



EUROPEAN CENTRAL BANK
EUROSYSTEM

Working Paper Series

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Monetary policy surprises with imperfect information

No 3292 / October 2026



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Abstract

High-frequency interest rate surprises around Fed announcements do not identify monetary policy (MP) shocks if markets are imperfectly informed. Instead, they can also reflect central bank information (CBI) shocks, when the Fed assesses the economy differently, and Fed-response-to-news (FRN) shocks, when markets misperceive the policy rule. The literature treats these as competing explanations; we show they are distinct, and jointly identify all three from the co-movement of interest rate and equity surprises, their predictability from public news, and heteroskedasticity between FOMC and non-FOMC communication. CBI effects are robust at daily and monthly frequencies; FRN matters only daily. Purging both strengthens monetary policy estimates.

JEL codes: E31, E32, E52

Keywords: Monetary policy shock, high-frequency identification, local projection, structural vector autoregression, Fed chair speeches

Non-technical summary

This paper studies how financial markets react to Federal Reserve communications and aims to better measure the true effect of monetary policy on the economy. It argues that changes in interest rates following Fed announcements can reflect more than just changes in policy. They may also reflect the Fed sharing new information about the economy or reacting more strongly to existing public news than markets expected. These different influences can distort estimates of how monetary policy affects inflation, output, and financial conditions.

To separate these effects, the paper examines Fed announcements—including not just policy statements but also speeches and the release of meeting minutes—using data on interest rate and stock market changes within a 30-minute window around each event. The central idea is that different kinds of surprises affect markets in different ways. If the Fed shares good news about the economy, both stock prices and interest rates tend to rise. If it reacts more forcefully than markets expected to already known economic data, then a surprise interest rate increase can be predictable and accompanied by a fall in stock prices. True policy shocks, in contrast, are both unpredictable and move interest rates and stock prices in opposite directions without being tied to new information or systematic policy misperceptions.

The paper develops a method that distinguishes between these three types of effects: the direct impact of temporary monetary policy shocks, the information conveyed by the Fed about the economic outlook, and the Fed's stronger-than expected reaction to already-known news. It uses the pattern of changes in stock prices and interest rates, the predictability of surprises from recent public data, and differences in market reactions to different kinds of Fed events. These tools allow the paper to estimate how each type of surprise affects the economy.

To further improve the precision of its estimates, the paper takes advantage of differences in how markets react to various types of Fed communications. Specifically, it uses a statistical technique which exploits the fact that the size and type of market responses vary systematically between formal policy announcements (FOMC meetings) and other Fed events such as speeches or the release of meeting minutes. These differences are used to help distinguish the underlying causes of market surprises. For example, responses to FOMC meetings are more strongly linked to public news, suggesting a greater role for the Fed's reaction to known data, while non-FOMC events often reflect new information being shared by the Fed. By exploiting this variation, the paper is able to sharpen the separation between true policy shocks, information effects, and responses to public news.

The findings show that the Fed often reveals new information about the economy, and this central bank information effect plays an important role in shaping market responses. While the Fed's response to public news does influence financial markets, especially interest rates and inflation expectations, its effect on economic activity and inflation is limited. Once both of these influences are removed, the remaining monetary policy shocks cause a clear decline in output and prices, and lead to tighter financial conditions, as expected by standard economic theory.

1. Introduction

What are the causal effects of monetary policy? Answering this question is central both to understanding policy transmission and to distinguishing between competing macroeconomic models (Christiano et al. 2005; Gagliardone and Gertler 2023). The identification requires exogenous variation in policy. The leading source of such variation is high-frequency interest rate surprises around Federal Reserve (Fed) announcements (Kuttner 2001; Gürkaynak et al. 2005; Gertler and Karadi 2015). But when markets are imperfectly informed, these surprises are not pure policy shocks: they also reflect surprises about the Fed’s systematic response to the state of the economy. This contamination can take two forms. If markets are imperfectly informed about the *economic outlook*, announcements reveal the Fed’s assessment of the economy – the central bank information (CBI) effect (Romer and Romer 2000; Jarociński and Karadi 2020). If markets are imperfectly informed about the *policy rule*, announcements reveal an unexpected extent of systematic response to recent public news – the Fed-response-to-news (FRN) effect (Bauer and Swanson 2023a,b; Hack et al. 2024). The literature has largely treated these as competing explanations. This paper shows that they are not: CBI and FRN shocks are conceptually distinct, have distinct empirical signatures, and can be jointly identified together with the monetary policy (MP) shock.

Our key insight is that CBI and FRN generate opposite high-frequency co-movements between interest rates and stock prices. An interest rate hike due to an unexpectedly aggressive policy rule is, on impact, contractionary, so stock prices *fall* in the announcement window, whereas a CBI shock moves stock prices and interest rates *in the same direction*. Combining this high-frequency co-movement with the predictability of interest rate surprises from fresh public news identifies all three shocks simultaneously. We formalize the argument in a stylized model of imperfect information, and implement the identification on an event set that extends standard FOMC announcements with non-FOMC Fed communication. We sharpen the inference by utilizing the heteroskedasticity arising from the systematic difference in the relative strength of the three shocks across the FOMC and non-FOMC events. Three results emerge: central bank information effects are a robust feature of the data even when FRN shocks are carefully controlled for; FRN shocks matter at the daily frequency but leave little trace in monthly data; and monetary policy shocks purged of both confounds generate a downturn in activity and prices and a deterioration of financial conditions, in line with theoretical predictions.

We start from a stylized model in which the two confounds arise from imperfect information about different objects. The Fed sets its policy rate i according to the rule $i = \alpha^F x^F + \varepsilon$, where x^F is the Fed’s assessment of the state of the economy (say, the output gap), α^F is the strength of its systematic response, and ε is a pure monetary policy shock – a temporary deviation from the rule. Just before the announcement, markets form an expectation of the policy rate, $E^M(i) = \alpha^M x^M$, where x^M is the market’s own assessment of the economy and α^M its perception of the Fed’s response coefficient;

both may differ from the Fed's. The interest rate surprise then decomposes into three distinct components:

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

The CBI shock arises from different assessments of the economy; it has two components, an underlying economic shock and the Fed communication that reveals it to markets, and both arrive as one piece of news in the announcement window. The FRN shock arises from misperception of the policy rule: markets observe the same public news as the Fed but underestimate how aggressively the Fed responds to it. The decomposition makes precise that the two are conceptually distinct rather than competing labels for the same phenomenon – yet both contaminate the surprise, and we show that both bias standard local-projection and VAR estimates of monetary policy effects. The CBI shock biases them towards zero, as does the FRN shock in the baseline case when markets underestimate α^F . The framework highlights the key role of persistent average misperception in the FRN ($\alpha^F > \alpha^M$ on average): an extension with a time-varying policy rule shows that transitory fluctuations in the policy rule are observationally similar to pure policy shocks, do not generate predictability of high-frequency surprises and do not bias the estimates.

Each strand of the literature has proposed a remedy for the confound it emphasizes. [Jarociński and Karadi \(2020\)](#) identify CBI shocks from the positive high-frequency co-movement of interest rates and stock prices around FOMC statements – good news about the economy raises both – and clean the surprises of this component. [Bauer and Swanson \(2023a,b\)](#) instead purge the surprises of the component predictable from fresh public news, attributing it to the FRN effect. Taken at face value, the two remedies undermine each other's identification: if both confounds are present, cleaning with the stock price response alone misattributes FRN shocks, while purging the predictable component alone discards CBI information revealed in the announcement. How can one estimate the effects of a pure monetary policy shock when markets are imperfectly informed about both the outlook and the rule – and does the FRN channel truly invalidate central bank information effects once both are controlled for?

Our unified framework answers these questions by exploiting the full set of restrictions that the two views jointly imply. An FRN shock must co-move with the component of interest rate surprises explained by fresh public news *and* generate a negative high-frequency co-movement between interest rates and stock prices: although the underlying public news is favorable, it is already incorporated into asset prices by the time of the announcement, so the only news revealed is the tighter-than-expected rule, which lowers expected near-term cash flows and raises discount rates. A CBI shock requires a *positive* co-movement: good news about the economy raises equity values even as markets anticipate a systematic tightening that partially offsets it. A monetary policy shock co-moves with the unexplained component of the surprises

and generates a negative co-movement.

We implement this identification on a sample of over 600 Fed communication events between January 1988 and March 2025. The new event set expands the standard FOMC announcements with non-FOMC announcements, like press conferences and Fed chair speeches, which have been shown to raise the relevance of high-frequency interest rate surprises (Swanson and Jayawickrema 2023; Swanson 2023; see Altavilla et al. 2025 for the ECB). The expanded sample does more than add observations: interest rate surprises are less forecastable from public news at non-FOMC events, indicating weaker FRN shocks, while the interest-rate–stock-price co-movement points to more prevalent CBI shocks in the non-FOMC subsample. This heteroskedasticity provides additional identifying information (Rigobon 2003), which we combine with the sign restrictions above. The output is a series of three shocks – MP, CBI, and FRN – for every Fed communication event in our sample.

We assess the impact of the identified shocks in two steps. First, we run daily local projections over horizons of up to 60 days on financial variables, including stock prices, inflation swaps, breakeven inflation, corporate bond spreads, and the VIX. All three shocks matter. Monetary policy shocks cause a persistent increase in short rates, a deterioration of financial conditions, and a decline in inflation expectations. A favorable CBI shock raises stock prices and inflation expectations and significantly improves financial conditions – even with FRN shocks controlled for. Hawkish FRN shocks are *contractionary*, lowering inflation expectations and worsening financial conditions, qualitatively similar to monetary policy shocks, though the latter die out somewhat faster. This is exactly what the daily frequency should reveal: pre-announcement asset prices already embed the recent public news, so the daily FRN response isolates the pure effect of the unexpected policy rate response.

Second, we track the dynamic effects of the shocks in a Bayesian VAR on monthly data over 1988:01–2025:03, with the identified shocks, aggregated to monthly frequency, serving as internal instruments. The VAR includes the 1-year Treasury rate as the policy indicator; a monthly interpolation of real GDP (Stock and Watson 2010); the PCE price index; and the S&P 500 and the excess bond premium (Gilchrist and Zakrajsek 2012; Favara et al. 2016) as indicators of financial conditions. The monthly results confirm the robustness of CBI effects: identified CBI shocks generate a significant temporary boom in all specifications. FRN shocks, in contrast, have only a marginal impact on monthly fluctuations. Unlike at the daily frequency, the monthly FRN shock combines the contractionary tighter-than-expected rule with the stimulative favorable news that triggered it, and the two components broadly offset each other. Indeed, abstracting from FRN effects altogether and using our framework to identify only CBI shocks yields similar results. More generally, we show that the high-frequency stock price response to Fed communication carries information about the macroeconomy over and above the interest rate surprise – information that our identification exploits.

What do our results imply for the measurement of monetary policy shocks? Mone-

tary policy shocks purged of both CBI and FRN effects generate a temporary downturn in activity and prices and a deterioration of financial conditions, in line with theoretical predictions. Controlling for the confounds matters. Purging both confounds yields the strongest estimated effects from the smallest interest rate impulse: the downturn in activity deepens, and the price level declines significantly – a response hard to obtain when purging only one of the confounds. Viewed through the lens of a structural model (Appendix A), the implications are stark: matching the responses to the raw surprise requires prices to reset only every two years and negligible financial frictions, at odds with microeconomic evidence, whereas the responses to the doubly-purged shock are consistent with realistic price rigidity and a meaningful role for financial frictions. If the three-way decomposition proves too demanding – as it does in some subsamples and specifications, where the predictable component of surprises varies too little to pin down the FRN shock – a two-way MP–CBI decomposition still provides meaningful results: it is markedly more robust across samples and yields monetary policy estimates close to the baseline. To foster adoption, we make the identified MP, CBI, and FRN shock series available for all Fed communication events in our sample.

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. 2021). It builds on the insight of Gertler and Karadi (2015), who use high-frequency financial market surprises around FOMC announcements (Kuttner 2001; Gürkaynak et al. 2005) 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 2015); 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 2023a,b), motivated by the observation that standard monthly specifications (Campbell et al. 2012; Nakamura and Steinsson 2018; Gertler and Karadi 2015; Jarociński and Karadi 2020) omit publicly available information on concurrent economic shocks. 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 2019; 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 simultaneously from both types 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. Such communication can move private expectations because the Fed has private information (Romer and Romer 2000; Pelin 2025), processes public information through different economic models (Melosi 2017; Nakamura and Steinsson 2018; Miranda-Agrippino and Ricco 2021), or coordinates private expectations (Morris and Shin 2002). 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 by Bauer and Swanson (2023a,b) is a valid alternative to the central bank information effect based on high-frequency identification (Jarociński and Karadi 2020; Miranda-Agrippino and Ricco 2021; Golez and Matthies 2025).

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, thanks to introducing heteroskedasticity, which can be exploited for identification.

Finally, our paper contributes to the growing line of research that combines sign restrictions with statistical identification in vector autoregressions (Drautzburg and Wright 2023; Carriero et al. 2024; Andrade et al. 2025). Heteroskedasticity-based identification helps to improve the precision of the set-identified results obtained by sign restrictions. Conversely, sign restrictions help give structural interpretation to the shocks identified by heteroskedasticity, which, by itself, is only a statistical approach assigning no labels to the identified shocks.

Structure. Section 2 presents a stylized model that decomposes monetary policy surprises into MP, FRN and CBI shocks and derives the restrictions that identify them. Section 3 describes the data and event windows, documents the co-movement of interest rate and stock price surprises, and reproduces the Bauer and Swanson (2023a,b) regressions. Section 4 identifies the three shocks by combining sign and magnitude restrictions with the heteroskedasticity between FOMC and non-FOMC events, and tracks their effects in daily local projections and a monthly Bayesian VAR. Section 5 reports results without exploiting heteroskedasticity, Section 6 checks robustness, and Section 7 concludes. Appendix A interprets the estimated monetary policy effects through the lens of a structural macro-finance model.

2. Theoretical framework

This section develops a theoretical framework that distinguishes between three sources of monetary policy surprises: (i) pure policy shocks, (ii) market misperception of the Fed policy rule (the Fed response to news effect), and (iii) different views on the state of the economy between the Fed and markets (the Fed information effect). We show that neglecting (ii) and (iii) biases standard estimates of monetary policy effects, and we propose a strategy to separately identify the three effects using high-frequency stock price responses.

2.1. Model setup and shock decomposition

Fed policy rule and market expectations. The 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:

$$i_t = \alpha^F x_t^F + \varepsilon_t \quad (1)$$

where α^F is the Fed's response coefficient, x^F is the Fed's assessment of the economy, and ε represents a pure monetary policy shock. The Fed announces its policy and its assessment of the economy at the end of period t .

The market forms an expectation about the to-be-announced policy rate just before the announcement, denoted $E_{t-\delta}^M(i_t)$:

$$E_{t-\delta}^M(i_t) = \alpha^M x_t^M \quad (2)$$

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. These may differ from the Fed's true coefficient and assessment.

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

$$MPS_t = i_t - E_{t-\delta}^M(i_t)$$

Decomposing the monetary policy surprise. Subtracting (2) from (1) and rearranging yields a decomposition of the monetary policy surprise into three distinct components (suppressing time subscripts):

$$\underbrace{i - E^M(i)}_{MPS} = \underbrace{\alpha^F(x^F - x^M)}_{CBI \text{ shock}} + \underbrace{(\alpha^F - \alpha^M)x^M}_{FRN \text{ shock}} + \underbrace{\varepsilon}_{MP \text{ shock}} \quad (3)$$

This decomposition reveals that markets can be surprised by the Fed's interest rate decision for three reasons. First, an unpredictable pure monetary policy shock (ε) can occur. Second, the market's assessment of the economy may differ from the Fed's

assessment ($x^F \neq x^M$), creating what we call a *Central Bank Information* (CBI) shock. Third, markets may misperceive the Fed's policy rule ($\alpha^F \neq \alpha^M$), creating what we call a *Fed Response to News* (FRN) shock. We explain the naming convention below after we specify the information structure of the economy.

Information structure and economic dynamics. We specify the evolution of the state of the economy as follows:

$$x_t = \rho x_{t-1} - \theta i_{t-1} + \underbrace{\eta_t}_{\text{public news}} + \underbrace{\eta_t^F}_{\text{CB information}} \quad (4)$$

Economic fluctuations are driven by two types of i.i.d. shocks. The first component, η_t (public news), is observed by both the market and the Fed. The second component, η_t^F (Fed private information), is observed only by the Fed. This asymmetric information gives rise to the central bank information effect, reflecting the Fed's superior information about the economy or better ability to process dispersed economic information. Parameter $\rho \in [0, 1]$ determines the persistence of the state of the economy and $\theta > 0$ determines the impact of Fed policy rates on the economy.

This information structure directly connects to the shock decomposition in equation (3). When the Fed observes a favorable private information shock ($\eta_t^F > 0$), it raises rates based on information that the market lacks. The market is surprised, generating the CBI term: $\alpha^F(x_t^F - x_t^M) = \alpha^F \eta_t^F$. Hence the name “Central Bank Information shock”—it captures the Fed's response to information (η^F) that only the central bank possesses.

The FRN term arises from policy rule misperception. When favorable public news arrives ($\eta_t > 0$), both the Fed and the market observe it and update their assessment of the economy. However, if the market underestimates how aggressively the Fed responds to this news ($\alpha^F > \alpha^M$), it will be surprised by the size of the rate hike. The FRN term $(\alpha^F - \alpha^M)x_t^M$ captures this surprise. We call it the “Fed Response to News shock” because it reflects the portion of the Fed's response to real-time economic news (η) (as well as the response to lagged state x_{t-1} , i_{t-1}) that the market fails to anticipate due to policy rule misperception.

To summarize, in the context of the information structure and economic dynamics postulated in (4) the interest rate surprise becomes

$$MPS_t = \alpha^F \eta_t^F + (\alpha^F - \alpha^M)(\rho x_{t-1} - \theta i_{t-1} + \eta_t) + \varepsilon_t \quad (5)$$

Two immediate implications. This simple framework has two immediate implications for the monetary policy analysis.

First, the MPS is contaminated by the economic shocks η_t^F and η_t through the CBI and FRN terms, respectively. This means that monetary policy surprises conflate pure policy shocks with the Fed's endogenous response to economic conditions.

Second, policy rule misperception implies that the MPS is predictable using publicly available economic indicators. Formally, a regression of MPS on indicators of economic activity known before the Fed announcement can have a positive R-squared. The reason is that the FRN term is a function of x_t^M , so any indicators related to lagged conditions (x_{t-1} , i_{t-1}) and real-time signals of η_t will have explanatory power. This predictability, documented by [Bauer and Swanson \(2023a,b\)](#), provides key evidence for policy rule misperception.

2.2. Bias in standard estimates and the identification of CBI vs FRN effects

Does this contamination bias standard estimates of monetary policy effects? And can one empirically distinguish the CBI and FRN effects? We answer both questions affirmatively; to provide intuition, we trace how each shock affects the economy in the short and in the longer run.

Forecast revisions and shock propagation. Consider a forecast revision of the future state (x_{t+1}) between periods $t-1$ and t . Such a forecast revision captures the change in the projected outlook, and describes how each contemporaneous shock ($\varepsilon_t, \eta_t^F, \eta_t$) affects next period's economic conditions.

$$E_t^M(x_{t+1}) - E_{t-1}^M(x_{t+1}) = \underbrace{-\theta\varepsilon_t}_{\text{MP}} + \underbrace{(\rho - \theta\alpha^F)\eta_t^F}_{\text{CBI}} + \underbrace{(\rho - \theta\alpha^F)\eta_t}_{\substack{\text{public news} \\ \text{policy rule misperception}}} - \underbrace{\theta(\alpha^F - \alpha^M)E_{t-1}^M x_t}_{\text{FRN}} \quad (6)$$

The decomposition reveals three distinct effects. First, a pure monetary policy shock ($\varepsilon_t > 0$) reduces the forecast revision proportionally with coefficient θ , the direct impact of monetary policy on the economy. This is the key parameter researchers aim to estimate (see equation 4).

Second, a favorable central bank information shock ($\eta_t^F > 0$) raises the forecast revision under reasonable parameterizations $\rho - \theta\alpha^F > 0$.¹ The information shock directly improves economic conditions, and this positive effect dominates the contractionary impact of the Fed's policy response.

Third, the FRN shock has two components. Favorable public news ($\eta_t > 0$) raises the forecast revision, again under the same reasonable parameter values. However, if markets underestimate the Fed's response coefficient ($\alpha^F > \alpha^M$), the unexpectedly large rate hike partially offsets this improvement. The net effect on the forecast revision typically remains positive.

Comparing the impact of contemporaneous shocks on (6) and (5) we note that $\varepsilon_t > 0$ increases the MPS and decreases the forecast revision, but η_t and η_t^F generate

¹This parameter restriction realistically requires that systematic monetary policy does not fully offset the impact of the central bank information shock on the outlook.

the opposite co-movement: $\eta_t > 0$ and $\eta_t^F > 0$ increase both the MPS and the forecast revision (the increase of the MPS after $\eta_t > 0$ relies on $\alpha^F > \alpha^M$). This observation serves as the intuition for the formal result stated next.

The bias in local projections. Suppose a researcher estimates the effect of monetary policy on the future state of the economy using a local projection, with MPS_t as a proxy for the monetary policy shock. (Equivalent estimates can be obtained with a VAR, see [Plagborg-Møller and Wolf 2021](#)). The researcher estimates

$$x_{t+1} = \mu + \theta^{LP} MPS_t + \delta_x x_{t-1} + \delta_i i_{t-1} + \xi_t,$$

where x_{t-1}, i_{t-1} are standard controls, or equivalently

$$x_{t+1} = \theta^{LP} \overline{MPS}_t + \xi_t,$$

where $\overline{MPS}_t = \varepsilon_t + \alpha^F \eta_t^F + (\alpha^F - \alpha^M) \eta_t$ is the MPS orthogonalized with respect to the controls (x_{t-1}, i_{t-1}) .²

It is straightforward to show that the population regression coefficient is

$$\begin{aligned} E(\theta^{LP}) &= \frac{\text{cov}(x_{t+1}, \overline{MPS}_t)}{\text{var}(\overline{MPS}_t)} = -\theta + \frac{\rho \alpha^F \text{var}(\eta^F)}{\text{var}(\overline{MPS})} + \frac{(\rho - \theta \alpha^M)(\alpha^F - \alpha^M) \text{var}(\eta)}{\text{var}(\overline{MPS})} \\ &= -\theta + \frac{\rho}{\alpha^F} \frac{\text{var}(CBI)}{\text{var}(\overline{MPS})} + \frac{\rho - \theta \alpha^M}{\alpha^F - \alpha^M} \frac{\text{var}(\overline{FRN})}{\text{var}(\overline{MPS})}. \end{aligned} \quad (7)$$

The researcher hopes to estimate the true effect $-\theta$ but instead obtains a biased estimate.³ The bias is unambiguously upward under the plausible restriction $\rho - \theta \alpha^F > 0$ and assuming $\alpha^F > \alpha^M$ as argued in [Bauer and Swanson \(2023a,b\)](#).

The economic interpretation is clear: when the Fed observes favorable information shocks ($\eta_t^F > 0$) or responds aggressively to positive public news ($\eta_t > 0$), it raises rates and the economy subsequently improves. The researcher attributes these output improvements to the policy shock, thus underestimating the contractionary effect of policy. In other words, the regression coefficient θ^{LP} conflates the true effects of monetary policy with the effects of the shocks to which the Fed responds. Standard high-frequency approaches therefore underestimate the strength of monetary policy's impact on the economy.

Identification of FRN vs CBI: High-frequency stock price responses. How can we separately identify these confounding shocks? Our key insight is that CBI and FRN shocks have *opposite* effects on stock prices in narrow windows around Fed announcements, despite both raising interest rates. This sharp prediction enables identification.

²The equality of θ^{LP} in the two regressions follows from the Frisch-Waugh-Lovell theorem.

³In the second line of (7) we define the variance of the CBI shock, $\text{var}(CBI) = (\alpha^F)^2 \text{var}(\eta^F)$ and the variance of the FRN shock orthogonalized w.r.t. lagged controls $\text{var}(\overline{FRN}) = (\alpha^F - \alpha^M)^2 \text{var}(\eta)$.

Stock price responses to policy surprises. To formalize this intuition in our stylized model, we define a ‘stock’ price s_t as the discounted value of next-period outlook:

$$s_t = E_t^M [x_{t+1} - i_t],$$

where the outlook correlates with future cash flow. The high-frequency change in the stock price—the change between just before and just after the Fed announcement—can be decomposed as follows:

$$s_t - s_{t-\delta} = E_t^M(x_{t+1}) - E_{t-\delta}^M(x_{t+1}) - MPS_t = \rho\eta_t^F - (1 + \theta)MPS_t =$$

$$\underbrace{(\rho - (\theta + 1)\alpha^F)\eta_t^F}_{\text{CBI}} - \underbrace{(1 + \theta)(\alpha^F - \alpha^M)E_{t-\delta}^M(x_t)}_{\text{FRN}} - \underbrace{(\theta + 1)\varepsilon_t}_{\text{MP}} \quad (8)$$

Contrasting high-frequency responses. The three shocks have distinct high-frequency effects on stock prices:

- *CBI shock* ($\eta_t^F > 0$): Stock prices *rise* under reasonable parameters ($\rho > (\theta + 1)\alpha^F$). There are two opposing forces: the revelation of positive private information leads markets to revise up their outlook by $\rho\eta_t^F$, but the accompanying rate hike ($\alpha^F\eta_t^F$) reduces both future activity and its present discounted value. The positive information effect dominates when the CBI shock’s impact on the outlook is not fully offset by monetary policy’s combined effect on growth and the discount rate. Empirically, [Jarociński and Karadi \(2020\)](#) show that interest rate surprises associated with stock price appreciation are indeed followed by stronger economic activity, consistent with this channel.
- *FRN shock* ($E_{t-\delta}^M(x_t) > 0$ with $\alpha^F > \alpha^M$): Stock prices *fall* unambiguously. Although positive public news (η_t) improves fundamentals, this information is already incorporated into prices at $t - \delta$ since markets observe it. The only *news* revealed in the announcement is that the Fed raised rates more than markets expected ($\alpha^F > \alpha^M$). This surprise reduces expected future activity by θ and increases the discount rate, both depressing stock prices. There is no offsetting positive dividend effect in the high-frequency window, as that effect has already been priced in.
- *MP shock* ($\varepsilon_t > 0$): Stock prices *fall*. A pure contractionary monetary policy shock reduces expected activity and increases discount rates. This is the standard channel.

Crucially, this identification strategy exploits the narrow announcement window. At monthly frequencies, public news η_t affects both interest rates and stock prices directly, obscuring the distinction between FRN and CBI shocks. But in high-frequency data, only information revealed *in the announcement* matters. Since η_t is already known while η_t^F is not, the FRN shock moves rates and stocks in opposite directions, while the CBI shock moves them in the same direction.

We use these opposite high-frequency co-movements to separately identify CBI and FRN shocks in our empirical analysis. Note also that the absence of a direct positive public news effect similarly applies to other high-frequency asset price responses to

FRN shocks, an observation we exploit in Section 4.3 to interpret impulse responses in daily regressions.

Extension: time-varying policy rule. One might object that markets should learn the policy rule over time, eliminating systematic misperception. A more realistic framework allows the Fed’s response coefficient to evolve as a random walk:

$$\alpha_t^F = \alpha_{t-1}^F + u_t. \quad (9)$$

In Appendix B we show that in this framework the FRN shock remains present in the MPS, but with two important differences from the baseline model: (1) it becomes largely indistinguishable from the pure monetary policy shock ε and does not lead to bias in estimates of monetary policy effects; (2) it does not imply predictability of the MPS using public information. Predictability relies only on the average misperception persisting throughout the sample (*average* $\alpha^F - \alpha^M > 0$), while fluctuations of this quantity are irrelevant for predictability.

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. \(2005\)](#) 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 inspect the co-movement of interest rate and stock price surprises in this dataset and run the [Bauer and Swanson \(2023b\)](#) predictive regressions with the interest rate surprises.

3.1. Data sources

We take high-frequency financial market data from two sources: TickData and LSEG Tick History.⁴ The main variables of interest are Eurodollar/SOFR futures⁵ and the S&P 500 futures. The first four futures tenors, ED1, ED2, ED3, ED4, come from TickData (until 2004), and LSEG Tick History (2005-2022). From January 2022 onward we use the matching SOFR futures ([Acosta et al. 2024](#)). We take the S&P 500 futures from TickData (until 2008), from 2008 onward we use E-mini S&P 500 futures from LSEG Tick History.⁶

⁴We have access to the LSEG 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 until 2019) which goes back to before 1988, when we start our analysis. Surprises calculated from different sources using overlapping samples are almost identical.

⁵Eurodollar 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 were 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.

⁶E-mini S&P 500 futures became the most liquid market due to their smaller contract size. The dataset contains also Fed funds futures and Treasury futures which we only use in the robustness exercises and

TABLE 1. Fed events: counts, window lengths, median absolute ED3 surprises, and the number of large surprises

Event type	Count	Duration (min)	Med(ED3)	# ED3 ≥ 3bp
FOMC Announcement	357	0	0.020	158
Non-FOMC Events	1256	-	0.010	339
<i>of which</i>				
Chair Speech	576	90	0.010	135
Minutes	217	30	0.010	35
Press Conference	81	60	0.015	29
Testimony	372	180	0.015	138
Testimony Release	10	30	0.000	2

Sample January 1988 - March 2025

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.

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,⁷ and the release of the FOMC meeting minutes. From 1997 onward, the source is the Bloomberg Economic Calendar and the Federal Reserve website. 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 \(2019\)](#). Table 1 reports the assumed standard 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. Next, we adjust these windows to account for any interfering events.

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. We choose the interfering events based on the results of [Kerssenfischer and Schmeling \(2024\)](#) who systematically study which types of events move financial markets the most. In particular, we use the set of 19 types of interfering events consisting of major US data releases, Treasury auction results and

report in more detail in the Appendix.

⁷In some cases 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.

ECB monetary policy decisions and press conferences.⁸ 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. The adjustment affects 248 windows, as reported in Table C2, which also provides further details on the interfering events and the adjustments.

Covid. 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 F.

Asset price surprises. We compute the asset price surprises, i.e., the changes of the main interest rates and of the S&P 500 stock index in the Fed event windows. We construct the interest rate surprise, MPS, as the first principal component of the ED1, ED2, ED3 and ED4 surprises. Table 1 reports some summary statistics: the number of events of each type, window lengths (before adjusting for interfering events), and 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. \(2005\)](#) 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 93% for all variables (see Table C1).

Subsamples of events. 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 2023a](#)). Given this definition, we create the following subsamples:

- Baseline: FOMC announcements and “big” non-FOMC events, 696 observations
- FOMC announcements, 357 observations
- “Big” non-FOMC events, 339 observations

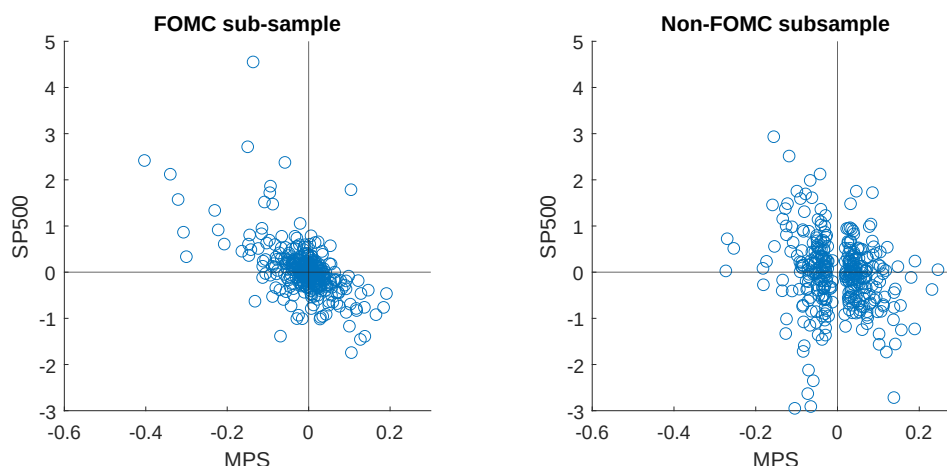
In the robustness section we also report the results for other definitions of the subsamples.

3.3. Co-movement of interest rate and stock price surprises, Bauer–Swanson regressions

In this section, we inspect the features of the data related to the theoretical framework: the co-movement of interest rate and stock price surprises, and the predictability of

⁸Table C2 reports the interfering events. We approximate the set of all the US events in [Kerssenfischer and Schmeling \(2024, Figure 1\)](#). Our interfering event types are not exactly the same as theirs because we use different sources. We take the US data releases from Informa Global Markets, via Haver database MMSAMER, as this source goes back to 1980s and further, and Treasury Auction Results from Treasury-Direct from 1979 to 2005 and from Bloomberg thereafter. [Kerssenfischer and Schmeling \(2024\)](#) focus on post-2002 data and they take their data from Bloomberg.

FIGURE 1. Scatter plots of interest rate (MPS) and stock price surprises (SP500) in FOMC and non-FOMC subsamples



The negative relation is stronger in the FOMC subsample, suggesting that CBI shocks are more prevalent in the non-FOMC subsample.

interest rate surprises. We look separately at the FOMC and the non-FOMC subsamples.

Figure 1 plots the relationship between interest rate and stock price surprises, separately for the FOMC and non-FOMC subsamples.⁹ The two scatterplots have interest rate surprises (MPS) on the horizontal axis and stock price surprises on the vertical axis. Each dot on the left scatterplot corresponds to an FOMC event and each dot in the right scatterplot corresponds to a non-FOMC event. We can see that the negative relation between interest rate surprises and stock price surprises is stronger in the FOMC subsample. In the non-FOMC subsample there are more cases of a positive co-movement. This suggests that the CBI shocks, which are the only ones that generate the positive co-movement, are more prevalent in the non-FOMC subsample.

Next, we replicate Bauer–Swanson regressions of the monetary policy surprises (MPS) on observable economic variables and decompose MPS into a fitted value (FIT) and the residual (RES).

$$MPS_t = \underbrace{\beta y_t}_{FIT_t} + \underbrace{e_t}_{RES_t}, \quad (10)$$

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 3 shows that on FOMC meeting days, which was used as a baseline sample in Bauer and Swanson (2023a,b), the regressors indeed predict a sizable fraction, around 18% of the surprises - similarly to the results emphasized by Bauer and Swanson.

⁹In this figure as in most of the paper we focus by default on the “big” non-FOMC events. Figure E4 shows analogous plots with all non-FOMC events.

TABLE 2. Explanatory variables of the Bauer–Swanson regressions

Variable	Used in†
Unemployment rate surprise	AER, IMF
Non-farm payrolls surprise	AER, MA, IMF
Real GDP surprise	AER, IMF
Core CPI surprise	AER, IMF
Core CPI median forecast	AER
6-month change in Core CPI	AER
BBK Index	AER
$\Delta \log$ SP500 (3m)	AER, MA, IMF
Δ yield curve slope (3m)	AER, MA
$\Delta \log$ commodity price (3m)	AER, MA, IMF
Treasury yield skewness (1m)	MA
Employment growth (12m)	MA
Δ 2-year Treasury (3m)	IMF
Δ 10-year Treasury (3m)	IMF
Δ Baa spread (3m)	IMF
Δ Shadow fed funds rate (3m)	IMF
Δ Chicago Fed NFCI (1m)	IMF

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

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 subsample and in the combined sample.¹⁰

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.

- 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)

¹⁰We are confident that this result is robust and not due to an omission of some important regressors, as we are using a very comprehensive set of regressors. Also, [Altavilla et al. \(2025\)](#) report a similar finding for the ECB Board Member speeches.

TABLE 3. Bauer–Swanson regressions over the baseline sample and its FOMC and non-FOMC subsamples

	Baseline	FOMC	Non-FOMC
(Intercept)	-0.011 (0.008)	-0.020* (0.010)	-0.003 (0.014)
Unemployment surprise	0.017 (0.017)	0.008 (0.020)	0.021 (0.029)
Payrolls surprise	0.017 (0.012)	0.015 (0.014)	0.024 (0.041)
Real GDP surprise	0.012** (0.006)	0.005 (0.007)	0.017* (0.009)
Core CPI surprise	0.023 (0.026)	0.028 (0.033)	0.006 (0.042)
Core CPI median forecast	-0.021 (0.036)	-0.016 (0.043)	-0.015 (0.060)
6-month change in core CPI	-0.006 (0.004)	-0.002 (0.005)	-0.013* (0.007)
BBK index	-0.001 (0.001)	-0.002 (0.002)	-0.000 (0.003)
$\Delta \log S\&P500$ (3m)	0.070 (0.049)	0.136** (0.065)	0.005 (0.072)
Δ yield curve slope (3m)	-0.073 (0.164)	-0.252 (0.213)	0.235 (0.245)
$\Delta \log pcommodity$ (3m)	0.110*** (0.039)	0.160*** (0.053)	0.050 (0.058)
Treasury yield skewness (1m)	0.028** (0.012)	0.029** (0.014)	0.037* (0.020)
Employment growth (12m)	0.422* (0.219)	0.519** (0.244)	0.124 (0.418)
Δ 2-year Treasury (3m)	-0.012 (0.050)	-0.074 (0.065)	0.092 (0.074)
Δ 10-year Treasury (3m)	0.020 (0.063)	0.092 (0.082)	-0.101 (0.094)
Δ Baa spread (3m)	-0.007 (0.011)	-0.014 (0.014)	0.018 (0.018)
Δ shadow fed funds rate (3m)	-0.007 (0.008)	0.014 (0.011)	-0.015 (0.012)
Δ Chicago Fed NFCI (1m)	0.060*** (0.017)	0.049* (0.025)	0.039 (0.026)
N	696	357	339
R-squared	0.060	0.180	0.064
Adj.R-squared	0.037	0.139	0.014

- 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: RES is a good proxy for the monetary policy (MP) shock, in the sense that the MP shock impacts the RES more than the FIT.
 - e. “Good proxy” restriction: FIT is a good proxy for the Fed response to news (FRN) shock, in the sense that the FRN shock impacts the FIT more than the RES.
- These restrictions can be represented as follows:

$$\begin{pmatrix} RES \\ FIT \\ SP500 \end{pmatrix} = \begin{pmatrix} + & c_{12} & c_{13} \\ c_{21} & + & c_{23} \\ - & - & + \end{pmatrix} \begin{pmatrix} MP \\ FRN \\ CBI \end{pmatrix} \quad (11)$$

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

$$c_{13} + c_{23} > 0, \quad \text{Assumption c} \quad (12)$$

$$|c_{21}| < c_{11}, \quad \text{Assumption d} \quad (13)$$

$$|c_{12}| < c_{22}, \quad \text{Assumption e.} \quad (14)$$

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 and consequently do not deliver very sharp conclusions on the effects of different shocks. We report these results in Section 5. However, we can sharpen the inference by bringing in the additional information contained in the heteroskedasticity between the FOMC and non-FOMC events.

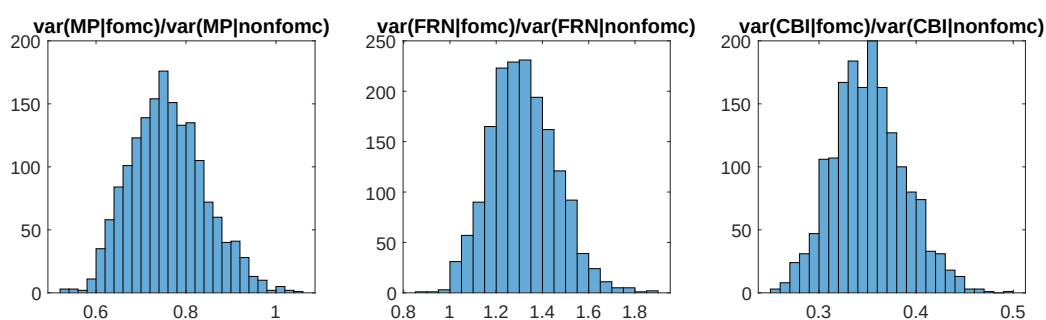
Two observations suggest that the mix of shocks in the FOMC and non-FOMC events is significantly different. The first observation comes from Figure 1: in the non-FOMC subsample there are more cases of a positive co-movement between interest rate and stock price surprises. This suggests that the CBI shocks, which are the only ones that generate the positive co-movement, are more prevalent in the non-FOMC subsample. The second observation on heteroskedasticity comes from Table 3: the R-squared of the Bauer–Swanson regressions is much higher in the FOMC subsample than in the non-FOMC subsample. This suggests that FRN shocks, proxied by the fitted values of the Bauer–Swanson regressions, are more prevalent in the FOMC subsample.

To exploit the information contained in the heteroskedasticity of our data, we estimate the following model generalizing equation (11):

$$y_t = C' u_t, \quad u_{nt} \sim \mathcal{N}(0, \sigma_{ns}^2), \quad s \in \{\text{FOMC}, \text{Non-FOMC}\} \quad (15)$$

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 ($n \in \{\text{MP}, \text{FRN}, \text{CBI}\}$) has a different variance on the FOMC and on non-FOMC events. The fact that C is identified in the presence of

FIGURE 2. Ratios of shock variances across the two subsamples



The figure shows that the mix of shocks changes across the two subsamples. Monetary policy shocks are somewhat smaller in the FOMC subsample, FRN shocks are somewhat larger in the FOMC subsample, whereas CBI shocks are much larger in the non-FOMC subsample.

such heteroskedasticity is known since [Rigobon \(2003\)](#) (see also, e.g., [Lanne et al. 2010](#); [Brunnermeier et al. 2021](#)). We estimate model (15) with Bayesian methods, using a Gibbs sampler described in detail in Appendix D. When sampling C and u_t , $t = 1, \dots, T$ we impose the sign and magnitude restrictions stated in Section 4.1. About 17% of the draws satisfy these sign and magnitude restrictions.¹¹

Figure 2 reports the posterior distributions of the shock variance ratios in the regimes. Heteroskedasticity-based identification only works if at least two of the shock variances change across the two subsamples (variance ratios must be different from one) and we can see that the variances do change (variance ratio of one is a very low probability event). The CBI shocks are much larger in the non-FOMC subsample, the MP shocks are larger in the non-FOMC subsample, and the FRN shocks are larger in the FOMC subsample.

TABLE 4. Variance decompositions in the estimated heteroskedastic model (15).

	RES	FIT	STOCK
MP	0.81 (0.10)	0.06 (0.05)	0.43 (0.14)
FRN	0.04 (0.03)	0.93 (0.05)	0.09 (0.05)
CBI	0.15 (0.09)	0.01 (0.01)	0.48 (0.14)

Posterior mean, standard deviation in parentheses.

Table 4 reports the resulting variance decomposition. The estimated C implies that 81% of the variance of the Bauer–Swanson residuals reflects monetary policy shocks, 4% FRN shocks and 15% CBI shocks. Bauer–Swanson fitted values mainly reflect the FRN shocks (93% of the variance), with some contamination by monetary policy shocks

¹¹However, it turns out that the draws that do not satisfy the sign and magnitude restrictions violate them only slightly in quantitative terms. In Appendix F, we report the results of heteroskedasticity identification without imposing these restrictions, and the results are quite similar.

(6%) and very little role for the CBI shocks.

4.3. Event study: Impact of shocks in daily data

Figure 3 reports local projections of daily financial variables on the raw interest rate surprise (MPS), and on the MP, FRN and CBI shocks constructed in the previous section. More in detail, we run regressions of the form $y_{t+h} - y_{t-1} = \alpha + \beta_h u_{nt} + \xi_t^h$, where y is a response variable, u_n 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.

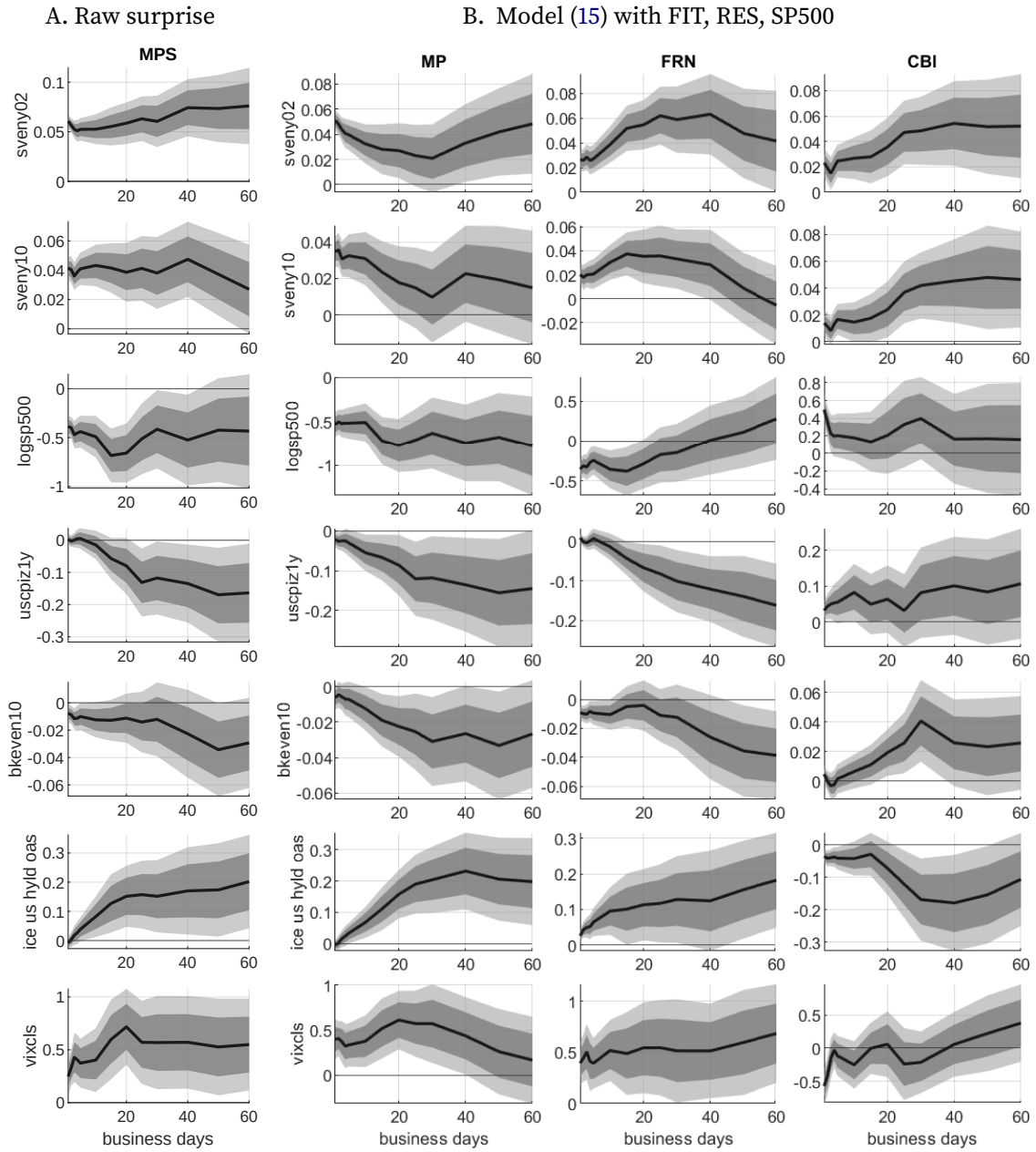
Two results stand out. First, the impact of the favorable FRN shock is contractionary. Similarly to the MP shock, it leads to a depreciation of the stock prices (logsp500), a decline in the inflation expectations (1-year inflation swap rate, uscpizly; 10-year breakeven inflation rate, bkeven10), and a worsening of financial conditions, as reflected in the increase in the corporate bond spreads (ice us hyld 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 a more pronounced impact on the inflation expectations. This is in line with the effects of systematic policy, which is associated with more persistent changes in policy rates and a larger cumulative impact.

Second, the effects of the CBI shock are different from those of the other two shocks. In spite of higher interest rates, financial conditions (stock price level and volatility, bond spreads) improve and inflation expectations (1-year inflation swaps, 10-year breakeven rates) increase. Most interestingly, the long-term interest rates exhibit a post-FOMC drift: after an impact increase they continue increasing further in the subsequent weeks. The post-FOMC drift in long term rates after FOMC announcements was first documented by [Brooks et al. \(2018\)](#). The figure suggests that the post-FOMC drift 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 data and five low-frequency macroeconomic variables. Low-frequency variables include the monthly 1-year Treasury rate as a monetary policy indi-

FIGURE 3. Daily local projections, $y_{t+h} - y_{t-1} = \alpha + \beta_h u_{nt} + \xi_t^h$

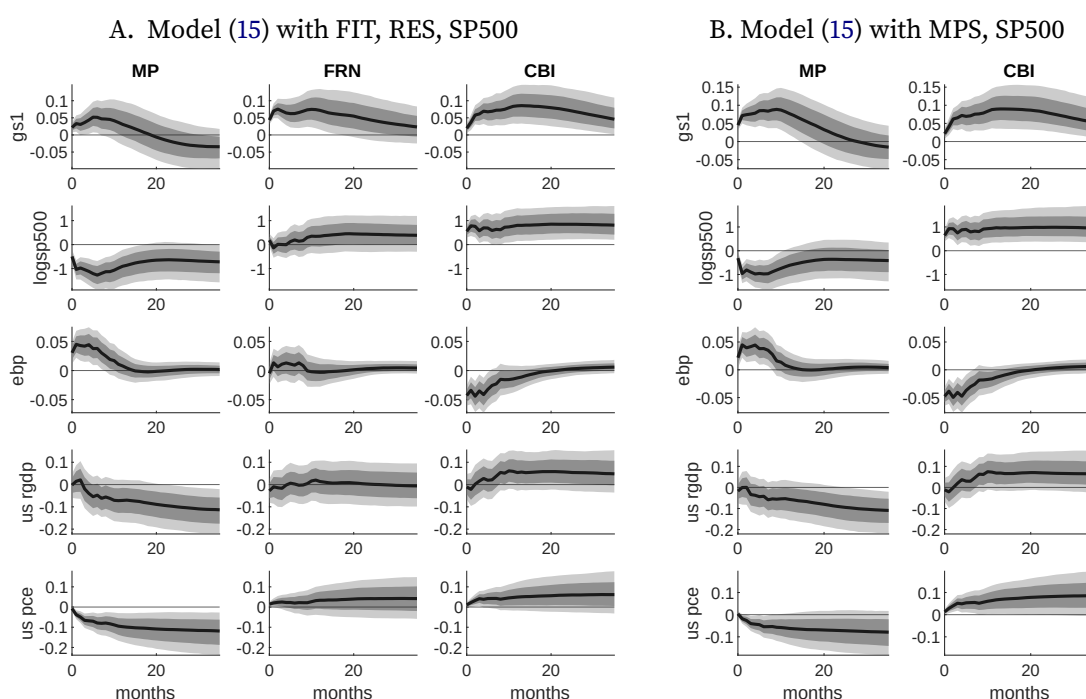


Panel A reports the response (β_h) with heteroskedasticity robust 68% and 90% bands, where u_{nt} is the raw interest rate surprise (MPS). Panel B reports the responses where u_{nt} is, respectively, a monetary policy (MP) shock, a Fed response to news (FRN) shock, and a central bank information (CBI) shock obtained from Model (15) with FIT, RES, SP500. The bands account for shock estimation uncertainty: for each draw of u_{nt} from the posterior we estimate the local projection by OLS and store the point estimate of β_h and its Eicker–Huber–White (EHW) variance. The reported plots represent the means of the point estimates and the total variances computed from the EHW variances and point estimates using the law of total variance. The figure highlights that while all three shocks raise persistently the 2-year (sveny02) and 10-year (sveny10) interest rates, MP and FRN shocks lead to a contractionary impact on stock prices (logsp500) and inflation expectations (1-year inflation swap rate, uscpiz1y; and 10-year breakeven rate, bkeven10), and a deterioration of financial conditions (corporate bond spreads, ice us hyld oas; market volatility, vixcls), CBI shocks reflect positive news about economic fundamentals and lead to favorable financial conditions.

cator (gs1); the logarithm of the monthly average S&P 500 stock price index (logsp500); the Gilchrist and Zakrajsek (2012) excess bond premium (ebp) as an indicator of financial conditions, a monthly interpolation of real GDP (us rgdp) and the PCE price index, both in log levels. We use the so-called “internal instruments” approach, i.e., we order the shocks first and identify the VAR recursively.

The VAR has 12 lags. The sample is monthly, from January 1988 to March 2025. 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 (15) and then draw the VAR parameters conditionally on the draw of the shocks. We report the results based on 2,000 draws from the posterior.

FIGURE 4. Dynamic effects of MP, FRN and CBI shocks in a monthly VAR. Heteroskedasticity-based identification.



The results indicate that FRN shocks tighten 1-year Treasury rates (gs1) but have limited effects on activity (us rgdp), prices (us pce), and financial conditions (excess bond premium, ebp), while CBI shocks have a significant positive impact on the macroeconomy. A monetary policy tightening due to MP shocks leads to lower stock prices and worsening financial conditions, whereas a tightening driven by a favorable CBI shock results in improved stock valuations and financial conditions, with temporary increases in activity and prices. The shaded areas show 68% and 90% posterior bands. The black solid line shows the median impulse response. The VARs are monthly 1988:01-2025:03. Baseline set of Fed events (FOMC and big non-FOMC).

Figure 4 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 tightening the monetary policy indicator for a few

months, leads to no significant response in either activity or financial conditions in the following months. This lack of a broad impact is consistent with the stimulative effects of favorable fresh public news and the contractionary effects of tighter than expected systematic monetary policy broadly offsetting each other. Second, central bank information shocks exert a significant dynamic impact on financial conditions and improve activity (Jarociński and Karadi 2020), albeit only marginally significantly. This happens even after we control for the potential presence of the Fed response to news channel. The impact of 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, leads to a worsening of financial conditions, and causes a persistent downturn. In contrast, a tightening caused by a favorable central bank information shock appreciates stock valuations, improves financial conditions and causes an upturn in activity and prices.

4.5. Two simplified approaches

The above analysis simultaneously accounts for both central bank information (CBI) and Fed response to news (FRN) shocks. What are the consequences of ignoring either one of these confounding shocks?

CBI shocks only. We first account for the CBI shock only. We skip the step of running the Bauer–Swanson regressions and use the MPS and the stock price surprise directly. Figure 1 displays these data. With these data we estimate the heteroskedastic model (15). 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 of Figure 4 reports the dynamic effects of these two shocks in the same monthly VAR. The effects of both shocks are similar to the baseline case with three shocks. The main difference is that the monetary policy shock implies a larger and more persistent response of the 1-year Treasury yield.

Fed response to news only. Second, we account for the Fed response to news only, following Bauer and Swanson (2023a,b). This approach relies on interest rate surprises only; it does not use the stock price surprises and disregards the existence of the central bank information effect. As neither the monetary policy shock nor the Fed response to news shock is able to generate a positive co-movement between interest rates and stock prices, this approach does not account for the cases of positive co-movement present in Figure 1, implicitly treating it as measurement error or noise. As we show next, events with positive co-movement are not the result of noise or measurement error either, because the extra information inherent in the high-frequency stock price surprises has a significant impact on the evolution of the macroeconomy.

Figure 5 implements the “pure” Bauer–Swanson approach. In this approach, we assume that the 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 identify the VAR recursively, putting the residual first, the fitted value second. We also include the S&P 500 surprise as a third variable. To justify this approach, note first that, since the residuals and the fitted values are mutually orthogonal, their ordering does not matter; we only put the residual first to have the monetary policy effects in the first column as in the preceding figures. Second, the inclusion of the S&P 500 surprise as the third variable does not affect the contemporaneous identification of the MP and FRN shocks.

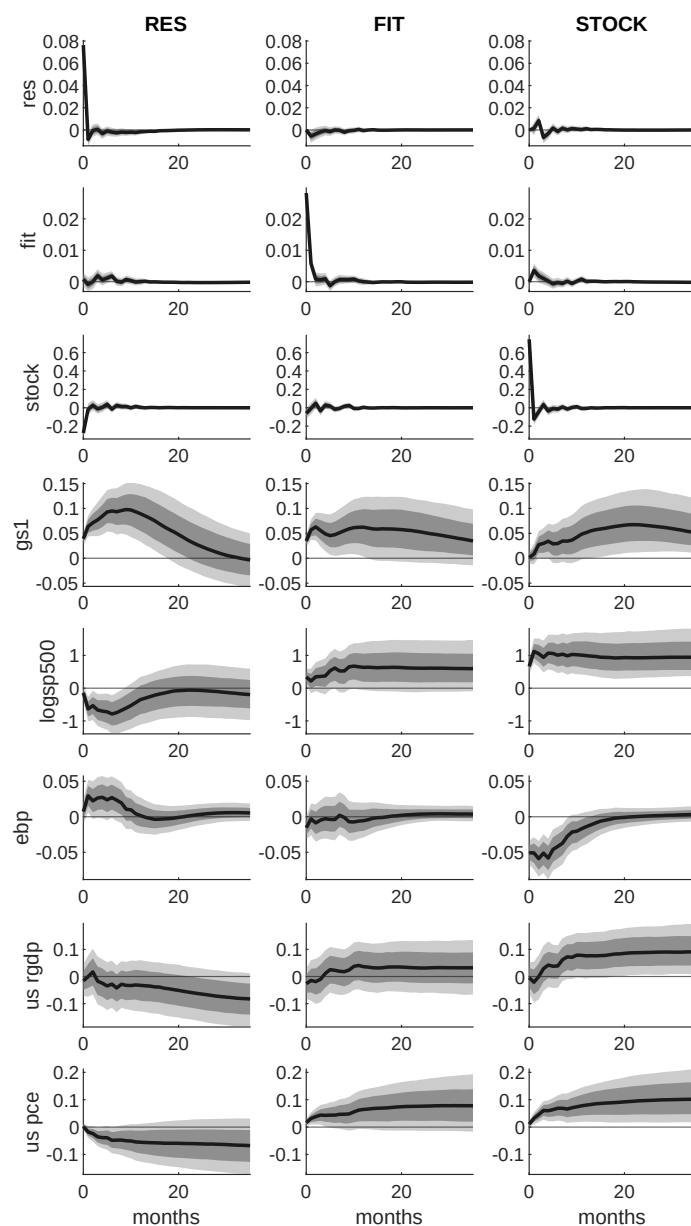
The results in Figure 5 are consistent with [Bauer and Swanson \(2023a\)](#) but at the same time raise a question about what may be missing in their approach.

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 “pure” Bauer–Swanson approach. By including the S&P 500 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 reactions reflect only this information, plus some noise. However, the results in Figure 5 challenge this view. They show that stock price movements not explained by interest rate news are followed by highly significant responses of 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 prices. 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. The point that stock price surprises carry important announcement-related information not spanned by the interest rate surprises is made also in [Kroencke et al. \(2021\)](#); [Boehm and Kroner \(2024\)](#).

How important is it to control for both central bank information and Fed response to news effects when identifying monetary policy shocks? Figure 6 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

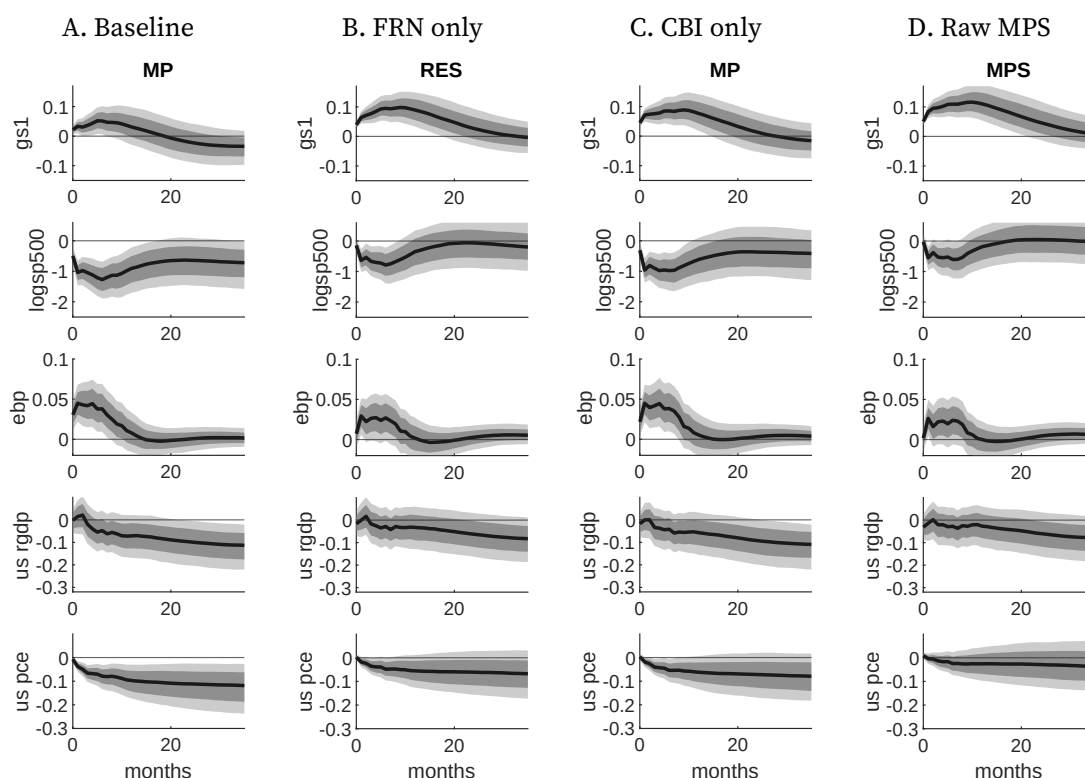
FIGURE 5. The “pure” Bauer–Swanson approach: dynamic effects of Bauer–Swanson residuals (RES), fitted values (FIT), and S&P 500 surprises (STOCK) in a monthly VAR. Baseline sample.



The results show that RES shocks have contractionary effects consistent with theoretical predictions, while FRN shocks are expansionary, indicating they capture an attenuation bias in interest rate surprises. The inclusion of the high frequency stock price surprise isolates stock price movements unexplained by interest rate news, revealing significant responses in key macroeconomic and financial variables omitted in an FRN-only approach. The two shades of grey show 68% and 90% posterior bands. The black solid line shows the median impulse response. The VAR is monthly 1988:01-2025:03. Baseline set of Fed events (FOMC and big non-FOMC).

the high-frequency interest rate surprise as an 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

FIGURE 6. Impulse responses to monetary policy shocks across different identification schemes. Baseline sample.



Impulse responses to monetary policy shocks under the baseline (Section 4.4), under the FRN-only approach (Section 4.5), under a CBI-only approach (Section 4.5) 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 1988:01-2025:03. Baseline set of Fed events (both FOMC and non-FOMC).

rate shock. Controlling for both channels leads to an even stronger effect (including a 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.

Interpretation through the lens of a structural model. The differences across identification schemes matter for structural inference. In Appendix A we ask what frictions a standard New Keynesian model with balance-sheet-constrained financial intermediaries (Gertler and Karadi 2011) requires to match the impulse responses in Figure 6 under each identification. Matching the responses to the raw surprise requires extreme nominal rigidity – prices reset on average almost every two years, far exceeding the 6–12 month frequencies documented in microdata (Nakamura and Steinsson 2008; Klenow and Kryvtsov 2008) – and negligible financial frictions, at odds with the observed response of credit spreads. Matching the responses to the doubly-purged shock instead requires no backward indexation, price resets somewhat more frequent than once a year – at the high end of the microdata evidence – and a meaningful role for financial frictions, consistent with the estimated response of the excess bond pre-

TABLE 5. Variance decompositions in the median rotation.

	res	fit	stock
MP contrib.	0.79	0.04	0.46
FRN contrib.	0.00	0.83	0.22
CBI contrib.	0.21	0.13	0.32

mium. The one-way corrections lie in between: they moderate, but do not eliminate, the implausible rigidity.

5. Identification using only sign and magnitude restrictions

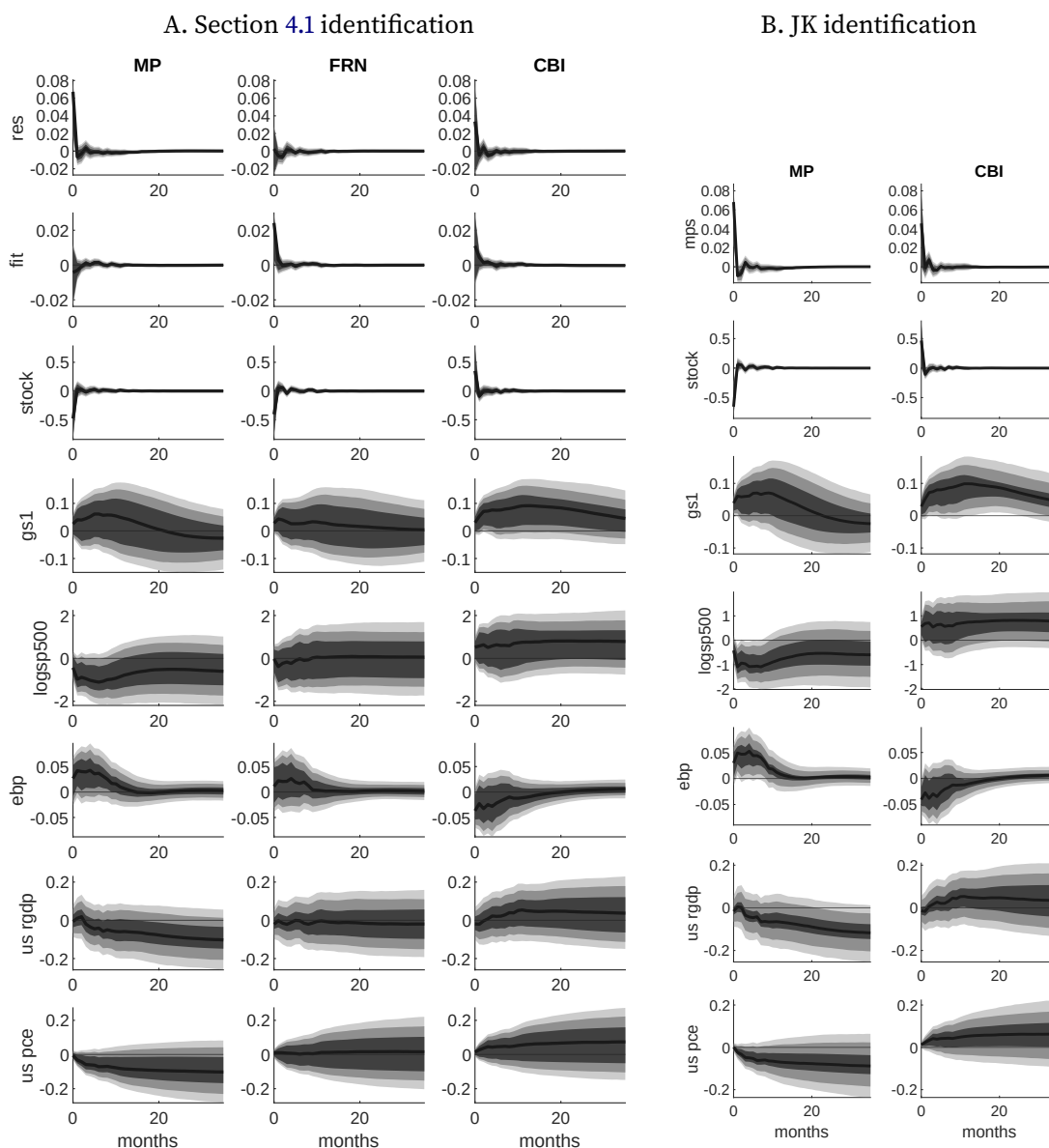
In this section, we identify the shocks using only sign and magnitude restrictions outlined in Section 4.1, without bringing in the information contained in the heteroskedasticity of the data. We find that the point estimates of the effects on the economy are similar to the baseline results and point to the same conclusions: both FRN and CBI effects bias the effects of monetary policy, with the CBI accounting for much of the bias in the monthly VAR. However, the error bands become too wide to make any precise statements about the relative role of FRN vs CBI shocks. This problem is further aggravated when we discard the information in the non-FOMC events and restrict ourselves to the FOMC subsample.

When using sign restrictions alone, the set of possible identifications consistent with the sign and magnitude restrictions includes many different cases (Wolf 2022). To give an example, we first characterize just one case: the median target shock (Fry and Pagan 2011). Table 5 reports the variance decomposition for this shock. 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). As 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 the central bank information (CBI) shock also explains a nontrivial fraction of FIT: the CBI accounts for 21% of the variance of RES and for 13% of the variance of FIT.

We report the dynamic effects of the median shocks in a daily local projection in Appendix Figure E2. The results are similar to those reported in Figure 3.

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&P 500 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 them up. In this VAR we identify three

FIGURE 7. 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.



While the median rotations are broadly similar to the baseline, the results illustrate the challenges with obtaining precise estimates with only sign and magnitude restrictions. 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 1988:01-2025:03. Baseline set of Fed events (both FOMC and non-FOMC).

shocks using the sign and magnitude restrictions from Section 4.1.

Figure 7 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 obtained under the standard, uniform (Haar) prior on shock rotations, 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, especially for financial conditions. 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.

For comparison, the right panel reports the results for the two-way decomposition of MPS and the stock price surprise into MP and CBI shocks using the sign restrictions of [Jarociński and Karadi \(2020\)](#). Impulse responses are similar to those obtained with identification by heteroskedasticity in the right panel of Figure 4, but with wider uncertainty bands, reflecting weaker identification assumptions.

In the Appendix we report the sign-restrictions-only VARs identified using only the FOMC events. In this case, of course, as we only have a single subsample, we have no option of using heteroskedasticity and we can only rely on the sign restrictions. The results, reported in Figure E3, suffer from the same issue: it is hard to judge the relative importance of the FRN and CBI contamination with any confidence, due to the wide uncertainty bands.

6. Robustness

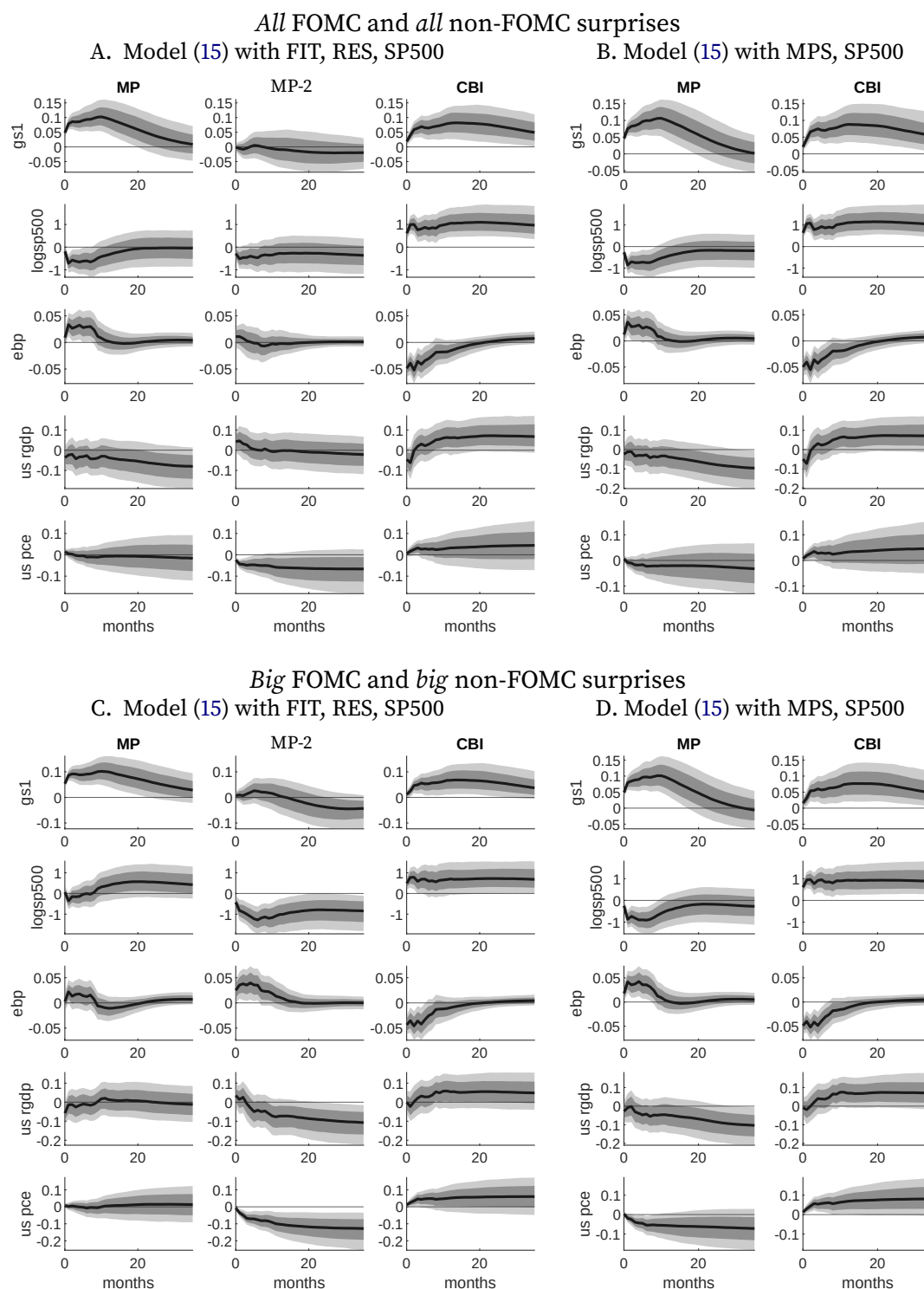
This section examines the robustness of our results. The exercises show that the three-way decomposition places heavy demands on the data: the split between the MP and FRN shocks deteriorates when we alter the event or time sample, while the identified CBI shock and its effects remain stable. Our interpretation is that identifying the FRN shock hinges on sufficient variation in the component of surprises predictable from public news, and this variation can become insufficient in some subsamples. The two-way MP–CBI decomposition, by contrast, is robust throughout.

Fed event samples with only “big” vs all surprises. In the baseline analysis we follow the earlier literature and include all FOMC surprises and big non-FOMC surprises: we take it for granted that all FOMC announcements are relevant for monetary policy, while some of the speeches and testimonies are on other topics so it makes sense to be selective there. In this section, we revisit this practice and report two other cases: including *all* FOMC and *all* non-FOMC surprises,¹² and including only *big* FOMC and *big* non-FOMC surprises (where, as before, “big” is defined as in [Bauer and Swanson \(2023a\)](#), as the events with an ED3 surprise of at least 3 basis points).

Figure 8 reports the dynamic effects of the shocks we identify with these alternative samples of surprises, all FOMC and all non-FOMC surprises in the top panel, big

¹²Figure E4 reports the scatterplots of interest rate and stock price surprises across these two subsamples.

FIGURE 8. Results with alternative sets of high-frequency surprises. Dynamic effects of shocks in a monthly VAR. Heteroskedasticity-based identification.



FOMC and big non-FOMC surprises in the bottom panel. In both cases the three-shock decomposition fails to detect the FRN shock, i.e., fails to detect a shock that would significantly affect the fitted values of the Bauer–Swanson regressions, in the sense

of the “good proxy” magnitude restriction (e.).¹³ Instead, all three shocks detected by heteroskedasticity identification predominantly impact the residual of the Bauer–Swanson regressions and have a small effect on the fitted values. Two of them depress the stock price and we label them MP and MP-2, and the third one increases the stock price and we label it CBI. With all FOMC and all non-FOMC events, the MP shock is contractionary except that it fails to affect the price level, while the MP-2 shock does affect the price level, but fails to move the Treasury yield. With big FOMC and big non-FOMC events, the MP shock raises the Treasury yield significantly but its contractionary effects are not significant, while the MP-2 shock fails to raise the Treasury yield significantly but has significant contractionary effects on the economy. The CBI shock raises the Treasury yield and is expansionary in both cases, except for a short-lived drop in real GDP in the case with all non-FOMC surprises.

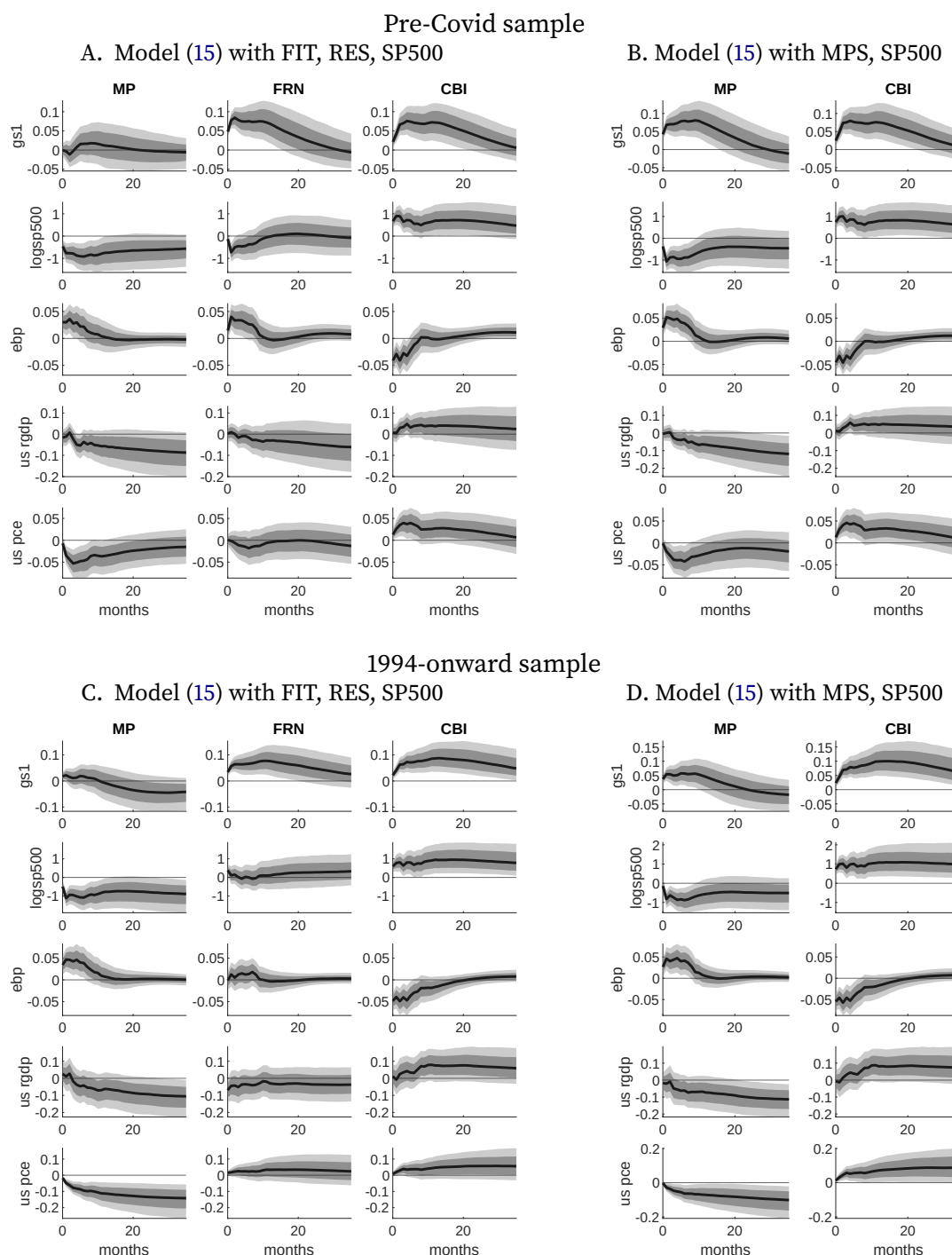
Our interpretation is that using all non-FOMC events introduces more noise into the surprises, while restricting to big FOMC events reduces the variation in the fitted values of the Bauer–Swanson regressions (which only fit the FOMC events); either way, the variation that identifies the FRN shock becomes insufficient and the MP–FRN split deteriorates. The CBI shock is affected less: the two-shock MP–CBI decomposition, shown in the right panels of Figure 8, produces dynamic effects similar to the baseline, with only a weaker and less persistent price-level response when all non-FOMC events are used.

Restricted time samples. We repeat the baseline analysis using alternative sample periods: a pre-Covid sample, which excludes observations from 2020 onward (rather than ending in March 2025), and a sample starting in 1994 (rather than 1988). We exclude observations from January 2020 onward to check how the results are affected by the Covid and the post-Covid evolution of the economy. We exclude the pre-1994 observations because the FOMC did not openly announce its decisions before 1994. In the baseline exercise we follow [Bauer and Swanson \(2023a\)](#) and in 1988–1993 measure financial market surprises around the discount rate change press releases or first open market operations following an FOMC meeting. The subsample starting in 1994 addresses the concern that these earlier surprises might be somehow different.

The main lesson is that the results of the three-shock decomposition are fairly sensitive to either restriction on the time sample, while the results of the two-shock decomposition into MP and CBI shocks are very robust. In the left-hand side panels of Figure 9 we see that the three-shock decompositions in both restricted time samples yield a CBI shock similar to that in the baseline sample, but the FRN shock is mostly contractionary rather than expansionary, while the MP shock moves the 1-year Treasury yield very little. In the right-hand side panels we see that the two-shock

¹³We also tried replacing restriction (e.) with a looser, but still intuitive, requirement that the FRN shock be the dominant shock in the variance decomposition of the FIT. Formally, this relaxed version of the “good proxy” restriction is $|c_{21}| < c_{22}$. However, the heteroskedasticity-identified shocks are incompatible with this relaxed version as well.

FIGURE 9. Results on restricted time samples. Dynamic effects of shocks in a monthly VAR. Heteroskedasticity-based identification.



decompositions into MP and CBI shocks remain fairly unaffected. The main exception is that the effects of MP and CBI shocks are transitory in the pre-Covid sample and become very persistent in the 1994-onward sample. Our interpretation is that dropping years of the sample reduces the variation in the fitted values that the identification of the FRN shock requires.

Alternative specifications of the Bauer–Swanson regressions. The identification of the FRN shock inherits the specification uncertainty of the Bauer–Swanson regressions. Our baseline conservatively combines the regressors of [Bauer and Swanson \(2023b,a\)](#); [Swanson \(2024\)](#); in Appendix F we repeat the analysis with the subsets of regressors used in the individual papers. With two of the three subsets the explanatory power of the regressions is lower, the fitted values vary too little, and the three-shock identification fails to recover a monetary policy shock that significantly moves interest rates. The two-shock MP–CBI decomposition is unaffected by the choice of regressors.

FIGURE 10. Results with alternative monthly variables. Dynamic effects of MP, FRN and CBI shocks in a monthly VAR with heteroskedasticity-based identification.

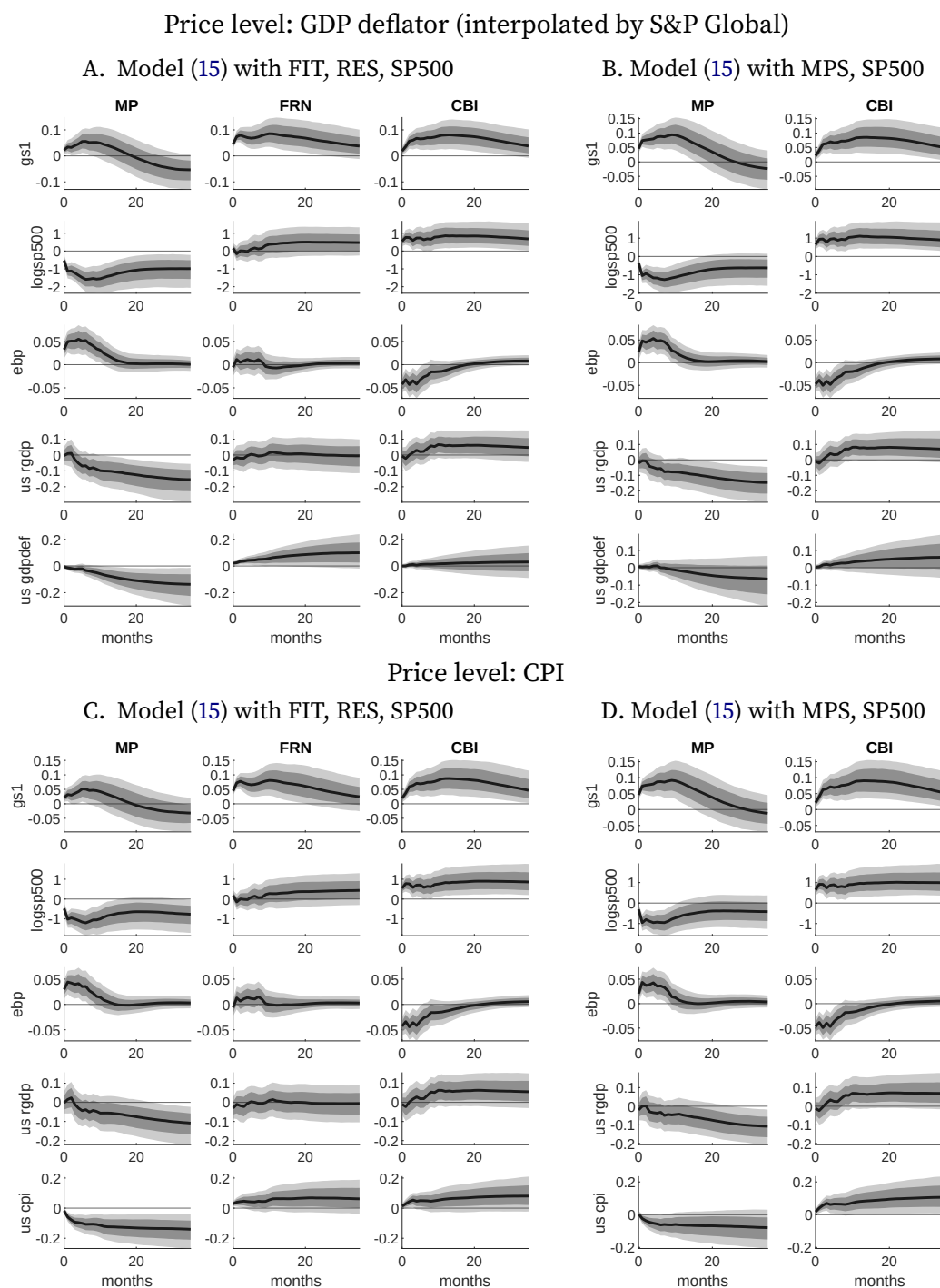
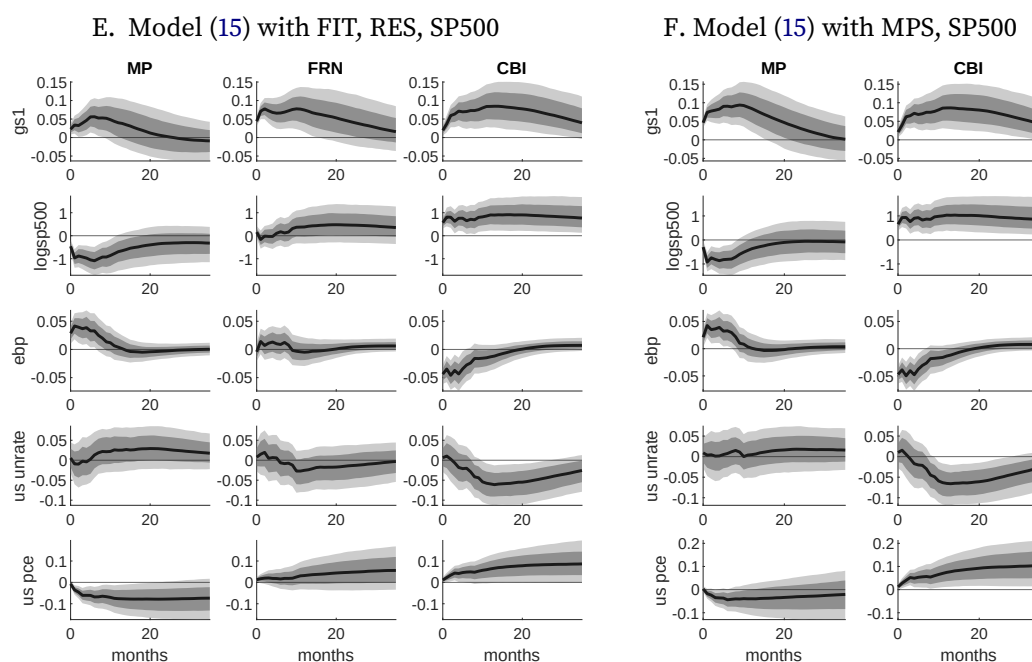
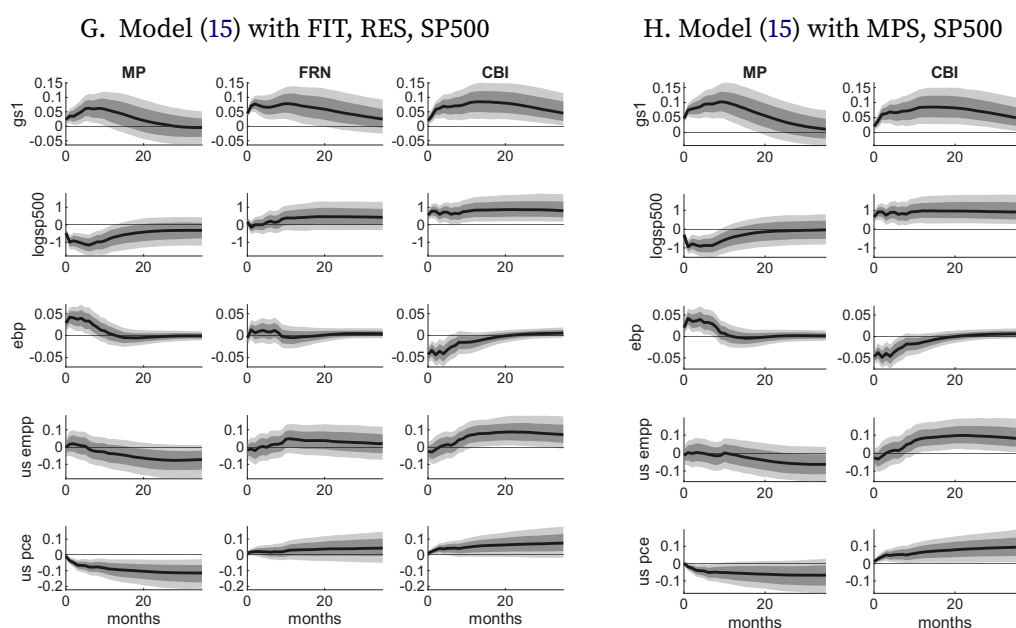


FIGURE 10. Results with alternative monthly variables - continued.

Real activity: Unemployment rate



Real activity: Nonfarm payrolls



Alternative variables in the monthly VARs. Finally, the choice of variables in the monthly VAR has no qualitative effects on the results. Figure 10 reports the VARs with alternative measures of the price level. When we use the GDP deflator (see the top panel), the main difference is that the GDP deflator responds significantly to the FRN shock but not to the CBI shock in the three-shock decomposition. Consistent with that, in the two-shock decomposition, the GDP deflator does not respond as strongly to the MP shock as in the three-shock decomposition. The impulse responses of other variables

are basically unaffected. The results with the CPI index (bottom panel) are basically the same as the results with the PCE index. The next two panels report the results with labor market outcomes as real activity measures. The responses of the unemployment rate are, as expected, mirror images of real GDP and the responses of nonfarm payrolls are very similar to those of real GDP, but in both cases the effects of MP on the labor market cease to be significant or stay only borderline significant. Again, the impulse responses of other variables are basically unaffected.

7. Conclusion

High-frequency interest rate surprises around Fed announcements are contaminated by two confounds that the literature has treated as competing explanations: central bank information (CBI) shocks, arising when the Fed assesses the economy differently from markets, and Fed response to news (FRN) shocks, arising when markets misperceive the policy rule. This paper shows that they are not alternatives. The two shocks are conceptually distinct, carry opposite high-frequency signatures in the co-movement of interest rates and stock prices, and can be identified jointly with the monetary policy (MP) shock. Our identification combines this co-movement with the predictability of surprises from fresh public news and sharpens the inference with the heteroskedasticity between FOMC and non-FOMC communication – additional identifying information made available by extending the event set to press conferences, chair speeches, and minutes releases.

Three findings emerge. First, CBI effects are a robust feature of the data at both daily and monthly frequencies, even when FRN shocks are carefully controlled for. Second, FRN shocks are contractionary in daily data but, in the specification with all three shocks, they have little influence on monthly activity, prices, or financial conditions, as the tighter-than-expected policy response and the favorable news that triggered it broadly offset each other. Third, monetary policy shocks purged of both confounds generate a temporary downturn in activity and prices and a deterioration of financial conditions – the strongest estimated effects from the smallest interest rate impulse, including a significant price-level decline that one-way corrections fail to deliver. Viewed through the lens of a structural model, the doubly-purged shock is consistent with realistic price rigidity and a meaningful role for financial frictions.

The results carry practical guidance for applied work. Researchers should control for both confounds where the data allow. The three-way decomposition is demanding, however: it critically requires sufficient variation in the component of surprises predictable from public news, and it becomes fragile in some subsamples and specifications. When the three-way decomposition proves too challenging, the two-way MP–CBI decomposition provides meaningful results: it is markedly more robust across samples and yields monetary policy estimates close to the baseline. To foster adoption, we make the identified MP, CBI, and FRN shock series for all Fed communication events in our sample publicly available.

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Appendix

Appendix A. Structural model

This section assesses whether a standard New Keynesian model can rationalize the empirical findings under different monetary policy shock identifications. Specifically, we ask: what combination of nominal and financial frictions is required to match observed responses to (i) our baseline monetary policy shock (purged of FRN and central bank information effects) versus (ii) the standard high-frequency identification and (iii) when only either the FRN or the CBI effects are purged from the measure? This exercise serves as a consistency check on our identification strategy through the lens of a structural model.

We employ a widely-used New Keynesian framework with balance sheet constrained financial intermediaries, closely following [Gertler and Karadi \(2011\)](#). The framework is well suited to analyze the quantitative impact of monetary policy shocks, which are modeled as temporary deviations from a systematic interest rate rule. In the model, monetary policy influences real allocations through two key frictions: nominal rigidities and financial frictions.

We structure the description of the model below along the lines of the transmission of monetary policy. To conserve space, we describe key equilibrium conditions and refer the reader to the original paper for their derivations. The framework has seven agents: representative households, financial intermediaries, intermediate-good and capital-good producers, retailers, a fiscal authority, and a central bank. Representative households consume a basket of differentiated goods, work, and save. Financial intermediaries collect deposits and lend to intermediate good firms. Intermediate good firms use capital and labor to produce intermediate goods and borrow from financial intermediaries and households to finance capital acquisitions. Capital-good producers use final goods to generate new capital. Retailers purchase intermediate goods, differentiate them, and sell them to households. The fiscal authority finances its expenditures with lump-sum taxes. The central bank sets interest rates.

The notation in this appendix is self-contained and may differ from that used in the main text.

A.1. Central bank

The central bank sets the nominal interest rate (i_t) following a Taylor rule:

$$\dot{i}_t = \kappa_\pi \pi_t + \kappa_x x_t + \varepsilon_t, \quad (\text{A1})$$

where π_t denotes the inflation rate, x_t is a measure of economic slack, $\kappa_\pi > 1$ and $\kappa_x > 0$ are parameters. We proxy economic slack with the log deviation of marginal cost of the intermediate good from its steady state, which is proportional to conventional output gap measures. The policy temporarily deviates from its systematic component

due to monetary policy shocks (ε_t). The shock follows a second-order autoregressive process $\varepsilon_t = \rho_1^{MP} \varepsilon_{t-1} + \rho_2^{MP} \varepsilon_{t-2} + \varepsilon_t^{MP}$, where we allow for AR(2) dynamics to better capture the hump-shaped response of the monetary policy indicators observed in the data.

A.2. Nominal rigidities

The real interest rate (r_{t+1}) is determined by the Fisher equation

$$i_t = r_{t+1} + E_t \pi_{t+1}. \quad (\text{A2})$$

Monetary policy influences the real rates temporarily as a result of nominal rigidities. Nominal wages are flexible; nominal rigidities arise from staggered price setting by retailers. Their behavior implies a standard New Keynesian Phillips curve with a backward-looking term:

$$\pi_t - \gamma_P \pi_{t-1} = \beta (E_t \{ \pi_{t+1} \} - \gamma_P \pi_t) + \frac{(1 - \gamma)(1 - \beta\gamma)}{\gamma} x_t, \quad (\text{A3})$$

where β is the steady state discount factor of the representative household, $\gamma \in [0, 1]$ is the Calvo parameter (the probability of unchanged prices), and $\gamma_P \in [0, 1]$ is the share of prices indexed to previous period inflation. These two parameters jointly determine price rigidity. The Calvo parameter determines the sensitivity of inflation to marginal cost (x_t): a high γ translates into low sensitivity, implying that the price level responds sluggishly to monetary policy disturbances that change marginal costs. Indexation influences how backward-looking the relationship is, with high γ_P implying high persistence in the inflation rate.

A.3. Real effects of monetary policy

The real interest rate influences aggregate demand through its impact on consumption, investment, and indirectly on government expenditures. Consumption is governed by the representative household's Euler equation:

$$E_t \{ \Lambda_{t,t+1} R_{t+1} \} = 1, \quad (\text{A4})$$

where $R_{t+1} = \exp(r_{t+1})$ is the gross real interest rate, and $\Lambda_{t,t+1}$ is the stochastic discount factor, given by

$$\Lambda_{t,t+1} = \beta \frac{\rho_{t+1}}{\rho_t}, \quad (\text{A5})$$

where ρ_t is the marginal utility of consumption:

$$\rho_t = (C_t - hC_{t-1})^{-1} - \beta h E_t (C_{t+1} - hC_t)^{-1}, \quad (\text{A6})$$

with $h \in [0, 1]$ governing the strength of consumption habits.

A persistent increase in the real rate following a monetary policy shock raises the opportunity cost of current consumption relative to future consumption. This reduces consumption, and the impulse response takes an empirically realistic hump-shaped form due to habits.

Investment is determined by capital good producers, who transform consumption goods into capital goods subject to an investment adjustment cost function (f) and sell them to intermediate good firms at price Q_t :

$$Q_t = 1 + f\left(\frac{I_t}{I_{t-1}}\right) + \frac{I_t}{I_{t-1}} f'\left(\frac{I_t}{I_{t-1}}\right) - E_t \Lambda_{t,t+1} \left(\frac{I_{t+1}}{I_t}\right)^2 f'\left(\frac{I_{t+1}}{I_t}\right) \quad (A7)$$

An increase in real rates reduces the value of capital Q_t , which equals the present discounted value of future capital returns. It declines because, first, higher real rates cause a downturn and reduce the marginal product value of capital and, second, higher interest rates increase the discount rate applied to future dividends. Low capital prices reduce incentives to invest, generating a realistic hump-shaped decline in investment due to the functional form of adjustment costs. Aggregate capital (K_{t+1}) evolves according to: $K_{t+1} = I_t + (1 - \delta)K_t$.

Government expenditure is assumed to be a fraction of aggregate output $G_t = \exp(\bar{g})Y_t$, where $\bar{g}$ is a constant. Aggregate demand net of investment adjustment costs equals the sum of consumption, investment and government expenditures.

Aggregate demand is fulfilled through the supply of intermediate good producers that serve the retailers. Intermediate goods producers combine capital and labor in a constant returns to scale technology:

$$Y_{mt} = AK_t^\alpha L_t^{1-\alpha}, \quad (A8)$$

where Y_{mt} is intermediate good production, $A = \exp(a)$ is a measure of aggregate technology (constant for simplicity), L_t is labor, and α is the capital income share. We denote the price of the intermediate good P_{mt} . The marginal product value of capital is $Z_t = P_{mt} \alpha \frac{Y_{mt}}{K_t}$. Equilibrium in the labor market requires $P_{mt}(1 - \alpha) \frac{Y_{mt}}{L_t} = \chi \rho_t^{-1} L_t^\varphi$, where χ is the relative utility weight of leisure and φ is the inverse Frisch elasticity of labor supply.

A.4. Financial frictions

We now describe how financial frictions are introduced into the model. Intermediate-good firms issue state-contingent corporate bonds S_t that they use to finance purchases of capital (K_{t+1}) from capital producers. They supply corporate bonds at the value

$$Q_t S_t = Q_t K_{t+1}, \quad (A9)$$

where Q_t is the real value of capital. The corporate bonds pay the marginal product value of capital (Z_t) every period and decay geometrically with a parameter $1 - \delta$,

where δ is the capital depreciation rate. Therefore, their value (Q_t) equals the value of capital.¹⁴ The (gross) corporate bond return is

$$R_{kt} = \frac{Z_t + (1 - \delta)Q_t}{Q_{t-1}}. \quad (\text{A10})$$

Demand for corporate bonds comes from both financial intermediaries (or bankers) and households:

$$S_t = S_{bt} + S_{ht}. \quad (\text{A11})$$

Bankers are part of a household with perfect consumption insurance. They continue as a banker each period with probability $\sigma \in [0, 1]$, and exit and return their net worth to the household with the complementary probability $1 - \sigma$. The share of bankers is kept constant by assuming that some workers become bankers every period. New bankers receive startup funds from the households. The aggregate startup funds amount to ω . Banks collect deposits from households and pay them the gross real return R_t . They combine deposits with their net worth and invest them into corporate bonds.

Financial intermediaries face an agency friction: they can abscond with a fixed fraction of assets under their management, losing the franchise value of their banking license. To prevent this, households limit deposits placed in financial intermediaries, effectively setting an endogenous leverage (ϕ_t) constraint. The leverage constraint ensures banks have enough ‘skin in the game’ to avoid absconding. It limits the amount of corporate lending financial intermediaries can supply (S_{bt}):

$$Q_t S_{bt} = \phi_t N_t, \quad (\text{A12})$$

where N_t is the aggregate net worth of the banking system.

Amplification mechanism. How do financial frictions amplify the impact of a monetary policy shock? A temporary increase in the nominal rate translates into a higher real rate r_{t+1} due to nominal rigidities. Higher real rates reduce consumption through a standard intertemporal substitution mechanism. Furthermore, higher real rates raise the funding costs of banks, causing them to require higher returns on corporate bonds ($E_t R_{kt+1}$). The higher discount rate on existing capital reduces its value Q_t , lowering incentives for investment. This channel operates even without financial frictions (with lax bank balance sheet constraints).

Binding leverage constraints amplify the shock through standard financial accelerator mechanisms. Lower corporate debt values reduce banking sector assets, deteriorating their balance sheet condition. The asset price drop causes an amplified decline in net worth, with a multiplicative factor equal to their leverage. Deteriorating balance sheet conditions further increase credit costs and worsen credit conditions,

¹⁴The corporate bonds can be understood as equity. Firms operate a constant returns to scale technology without profits. So the value of the firm comes only from the value of their capital holdings.

with additional negative impacts on investment. The worsening outlook further reduces asset prices, creating another negative feedback loop.

The financial intermediaries build net worth from retained earnings and from startup funds. Aggregate net worth evolves according to the following law of motion:

$$N_t = \sigma [(R_{kt} - R_t)\phi_{t-1} + R_t] N_{t-1} + \omega. \quad (\text{A13})$$

The first term captures net worth from retained earnings of surviving bankers, while the second term comes from startup funds of new bankers. Retained earnings are scaled by the survival probability σ because exiting bankers repay their net worth as dividends. Surviving bankers' retained earnings come from two terms: banks earn the gross real return R_t on their net worth and an excess return $R_{kt} - R_t$ on corporate bond holdings, the latter equaling the product of their net worth and leverage ϕ_{t-1} .

Households also lend directly to the corporate sector, subject to a portfolio adjustment cost as in [Gertler and Karadi \(2013\)](#). The household must pay $\frac{\kappa}{2}(S_{ht} - \bar{S}_h)^2$ if it purchases corporate bonds in excess of $\bar{S}_h$, where $\kappa \geq 0$ is a portfolio adjustment cost parameter. This parameter serves as our key measure of financial friction severity: as $\kappa \rightarrow 0$, households fully offset constrained bank lending, effectively eliminating financial frictions from the model. The household demand for corporate bonds is determined by

$$S_{ht} = \bar{S}_h + \frac{1}{\kappa} E_t \Lambda_{t,t+1} (R_{kt+1} - R_{t+1}), \quad (\text{A14})$$

where $\Lambda_{t,t+1}$ is the household's stochastic discount factor. The demand function implies that households respond to increases in corporate bond spreads by increasing their holdings. The parameter κ determines the sensitivity of their response. Importantly, as $\kappa \rightarrow 0$, households increase holdings without limits for any positive premium, issuing credit to intermediate good firms without constraints and fully replacing the constrained banking sector.

A.5. Pricing additional assets

Our baseline VAR includes a 1-year government bond yield and the excess bond premium. The latter is a yield spread between corporate and government bonds with an average duration of around seven years. In order to obtain analogous long-term yields in our model, we introduce multiple long-term bonds as perpetuities with geometrically decaying coupons. We calibrate the rate of decay of their coupons (σ_x) to match their duration. The assets are priced through no-arbitrage conditions but are not held in positive quantities in equilibrium. Government bonds are priced by households, who are assumed to trade them without portfolio adjustment costs. Corporate bonds, by contrast, are traded by the banks, which require excess return.

We denote by q_{xt} the nominal price of a government bond with duration x . It pays σ_x^i units in each quarter $i = 0, 1, 2, \dots$. Its steady state (yearly) duration is $1/[4(1 - \sigma_x/R)]$, where R is the steady state gross real rate (and steady state inflation is 0). Its (gross)

nominal yield to maturity is $Y_{xt} = 1/q_{xt} + \sigma_x$. The no arbitrage condition requires:

$$q_{xt} = E_t \left[\frac{1 + \sigma_x q_{xt+1}}{R_{t+1} \Pi_{t+1}} \right]. \quad (\text{A15})$$

Analogously, we denote by Q_{xt} the nominal price of a corporate bond with duration x . It pays σ_{kx}^i units in periods $i = 0, 1, 2, \dots$. Its steady state duration is $1/[4(1 - \sigma_{kx}/R_k)]$, where R_k is the steady state corporate bond return. Its gross yield to maturity is $Y_{kxt} = 1/Q_{xt} + \sigma_{kx}$. The no arbitrage condition implies:

$$Q_{xt} = E_t \left[\frac{1 + \sigma_{kx} Q_{xt+1}}{R_{kt+1} \Pi_{t+1}} \right]. \quad (\text{A16})$$

The (gross) excess bond premium in our model is measured as $EBP_t = Y_{kxt}/Y_{xt}$.

A.6. Calibration

We solve the model through first-order perturbation around a non-stochastic steady state. We estimate key parameters of the model through a standard impulse response matching exercise (Christiano, Eichenbaum and Evans 2005). In particular, we estimate three parameters: (i) the Calvo parameter γ , (ii) the inflation indexation parameter γ_P and (iii) the household portfolio adjustment cost parameter κ , together with the size and persistence of the monetary policy shock (σ_{MP} , ρ_1^{MP} , ρ_2^{MP}), to match impulse responses to a monetary policy shock in the model and in the VAR. The first two parameters determine the level of nominal frictions, and the third parameter influences the level of financial frictions in the model. Other model parameters are standard and borrowed from Gertler and Karadi (2011).

Our baseline impulse responses include five variables: the 1-year government bond yield, GDP and the price index, the S&P 500 stock market index, and the excess bond premium. In the model, we match these with the deviations of the following five variables from their steady state values: yield to maturity of a 1-year government bond ($\hat{y}_{1t}$), the output $\hat{y}_t$, the price level $\hat{p}_t = \sum_{s=1}^t \hat{\pi}_s$, the value of capital Q_t ($\hat{q}_t$)¹⁵ and the excess bond premium ($\widehat{ebp}_t$).

We transform monthly VAR impulse responses into quarterly impulse responses by taking simple averages over each quarter, giving us 12 moments for each observable. We simulate impulse responses from the model and stack the 5 times 12 differences of the VAR and model moments into a vector V . We estimate our model parameters to minimize $V' \Omega V$ scalar, where Ω is a weighting matrix. Following Christiano, Eichenbaum and Evans (2005), Ω contains the diagonal elements of the inverse of the variance-covariance matrix of the moments from the VAR.

¹⁵The equity value of financial intermediaries (N_t) in the model would be an alternative model variable for the S&P 500. The two variables move in tandem in the model, but the latter gets amplified by the leverage, as S&P 500 valuations are amplified by the average leverage of the financial and non-financial firms. We report both the evolution of Q and N in our figures and our results are robust to using N_t as a measure of stock market valuations.

FIGURE A1. Matched impulse responses to monetary policy shock, baseline and standard high-frequency identification, Model (black line), VAR mean (blue dashed line), 2-standard-deviations band.

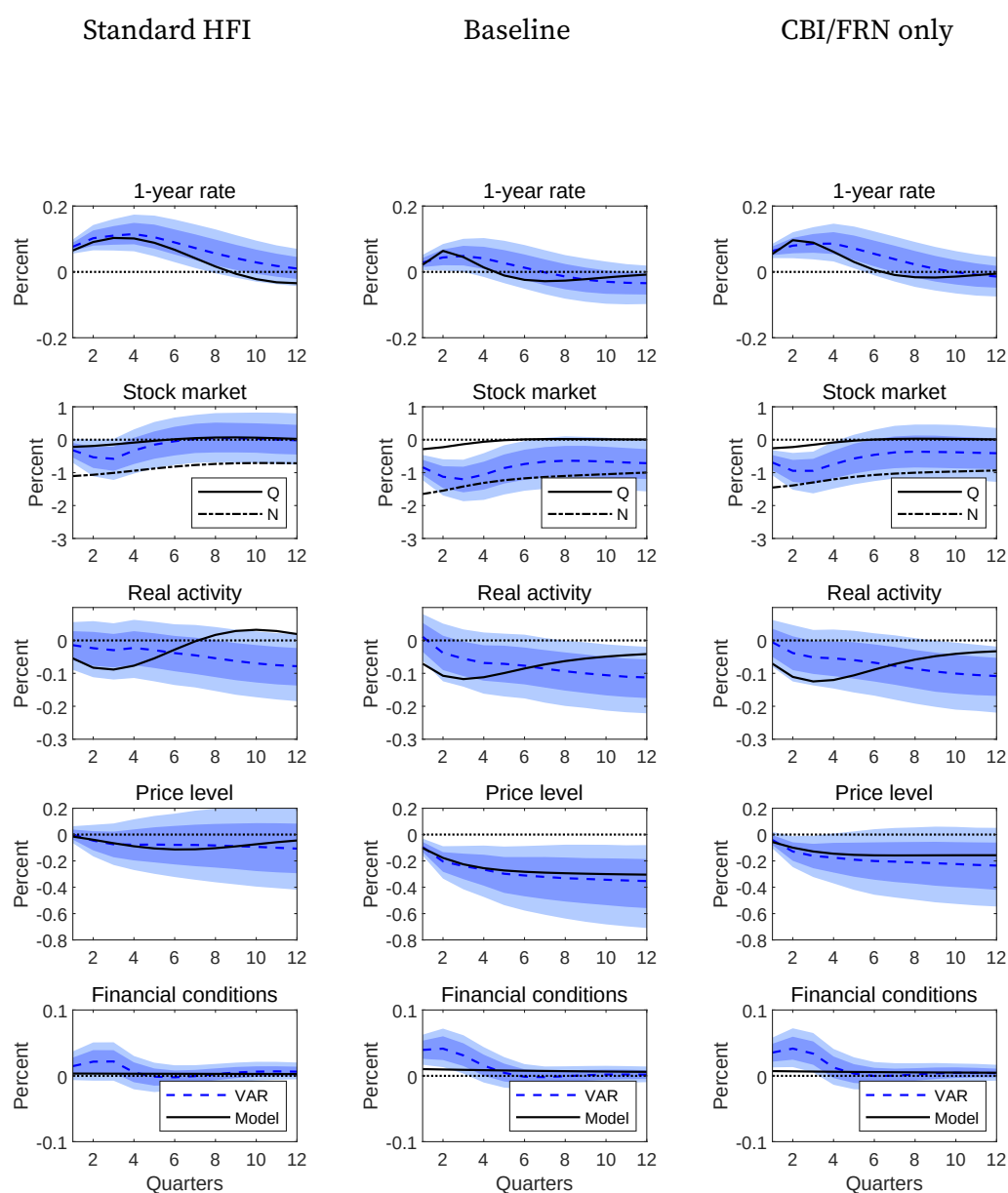


Table A1 lists the estimated parameter values. Figure A1 shows the impulse responses implied by the model and compares them to the impulse responses from the VAR.

TABLE A1. Estimated parameters

Parameters	Label	Standard HFI	Baseline	CBI/FRN only
Calvo parameter	γ	0.86	0.74	0.81
Inflation indexation	γ_P	0.996	0.000	0.000
Portfolio adjustment cost	κ	0.002	0.005	0.003
Stdev of monpol shock	σ^{MP}	0.0005	0.0016	0.0010
AR(1) parameter of monpol shock	ρ_1^{MP}	1.66	1.07	1.27
AR(2) parameter of monpol shock	ρ_2^{MP}	-0.81	-0.35	-0.48

Standard high-frequency identification. We first conduct the exercise using the impulse responses to the monetary policy shock from the standard high-frequency identification, which disregards both Fed response to news effects and central bank information shocks. The first column of Table A1 and Figure A1 show the results. The price level response is unreasonably sticky in this case, and the model requires extreme price-stickiness and indexation parameters to capture the impact. These parameters imply that prices are reset on average almost every two years, far exceeding the 6–12 month frequencies documented in microdata studies (Nakamura and Steinsson 2008; Klenow and Kryvtsov 2008). With such a high nominal stickiness, the interest rate shock causes an output decline that severely overestimates the responses predicted by the VAR, especially in the early years. This occurs even though the size and the persistence of the monetary policy shock somewhat underestimate the observed yield responses. Relatedly, financial frictions are estimated to be small: the model predicts close to zero corporate bond spread response, inconsistent with the VAR evidence. Had it estimated higher financial amplification, the model would have fared even worse in matching the observed output response.

Baseline identification. Next, we conduct the exercise using our baseline identification. This monetary policy shock is purged from the impact of both the central bank information shock and the Fed response to news effects. The second column of Table A1 and Figure A1 show the results. The monetary policy shock matches well the observed yield response. The price stickiness is now estimated to be smaller and the model requires no backward indexation to match the observed price level response. The Calvo parameter implies prices are reset somewhat more frequently than once a year, which is at the high end of the microdata evidence. The more moderate price stickiness, however, is insufficient to explain the output response, so the model estimates a significantly larger financial friction parameter. This approach also better matches the observed reaction of the excess bond premium.

One might wonder how small yield movements in our baseline calibration generate sizable output and price responses. The answer lies in general equilibrium feedback

through the Taylor rule. The underlying monetary policy shock would raise the federal funds rate by approximately 70bps (not shown). This generates declines in inflation (>40bps) and output gap (>20bps). However, the Taylor rule responds contemporaneously to these deteriorating conditions by easing systematic policy, partially offsetting the initial shock. The net equilibrium yield response peaks at only 5 basis points.

Controlling for CBI or FRN only. Lastly, we conduct the exercise using the monetary policy identification controlling for either only the Fed response to news effect or the central bank information effect. The two estimates are sufficiently close that they yield similar parameter estimates. The third column of Table A1 and Figure A1 show the results. Controlling for only one of the effects goes a long way in generating more reasonable nominal stickiness parameters: the model needs no backward indexation and its nominal stickiness parameter is more reasonable than under the standard HFI. Still, the magnitude of required nominal stickiness remains unreasonably high and significantly higher than under our baseline parametrization.

Implications. These results demonstrate that our baseline identification yields model implications broadly consistent with both microeconomic price-setting evidence and significant financial frictions. By contrast, the standard high-frequency identification requires implausibly rigid prices and minimal financial frictions—a combination inconsistent with both microdata and the observed credit spread responses. Therefore, our baseline identification approach is in line with a structurally more plausible model.

Appendix B. Time-varying policy rule

In the baseline framework (Section 2) we treat the Fed's response coefficient α^F as fixed but imperfectly perceived by the market. One might object that rational markets should eventually learn the true coefficient, eliminating systematic misperception. We address this concern by extending the model to allow the rule coefficient to follow a random walk. We show that the CBI results are unchanged, while the FRN results are modified in important ways: predictability of the MPS and attenuation bias in local projections both survive only to the extent that *average* misperception is non-zero—a weaker condition that relies on persistent, rather than permanent, underestimation of the Fed's reaction coefficient. The high-frequency identification strategy remains valid throughout.

Setup. We replace the fixed coefficient α^F with a time-varying coefficient

$$\alpha_t^F = \alpha_{t-1}^F + u_t, \quad (\text{B1})$$

where u_t is i.i.d. with mean zero and variance σ_u^2 , and is independent of all other shocks ($\varepsilon_t, \eta_t, \eta_t^F$). The policy rule is

$$i_t = \alpha_t^F x_t^F + \varepsilon_t. \quad (\text{B2})$$

The central bank announces α_t^F (and all other current shocks) contemporaneously with the policy announcement. Since u_t is not observable to markets before the announcement, their best estimate of the current rule coefficient, formed just before the announcement, is

$$\alpha_{t-\delta}^M = \alpha_{t-1}^F, \quad (\text{B3})$$

so the realized misperception at any given announcement is entirely driven by the current innovation: $\alpha_t^F - \alpha_{t-\delta}^M = u_t$.

MPS decomposition. Subtracting market expectations from the policy rule as in equation (3) yields

$$\underbrace{i_t - E_{t-\delta}^M(i_t)}_{\text{MPS}_t} = \underbrace{\varepsilon_t}_{\text{MP shock}} + \underbrace{\alpha_t^F \eta_t^F}_{\text{CBI}} + \underbrace{u_t \cdot x_{t-\delta}^M}_{\text{FRN}}, \quad (\text{B4})$$

where $x_{t-\delta}^M = \rho x_{t-1} - \theta i_{t-1} + \eta_t$ is the market's assessment of the current state. The structure of the three-way decomposition is unchanged, but the FRN term now reflects only the random innovation u_t rather than a fixed wedge $\alpha^F - \alpha^M$.

Predictability. A key implication of the baseline model (Section 2) is that the MPS is predictable using publicly available economic indicators, because the fixed wedge $\alpha^F - \alpha^M > 0$ implies $E[\text{MPS}_t \mid x_{t-1}, i_{t-1}, \eta_t] = (\alpha^F - \alpha^M)x_{t-\delta}^M > 0$ when economic

conditions are favorable. Under the random walk extension this calculation gives instead

$$E[MPS_t | x_{t-1}, i_{t-1}, \eta_t] = E[u_t] \cdot x_{t-\delta}^M = 0, \quad (B5)$$

since u_t has mean zero and is independent of all public information available before the announcement. *Predictability therefore vanishes entirely when average misperception is zero.* It survives only if there is a non-zero *average wedge* $E[\alpha_t^F - \alpha_{t-\delta}^M] > 0$ persisting throughout the sample, while period-by-period variation in the misperception (u_t) is irrelevant for predictability.

This distinction has direct empirical relevance. [Bauer and Swanson \(2023a,b\)](#) document significant predictability of high-frequency monetary policy surprises in the post-1994 FOMC subsample, which they interpret as evidence of persistent market underestimation of the Fed's reaction coefficient over that period. Our framework is consistent with this interpretation: the predictability they find reflects a positive *average* misperception during their sample, not a fixed structural feature of the economy. Indeed, predictability is notably weaker in the full event sample that extends beyond their subsample, suggesting that average misperception may be smaller or closer to zero over a longer horizon. This observation counsels against treating FRN-induced predictability as a permanent feature of monetary policy surprises.

Forecast revision and shock propagation. The forecast revision is analogous to the expression in the main text, with the fixed wedge $\alpha^F - \alpha^M$ replaced by u_t .

$$E_t^M(x_{t+1}) - E_{t-1}^M(x_{t+1}) = \underbrace{-\theta \varepsilon_t}_{\text{MP}} + \underbrace{(\rho - \theta \alpha_t^F) \eta_t^F}_{\text{CBI}} + \underbrace{(\rho - \theta \alpha_t^F) \eta_t}_{\substack{\text{public news} \\ \text{policy rule misperception}}} - \underbrace{\theta u_t E_{t-1}^M x_t}_{\text{FRN}} \quad (B6)$$

A positive monetary policy shock $\varepsilon_t > 0$ depresses the outlook and a favorable Fed information shock $\eta_t^F > 0$ or favorable public news $\eta_t > 0$ both improve the outlook as long as α_t^F stays in the reasonable range $\rho - \theta \alpha_t^F > 0$. Unlike in the baseline case, the change in the policy rule, and the resulting policy rule misperception, may either improve or worsen the outlook depending on the realization of u_t . Effectively, u_t acts as another monetary policy shock.

Attenuation bias. When analyzing the local projection of x_{t+1} on MPS_t , we can skip the step of orthogonalizing the MPS with respect to the lagged controls, as the MPS is already orthogonal to them: see the above discussion of MPS predictability. The population LP coefficient is then

$$E(\theta^{LP}) = \frac{\text{cov}(x_{t+1}, MPS_t)}{\text{var}(MPS_t)}$$

$$= \frac{-\theta \text{var}(\varepsilon_t) + \text{var}(\eta_t^F) E[(\rho - \theta \alpha_t^F) \alpha_t^F] - \theta \text{var}(u_t) E[(x_{t-\delta}^M)^2]}{\text{var}(\varepsilon_t) + \text{var}(\eta_t^F) E[(\alpha_t^F)^2] + \text{var}(u_t) E[(x_{t-\delta}^M)^2]} \quad (\text{B7})$$

In deriving the covariance term above, we used the expression of the future state as

$$\begin{aligned} x_{t+1} &= (\rho - \theta \alpha_t^F)(x_{t-\delta}^M + \eta_t^F) - \theta \varepsilon_t + \eta_{t+1} + \eta_{t+1}^F \\ &= (\rho - \theta \alpha_{t-1}^F - \theta u_t)(x_{t-\delta}^M + \eta_t^F) - \theta \varepsilon_t + \eta_{t+1} + \eta_{t+1}^F. \end{aligned}$$

The three terms in the numerator correspond to the three shocks. Notice that the FRN contribution to the numerator is $-\theta \text{var}(u_t) E[(x_{t-\delta}^M)^2]$ and to the denominator is $\text{var}(u_t) E[(x_{t-\delta}^M)^2]$. These exactly cancel in the ratio, contributing a term of $-\theta$: the FRN component of the random walk model yields an unbiased contribution to the LP estimate. Intuitively, the innovation u_t is equally likely to make policy tighter or looser than expected, so it acts as an additional source of exogenous variation rather than a confound. The only remaining source of upward bias is the CBI term:

$$E(\theta^{LP}) = -\theta + \frac{\rho E[\alpha_t^F] \text{var}(\eta_t^F)}{\text{var}(\overline{MPS}_t)} = -\theta + \frac{\rho E[\alpha_t^F]}{E[(\alpha_t^F)^2]} \frac{\text{var}(CBI_t)}{\text{var}(MPS_t)} > -\theta. \quad (\text{B8})$$

Attenuation bias therefore survives the random walk extension, but it originates exclusively from the CBI channel. *FRN-induced bias requires the same condition as predictability: a non-zero average misperception $E[\alpha_t^F - \alpha_{t-\delta}^M] > 0$. To the extent that average misperception diminishes over the full sample, so does the FRN contribution to the bias.* This reinforces the empirical importance of separately identifying and controlling for the CBI effect, which remains present regardless of whether average misperception is zero.

High-frequency identification. The high-frequency stock price decomposition (equation (8)) under the random walk becomes

$$s_t - s_{t-\delta} = \underbrace{-(\theta + 1)\varepsilon_t}_{\text{MP}} + \underbrace{(\rho - (\theta + 1)\alpha_t^F)\eta_t^F}_{\text{CBI}} + \underbrace{-(\theta + 1)u_t \cdot x_{t-\delta}^M}_{\text{FRN}}. \quad (\text{B9})$$

The structure is qualitatively unchanged. CBI shocks ($\eta_t^F > 0$) continue to appreciate stock prices under the same reasonable parametrization $\rho > (\theta + 1)\alpha_t^F$. The FRN term generates a negative co-movement between the MPS and the stock price: when it increases the MPS ($u_t x_{t-\delta}^M > 0$), the stock price falls (by $-(\theta + 1)u_t x_{t-\delta}^M$). Our identification strategy, which exploits the sign difference between CBI and FRN shocks in the high-frequency window, therefore remains valid under the random walk extension.

Appendix C. Construction of high-frequency surprises

Table C1 reports the correlations of the selected variables in the GSS dataset with the corresponding variables in our dataset. The GSS dataset we are comparing with

includes only FOMC announcements, and has data up to July 2019. The correlations are computed on the common samples of events, which may differ by variable. The last column reports the size of the common sample for each variable. The correlations are very high, between 0.932 and 0.989, showing that in spite of the differences in the computation and data sources we replicate the GSS dataset very closely.

TABLE C1. Correlations of selected variables 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	198
Front Eurodollar future	ED1	ED1	0.977	286
First back Eurodollar future	ED2	ED2	0.987	286
Second back Eurodollar future	ED3	ED3	0.989	286
Third back Eurodollar future	ED4	ED4	0.982	246
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	0.932	285
S&P500 (futures)	SP500FUT	SP500FUT	0.962	275

Table C2 provides information on the adjustment of the Fed event windows to account for interfering events.

TABLE C2. Interfering events

Fed Event Type	All in sample	FOMC announcement	Chair speech	Testimony	Testimony release	Total
Interfering Event						
US Treasury Auction Results	2296	0	32	99	0	131
U.S.: Composite Index of Leading Indicators	367	0	11	14	0	25
U.S.: New Home Sales	447	0	6	16	0	22
U.S.: University of Michigan Consumer Sentiment: Final	317	0	20	1	0	21
U.S.: Existing Home Sales	340	0	7	12	0	19
U.S.: ISM: Mfg Composite Index	422	0	6	8	0	14
U.S.: Chicago Purchasing Managers Index	318	0	6	7	0	13
U.S.: Initial Claims	1759	0	11	2	0	13
U.S.: ISM: Services Index	225	0	2	6	0	8
U.S.: Consumer Price Index	446	0	6	1	0	7
U.S.: Employees on Nonfarm Payrolls	447	0	5	0	0	5
U.S.: New Orders: Advance Durable Goods	447	0	3	1	1	5
U.S.: Producer Price Index	447	0	2	0	2	4
U.S.: Retail Sales	447	0	4	0	0	4
U.S.: PCE	447	0	2	0	0	2
U.S.: Real GDP: Final	140	1	1	0	0	2
U.S.: Real GDP: Advance	139	0	1	0	0	1
ECB Monetary Event	314	0	0	0	0	0
U.S.: Real GDP: Preliminary	139	0	0	0	0	0
Total	9904	1	125	167	3	296
Total (unique events)		1	104	140	3	248

Post-FOMC press conferences and the Releases of FOMC meeting minutes never coincided with the Interfering Events.

Some Fed events coincided with more than one Interfering Event. The row “Total (unique events)” counts the events of each type whose windows were adjusted by at least one Interfering Event.

Appendix D. 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 .

$$y_t = C' u_t, \quad u_{nt} \sim \mathcal{N}(0, \sigma_{ns}^2), \quad \text{for } n = 1, \dots, N, \quad s = 1, \dots, S \quad (\text{D1})$$

$t = 1, \dots, T$ 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 ($2 \leq S \leq T$). The variance of shock n in regime s is σ_{ns}^2 . This variance is allowed to be different in each regime.

Matrix C is identified as long as there is sufficient variation in the σ_{ns}^2 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 (D1) 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 \(2024\)](#).

D.1. Reparameterization, priors

Define $W = C^{-1}$ and $q_{ns} = (\sigma_{ns}^2)^{-1}$ and reparameterize (D1) as follows:

$$y_t = W^{-1'} u_t = W^{-1'} Q_t^{-1/2} z_t, \quad z_t \sim \mathcal{N}(0, I_N), \quad Q_t = \text{diag}(q_{1t}, \dots, q_{Nt}) \quad (\text{D2})$$

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

The likelihood of y_t in this parameterization is

$$p(y_t | W, Q_t) = |W^{-1'} Q_t^{-1} W^{-1}|^{-1/2} \exp\left(-\frac{1}{2} y_t' (W^{-1'} Q_t^{-1} W^{-1})^{-1} y_t\right) \quad (\text{D3})$$

The prior for W is a weakly informative Gaussian distribution,

$$p(W) = \mathcal{N}(\text{vec } W_0, \Omega). \quad (\text{D4})$$

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 $\nu/2$ and scale $2/\nu$ for all n and s ,

$$p(q_{ns}) = \mathcal{G}(\nu/2, 2/\nu) = \Gamma(\nu/2)^{-1} (\nu/2)^{\nu/2} q_{ns}^{\nu/2-1} \exp(-q_{ns}\nu/2). \quad (\text{D5})$$

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

$$\mathcal{G}_x(a, b) = \frac{1}{\Gamma(a)b^a} x^{a-1} \exp(-x/b) \quad (\text{D6})$$

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

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

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

- draw q_{ns}^j from the conditional posterior $p(q_{ns}|Y, W^{j-1})$, for $n = 1, \dots, N$, $s = 1, \dots, S$, collect them in matrix Q^j ;
- draw W^j from the conditional posterior $p(W|Y, Q^j)$;
- compute the objects of interest $C^j = (W^j)^{-1}$ and $U^j = YW^j$.

D.3. The conditional posterior of W

The conditional posterior of W is a nonstandard density

$$p(W|Y, Q_1, \dots, Q_T) \propto |W|^T \exp\left(-\frac{1}{2} \sum_{t=1}^T y_t' W Q_t W' y_t\right) p(W). \quad (\text{D7})$$

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

$$f(W) = \mathcal{N}(\hat{w}, (-\mathcal{H})^{-1}) \quad (\text{D8})$$

where $\hat{w}$ is the mode of $p(W|Y, \cdot)$ and $\mathcal{H}$ is 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

$$\min\left(1, \frac{p(W^*|Y, \cdot) f(W)}{f(W^*) p(W|Y, \cdot)}\right). \quad (\text{D9})$$

The literature has taken different approaches to drawing W (often denoted as A_0). [Brunnermeier et al. \(2021\)](#) use a standard Metropolis-Hastings algorithm, which converges slowly. [Lütkepohl and Woźniak \(2020\)](#) draw a candidate from a Gaussian distribution centered at the previous draw and with variance $\sum_t WQ_tW'$. The appealing feature of the present approach is that it constructs a substantially better proposal distribution (with the correct 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 $\log p(W|Y, Q_1, \dots, Q_T)$ is

$$\mathcal{J}(\text{vec } W) = T(\text{vec } W^{-1'})' - \sum_t \text{vec}(y_t y_t' W Q_t)' - \text{vec}(W - W_0)' \Omega^{-1} \quad (\text{D10})$$

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

$$\mathcal{H}(\text{vec } W) = -TK_{NN}(W^{-1'} \otimes W^{-1}) - \sum_t (Q_t \otimes y_t y_t') - \Omega^{-1} \quad (\text{D11})$$

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

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

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

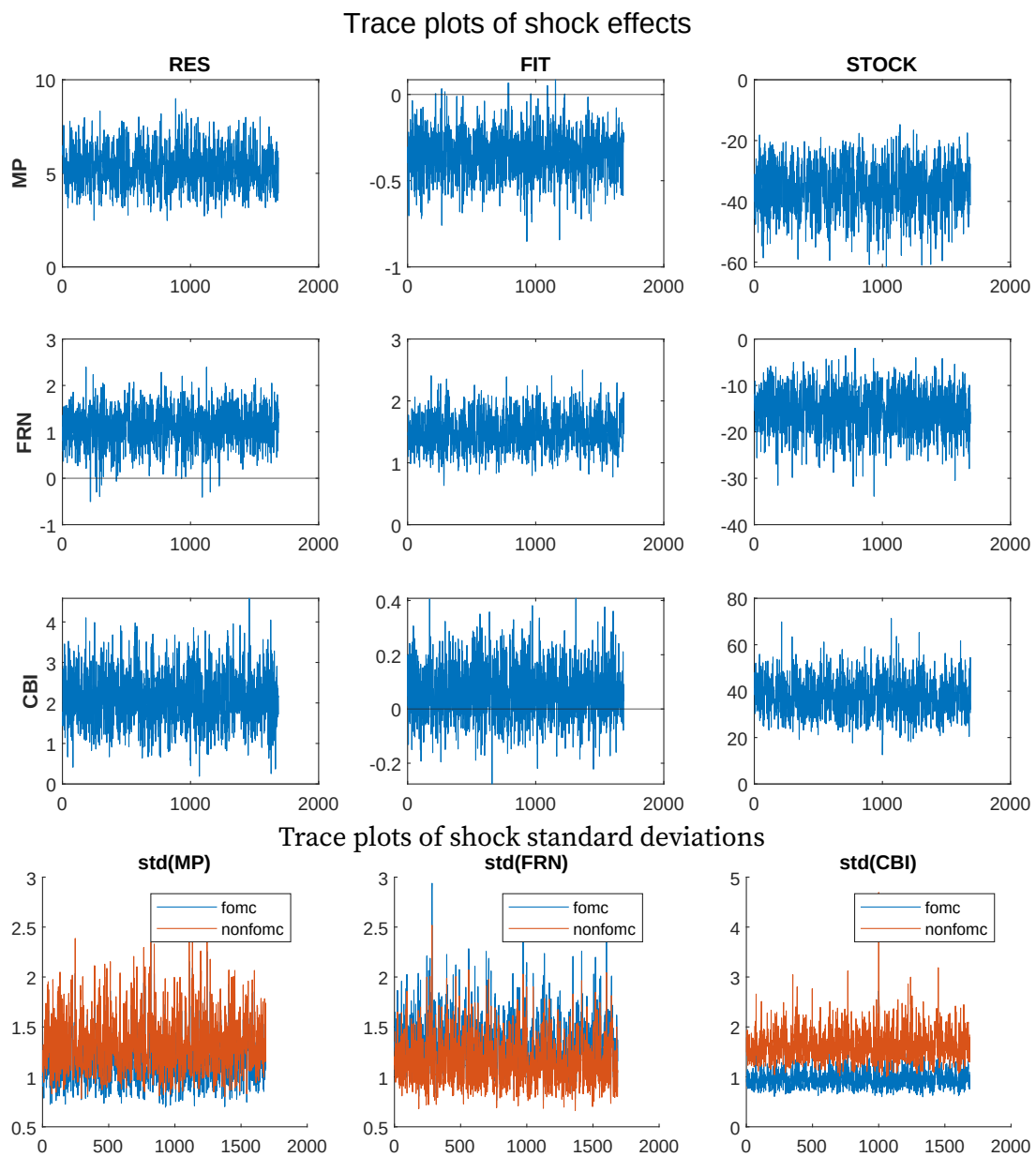
$$p(q_{ns}|Y, W) = \mathcal{G}\left((\nu + T_s)/2, 2/(\nu + \sum_{t \in s} u_{nt}^2)\right) \quad (\text{D12})$$

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

D.5. Simulation and convergence

We generate 202,000 draws from the posterior using the Gibbs sampler, discard the initial 2,000 as burn-in and save every 20th of the remaining ones, obtaining 10,000 draws. When drawing W , approximately 75% of the candidate draws are accepted. From the 10,000 saved draws we retain approximately 17%, those that satisfy the sign and magnitude restrictions. The whole simulation takes about 5 minutes on a standard laptop. The simulation length is conservative; the results are very similar also with shorter runs. Figure D1 reports the trace plots of the shock effects (entries of the C matrix) and shock standard deviations ($q_{ns}^{-1/2}$, for $n \in \{\text{MP, FRN, CBI}\}$, $s \in \{\text{FOMC, Non-FOMC}\}$).

FIGURE D1. Trace plots from the Gibbs sampler.



Appendix E. Additional results

TABLE E1. Heteroskedasticity identification without imposing the sign restrictions. Variance decompositions in the three-shock model.

	RES	FIT	STOCK
MP	0.71 (0.13)	0.17 (0.11)	0.35 (0.14)
FRN	0.15 (0.10)	0.83 (0.12)	0.16 (0.09)
CBI	0.14 (0.09)	0.01 (0.01)	0.49 (0.14)

Posterior mean, standard deviation in parentheses.

FIGURE E1. Heteroskedasticity identification without imposing the sign restrictions. Dynamic effects of MP, FRN and CBI shocks in a monthly VAR. Heteroskedasticity-based identification.

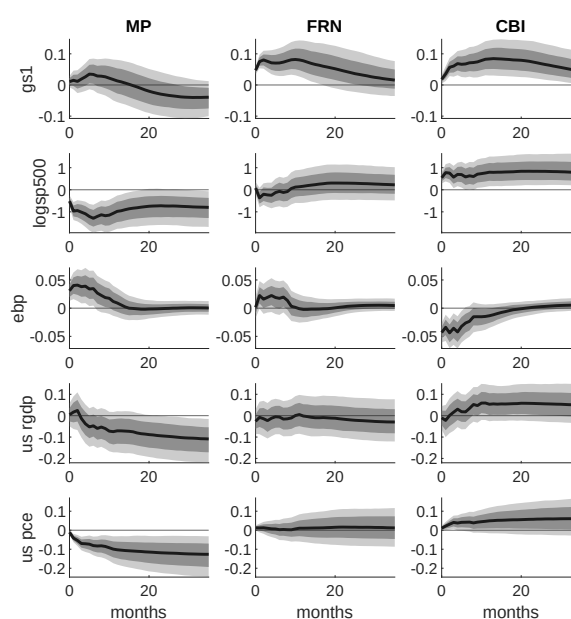
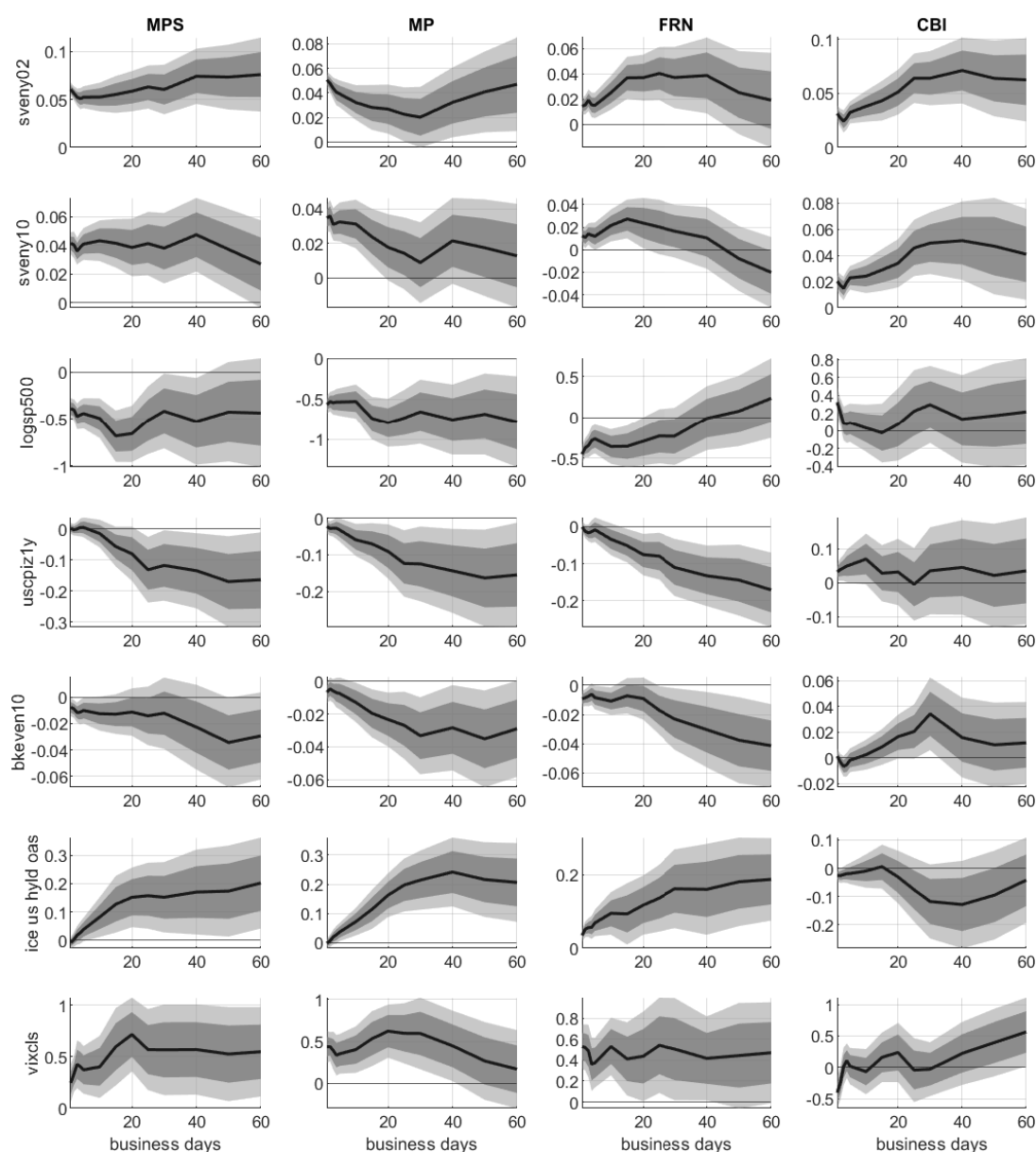


FIGURE E2. Daily local projections, $y_{t+h} - y_{t-1} = \alpha + \beta_h u_{nt} + \xi_t^h$: Median target shocks satisfying sign and magnitude restrictions of Section 4.1. Baseline sample.



Point estimates of the response (β_h), with heteroskedasticity robust 68% and 90% bands. Responses to raw interest rate surprises (MPS), monetary policy (MP) shocks, Fed response to news (FRN) shocks, and central bank information (CBI) shocks.

FIGURE E3. Dynamic effects of MP, FRN and CBI shocks in a monthly VAR. FOMC subsample.

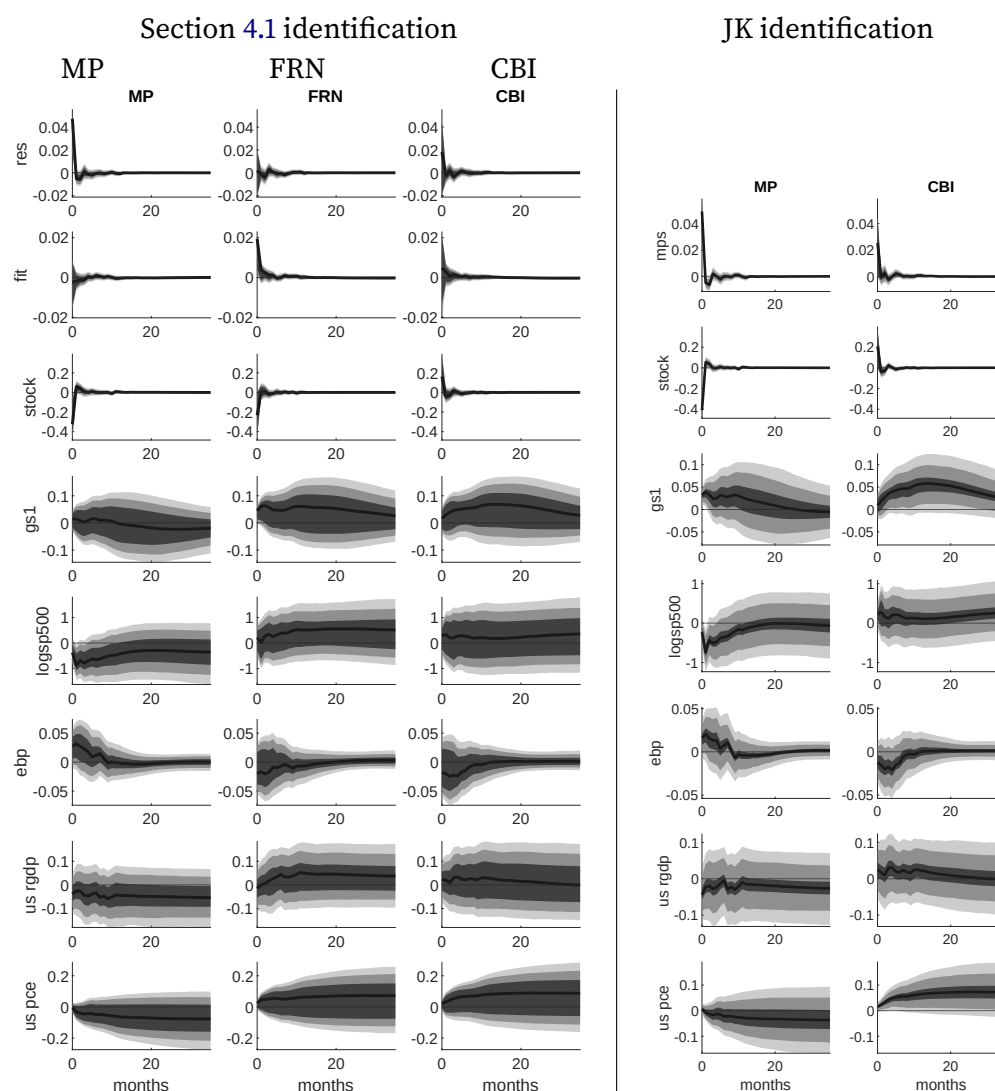
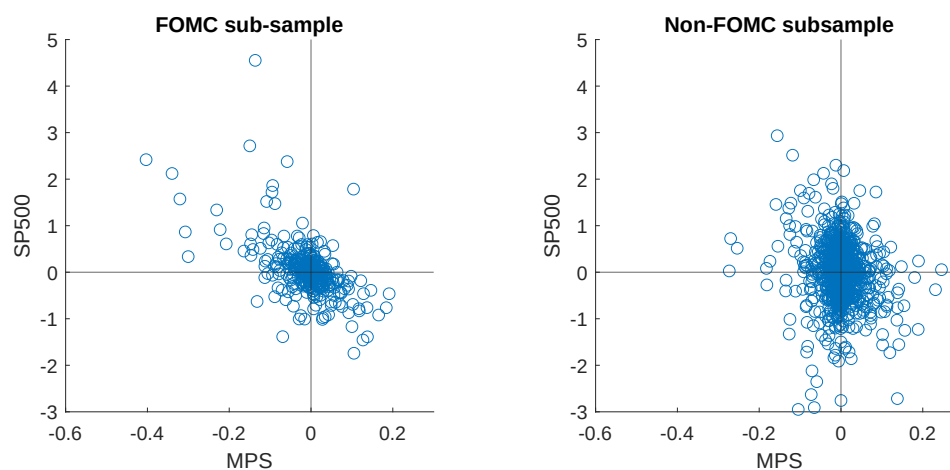


FIGURE E4. Scatter plots of interest rate (MPS) and stock price surprises (SP500) in FOMC and non-FOMC subsamples (all non-FOMC events)



Appendix F. Additional robustness exercises

FIGURE F1. Cumulated monthly interest rate and stock price surprises, real GDP and the federal funds effective rate, 2019-2024

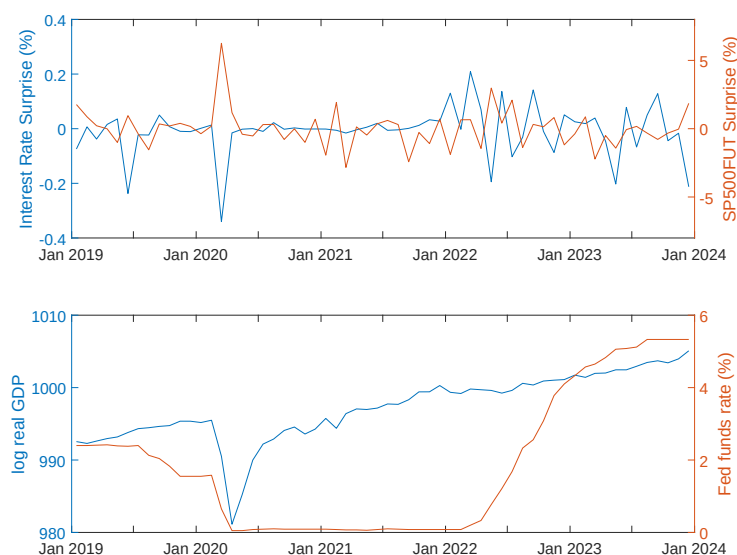
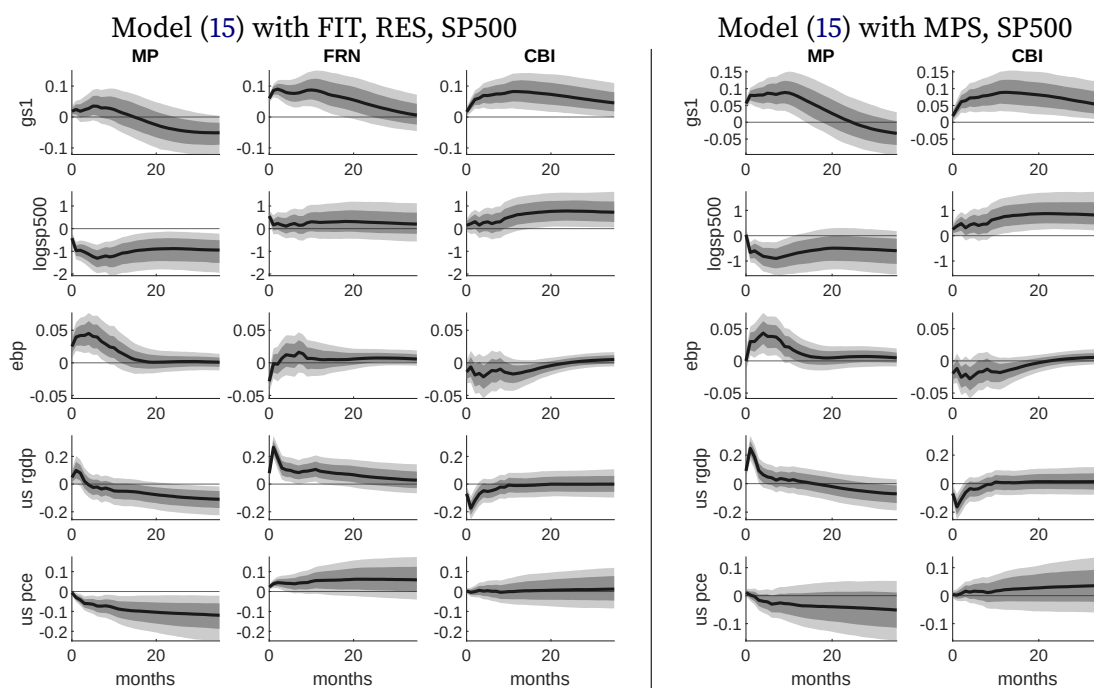


FIGURE F2. Results with the Covid surprises (March 2020). Dynamic effects of MP, FRN and CBI shocks in a monthly VAR. Heteroskedasticity-based identification.



Impact of March 2020 surprises on the estimates. In this section, we explain our decision to exclude the March 2020 Fed events, and the accompanying financial market surprises, 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. In this month the FOMC held two unscheduled meetings and additionally issued three statements. Among other things, on March 3 the FOMC surprised the markets with a 50 basis point rate cut, against the expectations of a 25 basis point rate cut, and on March 23 the FOMC announced quantitative easing policies which lowered the interest rates and caused an unprecedented 6.7% (!) increase in the S&P 500 futures within the 30-minute window, the largest absolute stock price surprise in the sample, amounting to 9 standard deviations and 1.5 times larger than the second largest stock price surprise.

Figure F1 reports the unusual size of the financial variables and real activity fluctuation in this episode. The top panel shows the high-frequency interest rate and stock price surprises cumulated to the monthly frequency. While the cumulated interest rate surprise of -0.36% is large but not unprecedented, the cumulated 7.3% stock price surprise is an outlier. The bottom panel shows the exceptionally sharp decline in real GDP (monthly interpolation) due to Covid lockdowns and the concomitant decline in the monthly Federal Funds Effective rate.

This combination of expansionary high-frequency surprises and lockdown-related economic outcomes represents a very influential observation for VARs and local projections. To accommodate this combination of unexpectedly expansionary monetary policy, reflected in the high-frequency surprises, and the immediate GDP contraction, VARs and local projections that include March 2020 feature strong short-lived effects of Fed shocks on real GDP. Figure F2 illustrates this: in response to all shocks in both identification schemes presented, real GDP jumps, with a peak in the second month and a fast reversion afterwards. These short-lived jumps in real GDP are clearly the result of this single unduly influential observation, and they disappear after March 2020 is excluded. We conclude that a linear VAR is not well suited for capturing the Covid episode, and we therefore always exclude March 2020 to avoid this outsized impact of a single episode. We keep all monthly data but exclude all Fed events in March 2020, thus omitting their accompanying high-frequency surprises. Excluding one or more months of surprises during the Covid episode is common practice in the macroeconometric literature.

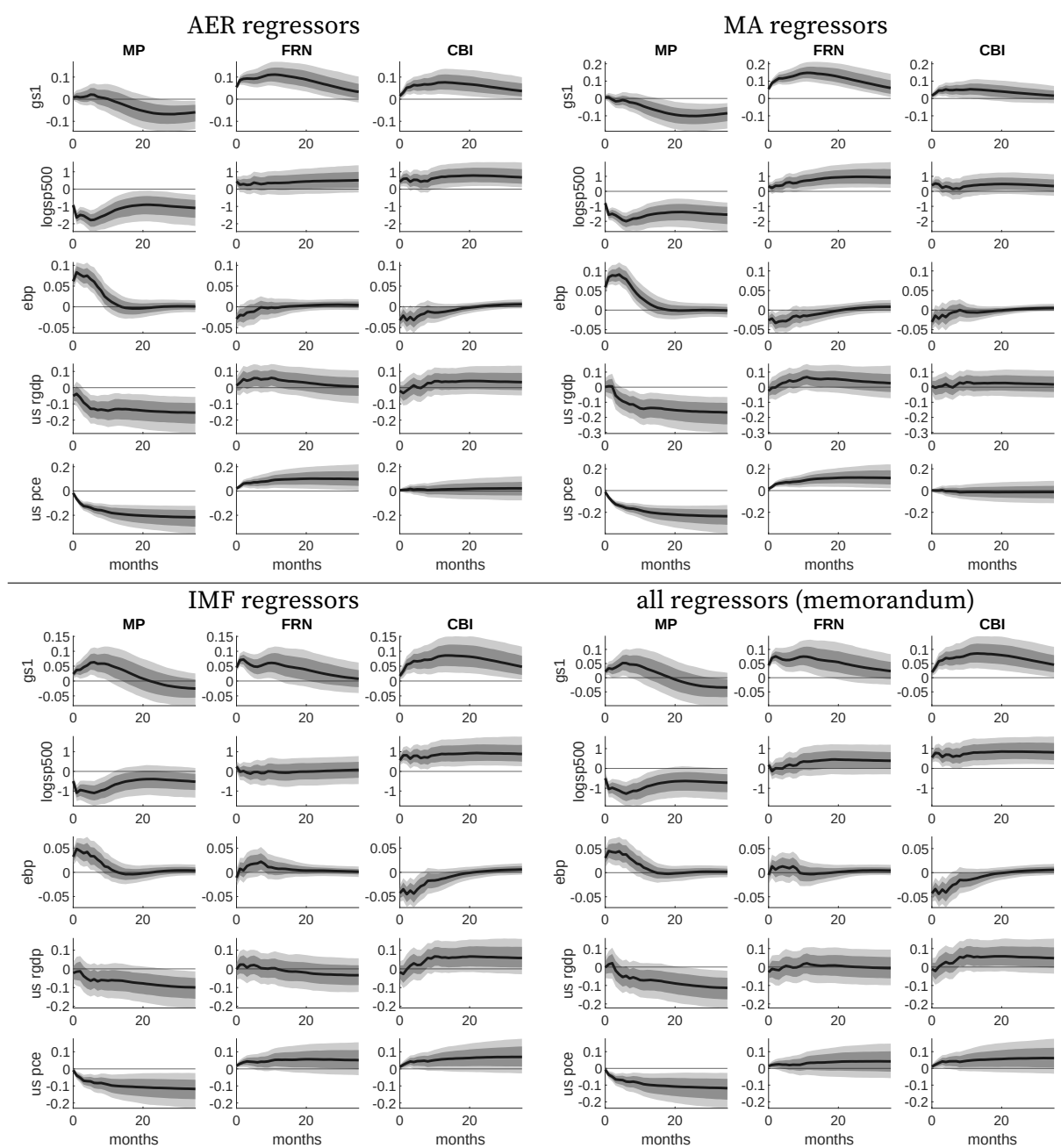
Using subsets of Bauer–Swanson regressors. In this exercise, when running the Bauer–Swanson regressions we only include the subsets of regressors used in individual papers, rather than combining regressors from all papers. Table 2 lists the regressors in each of the three papers we consider. In two of the three cases (corresponding to the sets of regressors from two of the three papers) the three-shock heteroskedasticity-based identification runs into a different problem and fails to find a significant monetary policy shock. More in detail, these smaller sets of regressors explain only 12 to 15% of the MPS in the FOMC events. Table F1 reports the Bauer–Swanson regressions with the AER regressors in the first three columns, the NBER Macro Annual regressors

in the middle three columns and the IMF Economic Review regressors in the last three columns. When the explanatory power of the regressors is small, the fitted values have limited variation and, as a result, for the AER and NBER Macro Annual regressors no draws from the posterior of model (15) satisfy the “Good proxy” magnitude restriction (e.), which requires that the FRN shock impacts the FIT more than the RES. FIT becomes too small for this restriction to be satisfied. To proceed further we relax this restriction and replace it with a looser but still intuitive requirement: that the FRN shock be the dominant shock in the variance decomposition of the FIT (formally, we require $|c_{21}| < c_{22}$). This looser requirement is satisfied by about 80% of the draws from the posterior. However, the resulting identification recombines the variation of the RES and FIT in such a way that the resulting candidate monetary policy shock fails to affect the interest rates in a significant way, which is of course a highly unsatisfactory feature for a monetary policy shock. Figure F3 reports the dynamic effects, note the response of the 1-year Treasury yield to the MP shock in the top left graph in the top two panels. The results with the IMF Economic Review regressors are very similar to the baseline results, suggesting that some of the new regressors in this paper are crucial for the identification to succeed. The two-shock decomposition into MP and CBI only is, of course, unaffected by the choice of regressors.

TABLE F1. Bauer–Swanson regressions over the baseline sample and its FOMC and non-FOMC subsamples: subsets of regressors used in individual papers

	Baseline	FOMC	Non-FOMC	Baseline	FOMC	Non-FOMC	Baseline	FOMC	Non-FOMC
(Intercept)	-0.011 (0.008)	-0.028*** (0.010)	0.006 (0.013)	-0.013*** (0.004)	-0.025*** (0.005)	0.002 (0.006)	-0.007** (0.003)	-0.012*** (0.004)	-0.001 (0.004)
Unemployment surprise	0.016 (0.017)	0.013 (0.020)	0.013 (0.028)				0.017 (0.016)	0.011 (0.020)	0.023 (0.028)
Payrolls surprise	0.012 (0.012)	0.011 (0.013)	0.021 (0.040)	0.007 (0.007)	0.010 (0.007)	0.024 (0.039)	0.013 (0.011)	0.009 (0.013)	0.018 (0.040)
Real GDP surprise	0.012** (0.006)	0.003 (0.007)	0.019** (0.009)				0.012** (0.006)	0.003 (0.007)	0.019** (0.009)
Core CPI surprise	0.033 (0.026)	0.026 (0.033)	0.010 (0.041)				0.029 (0.026)	0.032 (0.033)	0.008 (0.041)
Core CPI median forecast	0.015 (0.029)	0.064* (0.036)	-0.031 (0.046)						
6-month change in core CPI	-0.003 (0.004)	0.001 (0.005)	-0.006 (0.007)						
BBK index	0.000 (0.001)	0.001 (0.002)	-0.001 (0.002)						
$\Delta \log S\&P500$ (3m)	0.048 (0.040)	0.128** (0.055)	-0.013 (0.057)	0.047 (0.039)	0.112** (0.052)	-0.013 (0.056)	0.081* (0.046)	0.149** (0.062)	0.024 (0.066)
$\Delta \text{yield curve slope}$ (3m)	-0.019 (0.023)	-0.077*** (0.030)	0.029 (0.035)	-0.001 (0.023)	-0.052* (0.030)	0.036 (0.034)			
$\Delta \log pcommodity$ (3m)	0.094** (0.037)	0.164*** (0.050)	0.021 (0.054)	0.081** (0.034)	0.175*** (0.045)	-0.011 (0.049)	0.090** (0.036)	0.143*** (0.050)	0.028 (0.053)
Treasury yield skewness (1m)				0.023** (0.011)	0.030** (0.013)	0.021 (0.018)			
Employment growth (12m)				0.293* (0.164)	0.637*** (0.191)	-0.230 (0.275)			
Δ 2-year Treasury (3m)							0.014 (0.011)	0.010 (0.013)	0.021 (0.016)
Δ 10-year Treasury (3m)							-0.008 (0.011)	-0.007 (0.013)	-0.010 (0.017)
Δ Baa spread (3m)							-0.005 (0.011)	-0.008 (0.014)	0.010 (0.016)
Δ shadow fed funds rate (3m)							-0.002 (0.006)	0.023*** (0.008)	-0.020** (0.008)
Δ Chicago Fed NFCL (1m)							0.054*** (0.017)	0.042* (0.025)	0.037 (0.025)
N	696	357	339	696	357	339	696	357	339
R-squared	0.029	0.120	0.028	0.028	0.143	0.012	0.047	0.154	0.045
Adj.R-squared	0.015	0.095	-0.001	0.019	0.129	-0.006	0.032	0.127	0.013

FIGURE F3. Results with subsets of Bauer–Swanson regressors. Dynamic effects of MP, FRN and CBI shocks in a monthly VAR. Heteroskedasticity-based identification.



Acknowledgements

We are grateful to Refet Gürkaynak, Mathias Meier, Giorgio Primiceri, Morten Ravn, Giovanni Ricco, Christian Wolf as well as to participants at the BSE Summer Forum, EEA, IAAE, NBER Summer Institute: Methods and Applications for Dynamic Equilibrium Models, SED and seminars at the Banque de France, CERGE-EI, ECB, LMU Munich, Swiss National Bank for their comments and suggestions, and Federica Di Nicola, Veronica Gottardo, Marco Lami and Serena Sorrentino for excellent research assistance. We used AI software to polish the exposition and to check the text for internal inconsistencies and typographical errors. The analysis, results and conclusions are our own. The paper was circulated previously under the title "Disentangling Monetary Policy, Central Bank Information, and Fed Response to News Shocks".

The views expressed here are those of the authors and do not necessarily represent those of the ECB, or the Eurosystem.

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ISBN 978-92-899-8034-0

ISSN 1725-2806

doi:10.2866/2620059

QB-01-26-230-EN-N