot)	SP500	SP500	0.938	284
S&P500 (futures)	SP500FUT	SP500FUT	0.971	274

Appendix B. Bayesian estimation of the i.i.d. heteroskedastic model

The following model relates the vector of N observables y_t (here: high-frequency surprises around Fed events) to the underlying N structural (orthogonal) shocks u_t.

$$y_t = C' u_t, \qquad u_{nt} \sim \mathcal{N}(0, \sigma^2_{ns}), \quad \text{for} \quad n = 1, \dots, N, \quad s = 1, \dots, S \tag{A1}$$

$t = 1, \dots, T$ indexes the observations. C collects the effects of the shocks u_t on the observable quantities y_t. The key feature of the model is that each observation t belongs to one of S regimes ($2 \le S \le T$). The variance of shock n in regime s is σ^2_{ns}. This variance is allowed to be different in each regime.

Matrix C is identified as long as there is sufficient variation in the σ^2_{ns} across regimes. In particular, the mix of shocks needs to be different across regimes, i.e. the variances of different shocks should not change by the same proportion. This insight is due to Rigobon (2003). This paper and the subsequent literature (e.g., Lanne et al. 2010; Lütkepohl and Woźniak 2020; Sims 2021) provide formal conditions and/or tests for identification. The estimation approach outlined below breaks down (it runs into numerical problems) if the heteroskedasticity in the sample is not sufficient to identify C.

Model (A1) is estimated with a Bayesian approach, using the Gibbs sampler with a Metropolis step. For closely related estimation approaches see Lütkepohl and Woźniak (2020); Brunnermeier et al. (2021). The approach below uses a different strategy of sampling the C matrix than either of these papers. With the prior structure used in this paper, the extreme case of $S = T$ regimes is equivalent to the model with Student-t shocks and the Gibbs sampler below is a variant of the Gibbs sampler in Jarociński (2024).

B.1. Reparameterization, priors

Define $W = C^{-1}$ and $q_{ns} = (\sigma^2_{ns})^{-1}$ and reparameterize (A1) as follows:

$$y_t = W^{-1\prime} u_t = W^{-1\prime} Q_t^{-1/2} z_t, \quad z_t \sim \mathcal{N}(0, I_N), \quad Q_t = \text{diag}(q_{1t}, \ldots, q_{Nt}) \tag{A2}$$

where $q_{nt} = q_{ns}$ when $t \in s$.

The likelihood of y_t in this parameterization is

$$p(y_t|W, Q_t) = |W^{-1\prime} Q_t^{-1} W^{-1}|^{-1/2} \exp\left(-\frac{1}{2} y_t'(W^{-1\prime} Q_t^{-1} W^{-1})^{-1} y_t\right) \tag{A3}$$

The prior for W is a weakly informative Gaussian distribution,

$$p(W) = \mathcal{N}(\text{vec}\, W_0, \Omega). \tag{A4}$$

We take $W_0 = I_N$ and $\Omega = \kappa I_{N^2}$ where I_k denotes the identity matrix of order k. κ is a number large enough to ensure that the prior plays essentially no role. In practice we take $\kappa = 200$ as in Brunnermeier et al. (2021).

The prior for q_{ns} is a Gamma distribution with shape and scale both equal to $\nu/2$ for all n and s,

$$p(q_{ns}) = \mathcal{G}(\nu/2, 2/\nu) = \Gamma(\nu/2)^{-1}(\nu/2)^{\nu/2} q_{ns}^{\nu/2-1} \exp(-q_{ns}\nu/2). \tag{A5}$$

Note that we parameterize the Gamma distribution with shape a and scale b as

$$\mathcal{G}_x(a, b) = \frac{1}{\Gamma(a) b^a} x^{a-1} \exp(-x/b) \tag{A6}$$

with mean ab and variance ab^2. We take $\nu = 10$ implying that the prior has the mean of 1 and variance 0.2. This prior distribution is conservative in the sense of acting against finding any heteroskedasticity and instead shrinking all the variances to the same value of 1.

Let $Y = (y_1, \ldots, y_T)'$ be the matrix collecting the observations of y_t and let $U = (u_1, \ldots, u_T)'$ be the matrix collecting the shocks. In terms of these matrices, the model implies $Y = UC$ and $YW = U$.

B.2. Simulation of the posterior with the Gibbs sampler

Initialize the simulation with $W^0 = I_N$. Then, in step z

a. draw q^z_{ns} from the conditional posterior $p(q_{ns}|Y, W^{z-1})$, for $n = 1, \ldots, N$, $s = 1, \ldots, S$, collect them in matrix Q^z;
b. draw W^z from the conditional posterior $p(W|Y, Q^z)$;

c. compute the objects of interest $C^z = (W^z)^{-1}$ and $U^z = YW^z$.

B.3. The conditional posterior of W

The conditional posterior of W is a nonstandard density

$$p(W|Y, Q_1, ..., Q_T) \propto |W|^T \exp\left(-\frac{1}{2}\sum_{t=1}^{T} y_t' W Q_t W' y_t\right) p(W). \tag{A7}$$

Drawing from this density is the only non-trivial step in the simulation. Following Jarociński (2024) we draw a candidate W^* from the Gaussian proposal density

$$f(W) = \mathcal{N}\left(\hat{w}, (-\mathcal{H})^{-1}\right) \tag{A8}$$

where $\hat{w}$ is the mode of $p(W|Y, \cdot)$ and $\mathcal{H}$ the Hessian of $\log p(W|Y, \cdot)$. The key point is that the Jacobian and Hessian of $\log p(W|Y, \cdot)$ are available in closed form. Consequently, the mode is easy to find by numerical optimization and the Hessian is precisely and quickly computed without resorting to numerical derivatives.

The draw is accepted with probability

$$\max\left(1, \frac{p(W^*|Y, \cdot)\, f(W)}{f(W^*)\, p(W|Y, \cdot)}\right). \tag{A9}$$

The literature has taken different approaches to drawing W (often denoted as A_0). Brunnermeier et al. (2021) use a standard Metropolis-Hastings algorithm and the convergence is slow. Lütkepohl and Woźniak (2020) draw a candidate from a Gaussian distribution centered at the previous draw and with variance WQ_tW'. The appealing feature of the present approach is that it constructs a substantially better proposal distribution (with a good approximation of the true mean and variance) at a modest computational cost.

Using the methods in Magnus and Neudecker (2019) it is tedious but straightforward to find that the Jacobian of $\log p(W|Y, Q_1, ..., Q_T)$ is

$$\mathcal{J}(\operatorname{vec} W) = T(\operatorname{vec} W^{-1\prime})' - \sum_t \operatorname{vec}(y_t y_t' W Q_t)' - \operatorname{vec}(W - W_0)'\Omega^{-1} \tag{A10}$$

and the Hessian of $\log p(W|Y, Q_1, ..., Q_T)$ is

$$\mathcal{H}(\operatorname{vec} W) = -TK_{NN}(W^{-1\prime} \otimes W^{-1}) - \sum_t (Q_t \otimes y_t y_t') - \Omega^{-1} \tag{A11}$$

where K_{NN} is a commutation matrix of order N (Magnus and Neudecker 2019).

B.4. The conditional posterior of q_{ns}

The conditional posterior of q_{ns} is a gamma density

$$p(q_{ns}|Y, W) = \mathcal{G}\left((\nu + T_s)/2, 2/(\nu + \sum_{t\in s} u_{nt}^2)\right) \tag{A12}$$

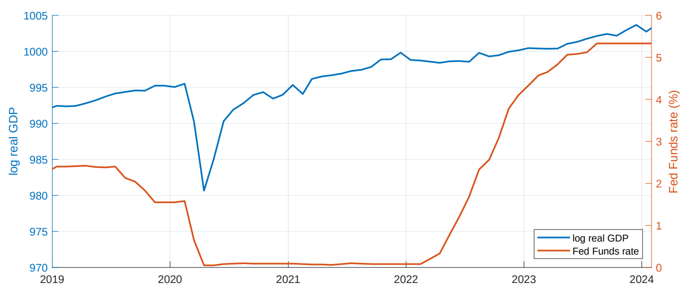
where T_s is the number of observations in this regime, and u_{nt} is the n, t-th element of YW.

Appendix C. Impact of March 2020 surprises on the estimates

In this section, we explain our decision to exclude the March 2020 Fed events from our baseline estimates.

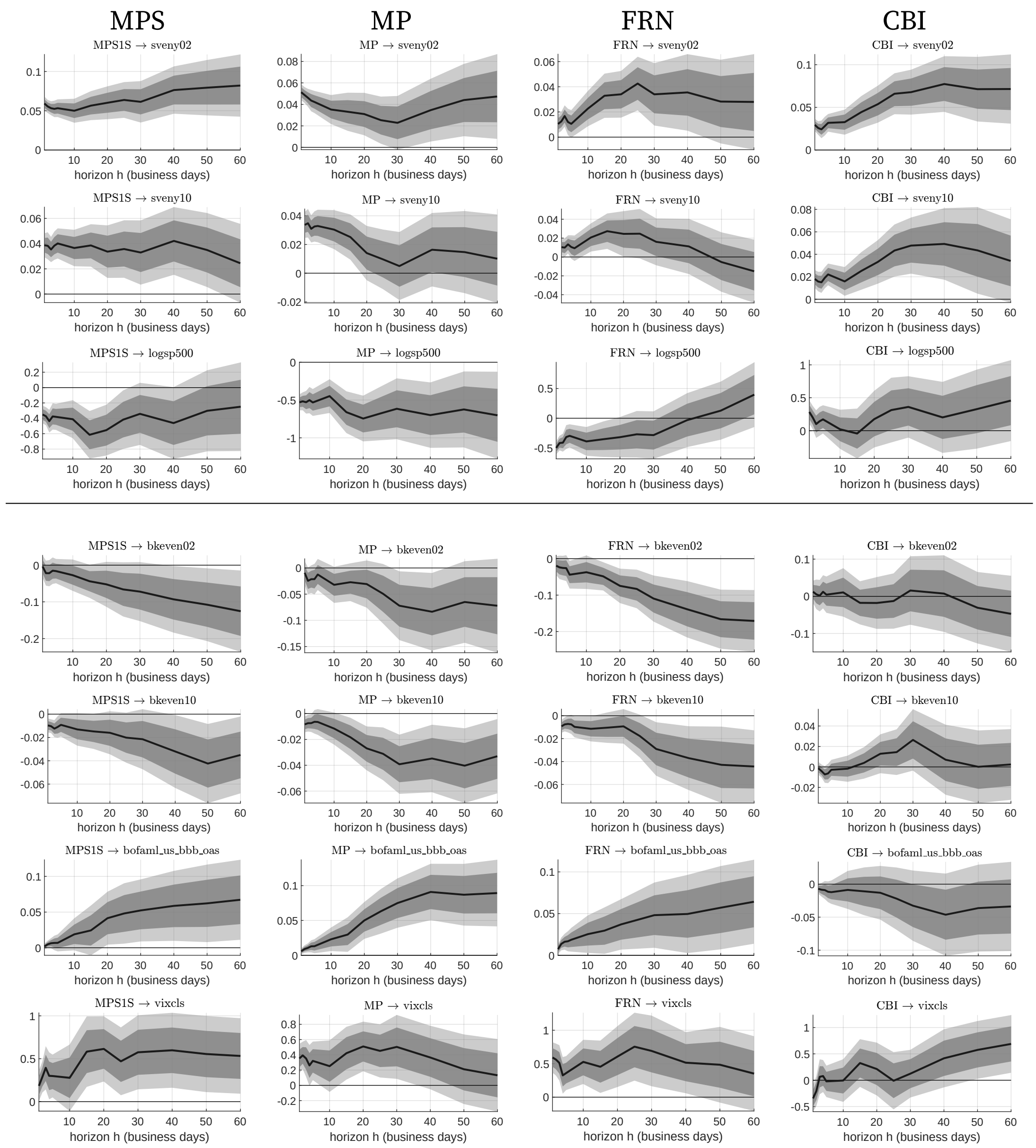
March 2020 features a combination of stronger than expected Fed policy easing and an unprecedented collapse of real activity due to lockdowns. Most importantly, on March 3 the FOMC surprised the markets with a 50 basis points rate cut, against the expectations of a 25 basis points rate cut. Figure A1 below demonstrates the unusual size of the interest rate and real activity fluctuation in this episode. VARs and local projections that include March 2020 find a temporary expansionary effect of contractionary monetary policy shocks, which goes away after excluding March 2020, so we decided to always exclude March 2020 to avoid this outsized impact of a single episode.

FIGURE A1. Real GDP and the federal funds rate, 2019-2024



Appendix D. Additional results for median sign-and-magnitude-identified shocks

FIGURE A2. Daily local projections, sign and magnitude restrictions, median target shock



Note. Point estimates of the response, with heteroskedasticity robust 68% and 90% bands.