Let the Market Speak: Using Interest Rates to Identify the Fed Information Effect*

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Abstract

I propose a novel method to disentangle the exogenous monetary shock from the signaling effect of a Fed announcement in real time. The method relies on the different ways monetary news and non-monetary news change the entire short end of the yield curve at high frequency, with the latter informed by market responses to macroeconomic data releases. The estimated revelation of Fed information is strongly correlated with the difference between market forecasts and the Fed's own forecasts. The monetary shock is found to have a bigger effect on the economy than suggested using an instrument without adjustment for the signaling effect.

Keywords: monetary policy, central bank information effect, high-frequency identification, macroeconomic data releases, factor analysis

JEL classification: E30, E40, E50, G10, C30

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1 Introduction

Quantifying the causal effects of monetary policy is a challenging task in empirical macroeconomics because in setting interest rates a central bank responds endogenously to other conditions in the economy. To identify exogenous monetary shocks, recent studies have favored a high-frequency event-study approach (Kuttner, 2001; Gürkaynak *et al.*, 2005b; Piazessi and Swanson, 2008; Wright, 2012; Gertler and Karadi, 2015; Hanson and Stein, 2015; Swanson, 2019). The idea is to look at how one or more interest rates change within a narrow window around a Federal Open Market Committee (FOMC) announcement. Under the assumption that only monetary information gets incorporated into asset prices within the window, the rate changes serve as direct measures of policy shocks.

However, rate changes can also signal a central bank's opinion on economic developments (Melosi, 2017). Earlier findings by Campbell *et al.* (2012) and Nakamura and Steinsson (2018) provide suggestive evidence for this channel by looking at how private economic forecasts as measured by Blue Chip respond to an announcement. If the FOMC announcement results in lower interest rates than the market had forecast, corresponding to an easing of monetary policy, one would expect private forecasts of variables like GDP and inflation to increase. In fact, forecasts of these variables declined, consistent with the interpretation that the FOMC announcement revealed to private forecasters information the Fed had of weaker economic fundamentals. These studies and the subsequent literature refer to the revelation of the Fed information on the state of the economy through FOMC announcements as "the Fed information effect".

The Fed information effect confounds the estimation of monetary policy effects. Figure 1 relates the high-frequency rate changes to *actual* economic outcomes. Each red bar plots a 30-minute change in one of five commonly-used interest rates around an FOMC announcement, averaged across the announcements one quarter following which an NBER recession occurred. The blue bars plot the averages across the rest of the announcements. Clearly, the Fed tended to surprise the market with large rate cuts when the economy was going into a recession.[1] This suggests that the Fed may have foreseen an upcoming recession better than the market. In this case, if one were to treat these rate changes directly as policy shocks, the estimates of monetary policy effects would be biased toward zero.

This paper proposes a novel approach to controlling for the Fed information effect when identifying monetary shocks at high frequency. Using only interest rate data, the approach

[1] One may notice that for each asset the *unconditional* mean of the rate change is also negative. Instead of looking for the driving forces behind the secular decline in interest rates, this paper focuses on the potential revelation of Fed information on business cycles. Even when the unconditional mean is subtracted from the whole sample, surprising rate cuts before recessions are still evident as shown in Figure A1 in the Appendix.

isolates the contribution of the revelation of Fed information to rate responses from that of a policy shock in real-time. The key intuition is to think of an FOMC announcement as a sum of a macroeconomic data release and a pure monetary announcement, and use responses of a cross section of interest rates to the data release to pin down the Fed information component.

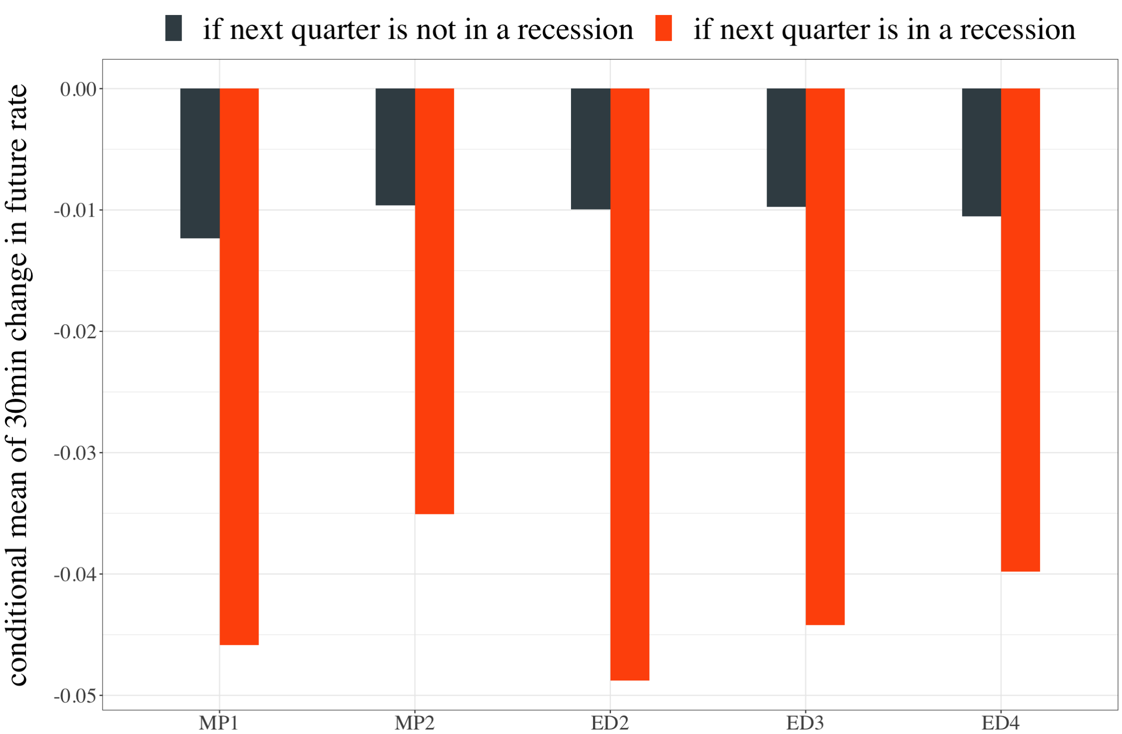


Figure 1: Easing policy consistently surprised interest rate futures market before recession

Listed on the x-axis are five assets reflecting market expectations of interest rates for various horizons. Y-axis plots the average change in the rate of each asset during a 30-minute window around an FOMC announcement across two samples. MP1 and MP2: federal funds future contracts to be settled at the end of the current month and the third month after the FOMC announcement. ED2, ED3 and ED4: Eurodollar future contracts to be settled at the end of the second, third and fourth quarter. Sample from February 1990 to March 2019.

The approach postulates that two common, orthogonal shocks drive the responses of interest rates with various maturities to an announcement. One is an economic news shock that captures the market learning of Fed's information on economic fundamentals from the announcement. I hereafter refer to this as an "information shock". The other is an exogenous monetary shock, capturing the Fed's deviation from its policy rule.

For identification, the approach relies on key assumptions that: (1) the two shocks elicit different responses of short-term interest rates over a 30-minute window around an FOMC announcement; (2) the *relative* magnitude of the responses across maturities to an information shock is the same as that to economic news caused by macroeconomic data releases; (3) the two shocks are orthogonal to each other over a sample of FOMC announcement windows. The method identifies the *market-perceived* information effect and the *market-perceived* monetary shock with publicly available data.

I apply the method to the FOMC announcements from 1991 to 2019. I find that communications on the assessment of economic prospects play a nontrivial role in driving high-frequency interest rate movements. My decomposition can directly account for the revision in Blue Chip forecasts following an FOMC announcement. I find that the positive revision of private forecasts of output and inflation to a contractionary announcement can be explained entirely by my measure of the information component of the FOMC announcement.

I provide further corroborating evidence by comparing Blue Chip forecasts with those prepared by Fed staff as reported in the Greenbook. I find that the information component is biggest when Greenbook forecasts differ the most from Blue Chip forecasts, and that Blue Chip forecasts get revised in the direction that would be implied if the Fed had simply announced the Greenbook forecast itself. This evidence is consistent with approaches to eliminating the information component with forecast data suggested by Romer and Romer (2000), Zhang (2019), Miranda-Agrippino and Rico (2021) and Bachmann *et al.* (2021).

My approach has several desirable features relative to the ones that rely on forecast data to control for the Fed information effect. First, for scheduled announcements for which Fed forecasts were prepared, the measure proposed here can be constructed in real-time from publicly available data, whereas researchers have to wait five years for release of the Fed forecasts.

Second, the approach works for unscheduled FOMC announcements for which no Fed forecasts were prepared. The Fed information effect is likely to be substantial precisely for those events, because when the Fed found it urgent and necessary enough to hold an unscheduled meeting, it was likely to review aspects of economic and financial developments that the market had yet to know. Indeed, Lakdawala and Schaffer (2019b) provide suggestive evidence for the special role of unscheduled meetings in studying the Fed information effect. Hence, we would not want to leave unscheduled meetings out of such discussions.

Third, the approach can capture the information gap between the Fed and the private sector at any instant as it takes advantage of the efficiency in asset prices, whereas the forecast data are not directly comparable due to their timing inconsistency. Blue Chip solicits private forecasts at the beginning of every month whereas Fed staff make forecasts right before every FOMC announcement which could take place at any date during a month. If an announcement is made towards the end of a month, private forecasters may have already updated their economic outlook by the time of the announcement given various news arriving in the month. What appears to be a Fed information advantage in the forecast data may well be an advantage that the Fed had in timing.

Another creative approach taken by researchers to identifying the Fed information effect is to impose sign restrictions on financial data. Jarociński and Karadi (2020) and Cieslak and Schrimpf (2019) exploit the opposing signs of the effect of monetary news versus non-monetary news on interest rates and stock prices. Along the same lines but focusing on forward guidance policy, Andrade and Ferroni (2019) impose sign restrictions on future interest rates and breakeven inflation rates. These methods are appealing in that they impose limited restrictions on a model and also achieve identification in real-time. Nonetheless, having limited restrictions is also a liability in that they do not yield point estimates; in fact, a range of estimates would be consistent with sign restrictions, and the confidence ranges typically reported by researchers significantly understate the range of possible answers that are consistent with the data (Moon and Schorfheide, 2012; Baumeister and Hamilton, 2015, 2020, 2022; Watson, 2019; Giacomini and Kitagawa, 2021). By contrast, the shocks in this paper are point identified and the analysis based on them can be interpreted in a classical way. Different from Bu *et al.* (2020) which also impose fully identifying assumptions on financial data, this paper brings other macro events into the picture and makes use of the valuable information in their impact on short-term interest rates.

In another interesting study, Nunes *et al.* (2022) propose to deal with the Fed information effect directly in a structural vector-autoregression model. They use the response of the three-month-ahead Fed funds futures to labor-market data releases as an external instrument for the information shock. My approach is fundamentally different from theirs in that I identify the monetary shock to be orthogonal to the macro news component of FOMC announcements and that I estimate this component independently from the news component of any macro data release. Without having to rely on any assumptions behind the VAR, my approach separately identifies and thus controls for the true economic news brought about by an FOMC announcement regardless of whether the market learns anything from the data releases in the same period. It achieves so by using a factor model to match the observed market responses in the two types of days, respectively. Furthermore, the framework here allows for a different variance of the macro news component of an FOMC announcement from that of a data release in population, with the variance inferred directly from the observed market response on the corresponding type of days.

Using the newly-constructed monetary shocks, I evaluate the effect of monetary policy on output, inflation and risk premium in a structural vector-autoregression (VAR) model (Christiano *et al.*, 1996; Faust *et al.*, 2004b; Cochrane and Piazzesi, 2002; Boivin *et al.*, 2010;

Barakchian and Crowe, 2013; Gertler and Karadi, 2015; Amir-Ahmadi *et al.*, 2015). When the Fed surprisingly lowers the interest rate because it views the economy as becoming weaker than the market projects, traditional monetary surprises can introduce positive omitted variable biases to the estimate of the effect of monetary policy; if any, the economic downturn is the reason for, not a consequence of, policy easing. Likely for this reason, the VAR literature often finds the effect of monetary policy on price levels or output growth with puzzling signs when the high-frequency identification approach is used. I show in this paper that, once the Fed information effect is removed, a tightening of monetary policy clearly dampens the economy, leading to a significant drop of output growth and price level. Not only are the signs consistent with standard monetary models but the magnitudes of the effects are also larger than what one would obtain with direct high-frequency measures. For the sample from 1991m7 to 2019m3, a monetary shock that raises the three-month-ahead fed funds futures rate by 1% leads the industrial production to drop on impact and eventually decreases by as much as 4.0% in 10 months. It causes CPI to adjust quickly and shift down by nearly 1.5% in the long run. The pronounced effect on output and the quick adjustment of the price level are consistent with the findings of Miranda-Agrippino and Rico (2021). The VAR exercise here points to the time-varying risk premium in the financial sector as the potential transmission channel of monetary policy (Jarociński and Karadi, 2020).

To justify the identification method, I compare the monetary shocks proposed here with several alternative proposals in the literature. A monetary shock that corresponds to a policy easing should have the following characteristics: (1) it has no forecasting ability to predict current and future recessions, and (2) it does not lead Blue Chip forecasters to revise down their economic outlook or inflation expectations following the FOMC announcement. In these regards, the shocks proposed here perform better than the other proposals that take no account of the Fed information effect. They are also comparable to estimates by other researchers that deal with the information effect.

This paper contributes to a growing literature that discusses asymmetric information between central banks and the public on the state of the economy and its relevation by policy announcements. Romer and Romer (2000) show that the Fed possesses private information on future inflation and signals it to the public via FOMC announcements, which explains why long-term Treasury yields respond to surprise changes in federal funds futures around an announcement. Hamilton (2018) discusses the relevance of information asymmetry for evaluating the efficacy of Quantitative Easing programs in narrow windows around FOMC announcements. Lakdawala (2019a) provides evidence for information asymmetry in a structural vector autogression. Bauer and Swanson (2022) question the econometric specifications of Campbell *et al.* (2012) and Nakamura and Steinsson (2018) and interpret their evidence as the Fed's and the market's common responses to public news. The analysis here points out the key role of stale news in reconciling these two views and provides suggestive evidence that the Fed interpreted stale news differently from the private sector.

Last but not least, the paper contributes to the macroeconomic event study literature by presenting another reason why different types of macroeconomic events should be analyzed within a single framework. A few papers have recently advocated modeling them together to compare or justify the relative magnitude of asset price responses across events, including Bauer (2015b), Gilbert *et al.* (2017), Ehrmann and Sondermann (2012) and Lapp and Pearce (2012). Importantly, Gürkaynak *et al.* (2018) find that news across various data releases, whether observed or unobserved, elicit the same hump-shaped response from the yield curve. This paper confirms the findings of Gürkaynak *et al.* (2018) for the short end of the yield curve. I show it is useful to consider FOMC announcements together with macroeconomic data releases for the purpose of identifying the Fed information effect.

The rest of the paper is organized as follows. Section 2 describes the interest rate movements around FOMC announcements and around macro data releases jointly in a factor model and presents the identification strategy, using data from 1991 to 2008 as an illustration. Section 3 corroborates the strategy by connecting the identified shocks to economic forecasts made by the Fed and the private sector. Section 4 extends the analysis to the zero lower bound (ZLB) and the post-ZLB periods, producing a composite monetary shock series. Using the composite series as an instrument, Section 5 evaluates the effects of monetary shocks on the macroeconomy in a structural VAR. Section 6 shows the advantages of the composite series over some popular monetary instruments in the literature.

2 Methodology

This section presents the econometric framework to disentangle the monetary shock from the Fed information effect given a set of interest rate changes around an FOMC announcement. The framework achieves identification by connecting the market response to FOMC announcements with that to major macro data releases. In Section 2.1, I define what data releases are considered "major" and describe the interest rate changes around them. I show that a one-factor model is well-suited to capture the market response to economic news across different types of data releases. I embed this insight into modeling the interest rate responses to FOMC announcements in Section 2.2, and use it to motivate the identifying assumptions in Section 2.3.

Throughout the analysis, I focus on the short end of the yield curve, including the interest rates on the three-month-ahead federal funds futures contracts, the two-, three-, and four-quarter-ahead eurodollar futures contracts and the two-year nominal Treasury bond. The list captures the expected path of the federal funds rate in the next two years without overlap.[2]

To demonstrate the key idea of the approach, I analyze the FOMC announcements from 1991m7 to 2008m12 in Section 2 and 3. Later in Section 4, I will extend the sample to 2019m3 and show robustness of the approach. The starting and the ending dates of the analysis are determined by the availability of intraday data on the interest rates.

2.1 Interest rates around major macroeconomic data releases

I begin the analysis by characterizing the factor structure of the interest rate responses to major macro data releases.

Let t denote a day and $\tilde{y}_t$ be an $(N \times 1)$ vector of changes in the set of interest rates above from the end of Day $t-1$ to the end of Day t. Building on the framework of Gürkaynak *et al.* (2018), I estimate the responses of the interest rates to a major macro data release with a latent factor model:

$$\tilde{y}_t \quad = \quad \tilde{d}_t \; \tilde{\gamma} \; \tilde{\xi}_t \quad + \quad \tilde{u}_t. \tag{1}$$

Here, $\tilde{d}_t$ is a dummy variable taking the value of 1 if there is at least one major data release (to be defined below) on Day t and 0 otherwise.[3] When there is a major release on Day t, the news content of it is captured by a latent factor, $\tilde{\xi}_t \sim$ iid $(0, 1)$, which elicits responses of N interest rates with various maturities via an $(N \times 1)$ loading vector, $\tilde{\gamma}$. In addition to the release, some background noises could also change the yield curve, just as they do on a no-release day. I summarize them in an $(N \times 1)$ vector, $\tilde{u}_t \sim$ iid $(0, \Sigma_{\tilde{u}})$, where $\Sigma_{\tilde{u}}$ is assumed to be the same across release days and no-release days and is allowed to be non-diagonal.

I define a data release to be a major one if it has significantly changed the short end of the yield curve. For each type of the releases in the first column of Table 1, I conduct a bootstrap test along the lines of Wright (2012) and a Box's M-test to determine if the change is significant. For both tests, the null hypothesis is that the covariance matrix of daily rate changes on a day with a given type of release is identical to that on a day without any releases. Whenever I reject the null at the 10% level, I consider the release to be a major one. The second and the third columns of Table 1 report for each release the p-values of the

[2]It is conventional in the literature to use the short end of the yield curve, especially the listed assets in the main text, to identify monetary shocks. See Gürkaynak *et al.* (2005b), Nakamura and Steinsson (2018), Kuttner (2001) for example. I omit the current-month federal funds future contract because its rate was insensitive to shocks during the zero lower bound period.

[3]An FOMC announcement could take place on the same day as a data release. To isolate the effect of data releases, I omit all the days with both an FOMC announcement and a data release in the analysis of Section 2.1.

Table 1: Selection of major macroeconomic data releases

Type of release	P-value from Wright (2012) test $\times 10^{-2}$	P-value from Box's M-test $\times 10^{-2}$	Major?
CPI / Core CPI	0.12	0.00	Yes
Nonfarm Payrolls	0.02	0.00	Yes
Employment Cost Index	0.06	0.11	Yes
GDP (advance)	0.08	0.00	Yes
ISM Manufacturing	0.42	0.00	Yes
Industrial Production	0.44	0.00	Yes
Initial Jobless Claims	0.24	0.00	Yes
PPI / Core PPI	0.20	0.00	Yes
Retail Sales (advance)	0.42	0.00	Yes

The first column lists the types of data releases that I start with. For each type of release indexed by k, the second column shows the bootstrapped p-value from the Wright (2012) test where H_0: $\Sigma_k = \Sigma_{\tilde{u}}$ vs. H_a: $\Sigma_k \neq \Sigma_{\tilde{u}}$. Σ_k is the covariance matrix of daily rate changes on a day with a Type-k release and $\Sigma_{\tilde{u}}$ on a day without any type of release. The third column displays the p-value from the Box's M-test for the same hypothesis. The last column indicates whether a Type-k release is determined to be a major one.

two tests applied to the sample from 1990m1 to 2008m12. Clearly, all the data releases here pass the significance tests and will be considered as major releases. Henceforward, I will use "major data release(s)" and "data release(s)" interchangeably for succinctness.

To characterize the market response to a data release, Equation (1) uses a latent factor model instead of regressing each interest rate on the market surprise at the headline statistic. By doing so, it is able to capture all the news content in a release. Gürkaynak *et al.* (2018) establish the importance of doing so for identifying non-headline news.

In general, one may use more than one latent factor to capture the market response to the different types of data releases. However, I find that one factor is sufficient to do so for the sample from 1990m1 to 2008m12. To see this, I conduct another bootstrap test proposed by Wright (2012). If we group all the days with a major release together regardless of the release type, denote the covariance of the rate changes on those days with Σ^D, and keep using $\Sigma_{\tilde{u}}$ for the covariance on no-release days, the null hypothesis is $\Sigma^D - \Sigma_{\tilde{u}} = \tilde{\gamma}\tilde{\gamma}'$ for $\tilde{\gamma}$ an $(N \times 1)$ vector. Table 2 shows that one cannot reject the null hypothesis at the 5% level. That is, one factor is sufficient to capture the variations in the changes of short-term interest rates around different types of releases.[4] This implies that the bond market consistently perceived and cared about only one dimension of economic news as reflected in these short-term interest rates.

[4]Relatedly, Gürkaynak *et al.* (2018) find that different types of macroeconomic data releases have similar relative effects at different points on the entire yield curve and that one factor is sufficient to capture those effects. The analysis here confirms their findings for the short end of the yield curve with a statistical test.

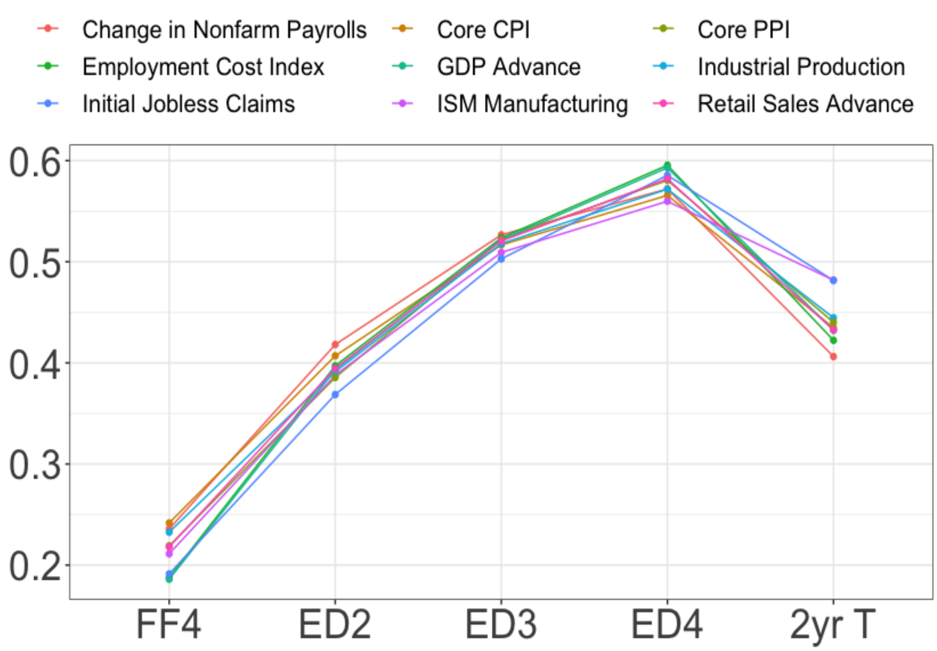
To further justify the one-factor specification, Figure 2 shows how similar the response of the short end of the yield curve was to different data releases. For each type of release, the figure plots the estimated eigenvector associated with the first principal component of the covariance matrix of $\tilde{y}_t$. Strikingly, no matter which economic indicator got released, the short end of the yield curve turned out to always respond with a hump shape, with the maximum effect taking place in the rate of the Eurodollar future maturing in four quarters. In the next two subsections, I will bring this insight into modeling the interest rate responses to FOMC announcements.

Table 2: Wright (2012) test for the number of news shocks

	Sample period	Dimension of $\tilde{\xi}_t$ ($N_{\tilde{\xi}}$)	p-value
pre-ZLB	1990m1 - 2008m12	1	0.079

The null hypothesis is that $\Sigma^D - \Sigma_{\tilde{u}} = \tilde{\gamma}\tilde{\gamma}'$, where $\tilde{\gamma}$ is an $(N \times N_{\tilde{\xi}})$ matrix, Σ^D is the covariance matrix of daily interest rate changes on a day with a major data release (listed in Table 1 with a "Yes"), and $\Sigma_{\tilde{u}}$ is the covariance matrix on a day without any major data releases.

Figure 2: Similarity of normalized interest rate responses to major data releases



For each type of major data release, the line plots the eigenvector associated with the first principal component of the sample covariance matrix of $\tilde{y}_t$. The sample goes from 1990m1 to 2008m12.

2.2 Interest rates around FOMC announcements

This section models the responses of interest rates to an FOMC announcement. As a key innovation to the high-frequency identification approach, I treat an FOMC announcement as a sum of a major macro data release and a purely monetary announcement.

Let y_t $(N \times 1)$ collect the changes in the same set of interest rates as above during a thirty-minute window around the time of an FOMC announcement on Day t. Again, I use a factor model to summarize the various reasons why the interest rates may move in this window:

$$y_t = \underbrace{\gamma\, \xi_t}_{\text{Fed information}} + \underbrace{\beta\, \eta_t}_{\text{monetary}} + \underbrace{u_t}_{\text{idiosyncratic}} + \theta_0, \tag{2}$$

where $\xi_t \sim$ iid $(0, \sigma_\xi^2)$ is a Fed information shock, $\eta_t \sim$ iid $(0, 1)$ is an exogenous monetary shock, and $u_t \sim$ iid $(0, \Sigma_u)$ is an $(N \times 1)$ vector of white noises with a diagonal covariance matrix. Each element of u_t captures the idiosyncratic movement of an individual interest rate.

Fed information shock, ξ_t. The first latent factor captures the first reason why the market might be surprised by an FOMC announcement: the market learned something new about the state of the economy from the announcement. Because the Fed sets interest rates partly by reacting to changes in output growth and inflation, any private information held by the Fed that indicates a worsening economy would lead to an announcement cutting the interest rate relative to what the market expected. A non-zero ξ_t corresponds to the revelation of such information to the market.

Monetary shock, η_t. The second latent factor accounts for the changes of interest rates due to the Fed announcing an unexpected course of policy commitments. Because the factor summarizes the information in interest rates of a range of maturities, it captures the Fed's commitment to changing the federal funds rate not only in the near term but also at longer horizons.[5] This is important because changes in the near-term federal funds rate have largely been anticipated by the market since the onset of the Great Financial Crisis and the Fed has increasingly used forward guidance as a policy tool (Gürkaynak *et al.*, 2005b; Nakamura and Steinsson, 2018; Swanson, 2019; Zhang, 2019).

[5]Thus, the monetary shock here contains the "Odyssean forward guidance" in the language of Campbell *et al.* (2012), the case in which the Fed discloses information about its commitment to changing policy rates in the future regardless of how the economy is going to evolve.

2.3 Identifying Assumptions

My main assumption is that the revelation of Fed information about economic fundamentals, ξ_t, has similar effects on the cross section of short-term interest rates as the information $\tilde{\xi}_t$ associated with macro data releases described in Section 2.1. Since the information about economic fundamentals in a typical macro data release can be described by a scalar $\tilde{\xi}_t$, it is natural to assume that the information about economic fundamentals that is revealed by an FOMC announcement can also be described by a scalar, ξ_t.

Assumption 1: $\gamma = \tilde{\gamma}$, with σ_ξ being a free parameter.

Assumption 1 formalizes the partial resemblance of FOMC announcements to data releases by connecting the factor loadings in Equation (1) and (2). Note that the size and the sign of ξ_t are estimated to be different for every day t. Furthermore, the amount of information about economic fundamentals revealed by a typical FOMC announcement might be considerably greater or smaller than that by a typical data release, so the variance of the information shock caused by FOMC announcements, σ_ξ, is allowed to be different from 1 which is the normalized variance of news content in data releases. Thus, Assumption 1 only requires interest rates of various maturities to always respond in the same proportions to economic news. It does not restrict the magnitude of the yield curve shift in any way.

The free parameter σ_ξ also flexibly accommodates the different width of event windows for FOMC announcements from data releases. In this paper, I use a 30-minute window to compute the changes in interest rates around an FOMC announcement and a daily window for data releases (hence the tilde in $\tilde{y}_t$). Although the choice of windows is mainly dictated by data availability, it should not raise concern about the validity of the strategy. On the one hand, daily changes seem to capture the market response to data releases better than intraday changes. Altavilla *et al.* (2017) find that macro data releases have a persistent effect on nominal bond yields. Bauer (2015a) also argues for a slightly delayed response of the TIPS market to such events that can be missed by intraday windows. On the other hand, the yield curve tends to respond to a FOMC announcement fairly quickly within the 20 minutes after the event (Gürkaynak *et al.*, 2005b). Using a daily window instead would introduce too much noise into the identification of their impact (Nakamura and Steinsson, 2018).

One concern that researchers may have about Assumption 1 is what if the market would want to learn certain aspects of fundamentals only from FOMC announcements. In Section 3, I provide corroborating evidence to show that this is not the case.

To fully identify the model, I rule out the possibility that the monetary shock elicits short-term interest rate responses in the same proportions as the Fed information shock does, i.e.

Assumption 2: There exists no constant $c \in \mathcal{R}$ such that $c\beta = \gamma$.

Finally, I impose the orthogonality condition below. Even though Assumption 3 is not essential for the identification of the model, it is imposed here to give monetary shock the usual interpretation that it is the deviation from the Fed's policy rule. It also helps with the interpretations of results in the next section.

Assumption 3: ξ_t is orthogonal to η_t in FOMC announcement windows.

With the three identifying restrictions above, I impose normality on the shocks and estimate the model by maximum likelihood. Details of the estimation procedure are outlined in Appendix A.2. In the next section, I validate these identifying restrictions by testing two predictions of the model with the estimated η_t and ξ_t.

3 Corroborating Evidence

This section validates the structural interpretations of the identified shocks. I do so by relating them to two sets of forecasts data, one by the Fed and the other by the private sector. Section 3.1 shows that when the information shock is identified to raise interest rates during an announcement, the Fed did on average anticipate a stronger economy going forward than the private sector. Section 3.2 shows that the identified shocks explain the changes in the private sector's economic forecasts following an FOMC announcement.

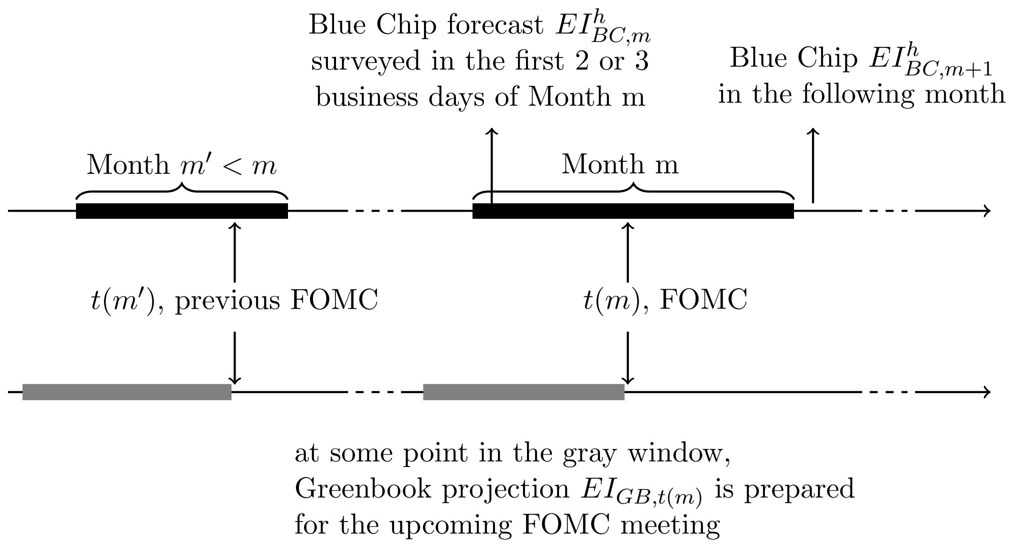
3.1 Differences in Forecasts Between the Fed and the Private Sector

If the information component captures the Fed information effect, one would expect it to be disproportionately positive when the Fed is more optimistic about the economy than the private sector at the time. To test this prediction, I use two sets of forecast data below.

The first data set is called the Greenbook. Before every FOMC meeting the research staff of the Federal Reserve Board of Governors makes projections for key macroeconomic variables for up to nine quarters into the future. The Greenbook contains these projections and serves as an important input for policy decisions in the upcoming FOMC meeting. A number of researchers have used them to study the Fed information effect (Campbell *et al.*, 2012; Nakamura and Steinsson, 2018; Miranda-Agrippino and Rico, 2021; Zhang, 2019).

The second data set is the Blue Chip Economic Indicators. It is widely used in the literature to characterize the private sector's view of the state of the economy at a monthly frequency. During the first two to three business days of every month [6], Blue Chip solicits projections for key macroeconomic variables from about fifty professional forecasters. Following Campbell *et al.* (2012) and Nakamura and Steinsson (2018), I use the consensus forecast of a given variable in a given horizon at the beginning of the month to capture the market expectation for it before an FOMC announcement. Figure 3 sketches the timeline of the two sets of data around a typical FOMC announcement.

Figure 3: Timeline of actions around an FOMC announcement



Conveniently, six variables are commonly predicted by the Greenbook and the Blue Chip. For each of them and for each horizon, I look at the difference between the projections and regress the information shock on that difference:

$$\xi_{t(m)} = \phi_0^h + \phi_\xi^h \left(EI^h_{GB,t(m)} - EI^h_{BC,m} \right) + e^h_{t(m)} \tag{3}$$

where $t(m)$ denotes the day in Month m on which an FOMC announcement was made;[7] $EI^h_{GB,t(m)}$ is the Greenbook forecast of the h-quarter-ahead EI (economic indicator) prepared for the announcement on Day $t(m)$; $EI^h_{BC,m}$ is the Blue Chip consensus forecast of the same variable solicited at the beginning of Month m; and $\xi_{t(m)}$ is the estimated information shock, normalized so that a unit increase in $\xi_{t(m)}$ raises the three-month-ahead federal funds future rate by 1% on average during announcement windows from 1991m7 to 2008m12.

[6]Surveys of the Blue Chip Economic Indicators were carried out during the first three business days of every month prior to 2000m12 and the first two business days beginning in 2000m12 (Bauer and Swanson, 2022). The forecast data are published on the 10th of each month.

[7]Historically, there has been no more than one scheduled FOMC announcement in a given month. For all the regressions involving Greenbook data in this paper, I include only scheduled FOMC announcements because Greenbook projections were not prepared for unscheduled ones.

Table 3 shows the OLS estimate, ϕ_ξ^h, from Equation (3), using one economic indicator for one horizon at a time. Column (1)-(3) present the results for pro-cyclical, real economic indicators, including real GDP, real personal consumption expenditures and industrial production. A positive forecast difference on the right-hand side suggests that the Fed expects a stronger economy than the market prior to an FOMC announcement. In that case, one would expect $\xi_{t(m)}$ to be positive, reflecting the market's learning of the more optimistic view on the economy. The consistently positive coefficients in Column (1)-(3) confirm this prediction. To highlight a few significant correlations at the 5% level, an increase in interest rates due to $\xi_{t(m)}$ is strongly associated with the Fed projecting a higher growth rate of real GDP than professional forecasters for two quarters into the future and a higher growth rate of industrial production for the current quarter.

By contrast, one would expect $\phi_\xi^h < 0$ for a counter-cyclical variable, such as the unemployment rate. This is because if the revelation of information raised interest rates we would expect the Fed to have predicted a lower unemployment rate than the private sector, as reflected by a negative forecast difference in Equation (3). Column (4) shows that it is indeed the case for all horizons even though none of the coefficients is significantly different from zero.

Finally, Column (5) and (6) show the estimated ϕ_ξ^h for two price variables, the GDP Price Index and the CPI. At the 5% significance level, the coefficient on CPI for the current quarter and that on GDP Price Index in six quarters are significantly positive at the 5% level, again consistent with what one would expect for a pro-cyclical indicator.

The exercise above confirms the prediction that the information shock tends to be positive when the Fed is more optimistic about economic fundamentals than the market. It suggests that the shock does capture some Fed information about the state of the economy that the market does not know. However, does it capture all that information? The answer is yes. I check this by replacing the dependent variable in Equation (3) with the monetary shock $\eta_{t(m)}$ and see if it predicts the forecast differences in the same way as $\xi_{t(m)}$ does. Table 4 shows that most of the predictive coefficients for the monetary shock are insignificant at the 10% level. When the coefficients are significant, they have the opposite sign; before an announcement associated with a contractionary monetary shock, the Fed tends to predict a significantly lower GDP Price Index in six quarters, lower real personal consumption expenditures in one quarter and a slightly higher unemployment rate in six quarters than Blue Chip forecasters. This direction of predictability can arise for two reasons. First, the staff of the Fed may have been able to factor in the contractionary effect of the monetary shock when they made the projections because they were also better informed of the monetary shock than the private sector. Second, the significant coefficients could arise as false positives due to the size of the

Table 3: Predictability of GB-BC forecast differences for Fed information shock ξ_t

h (quarter)	Real GDP (1)	Real PCE (2)	Industrial Production (3)	Unemp. Rate (4)	Consumer Price Index (5)	GDP Price Index (6)
0	**1.79***** (0.56)	0.63 (0.53)	**0.53**** (0.22)	-0.24 (5.71)	**1.33**** (0.53)	-0.23 (0.73)
1	**2.17**** (0.95)	**1.25**** (0.53)	**0.53*** (0.30)	-0.19 (0.39)	0.59 (0.67)	-1.46 (1.27)
2	**1.39**** (0.69)	0.49 (0.40)	0.18 (0.29)	-2.32 (2.14)	-0.78 (1.15)	-1.22 (1.65)
3	0.95 (0.79)	0.76 (0.58)	0.18 (0.47)	-2.05 (1.65)	-0.06 (1.36)	-1.65 (1.33)
4	**1.41*** (0.84)	**1.59**** (0.80)	0.49 (0.48)	-2.11 (1.55)	1.00 (1.48)	-0.10 (0.91)
5	1.30 (0.99)	**2.18**** (0.97)	0.49 (0.65)	-2.41 (1.66)	0.23 (1.79)	-0.42 (1.11)
6	1.29 (1.56)	2.10 (1.83)	0.91 (1.00)	-2.62 (2.29)	-0.89 (2.21)	**0.38***** (0.08)
7	1.84 (2.15)	**3.95*** (2.01)	-0.43 (2.13)	-3.33 (2.70)	-1.76 (2.42)	-2.16 (2.00)

Each cell reports a coefficient, ϕ_ξ^h, from a separate regression: $\xi_{t(m)} = \phi_0^h + \phi_\xi^h(EI^h_{GB,t(m)} - EI^h_{BC,m}) + e^h_{t(m)}$, using one economic indicator (EI) for one horizon at a time. $EI^h_{GB,t(m)}$ is the Greenbook forecast of the h-quarter-ahead EI prepared for the FOMC meeting on Day t of Month m, $EI^h_{BC,m}$ is the Blue Chip forecast of the same variable at the beginning of Month m. The sample goes from 1991m7 to 2008m12. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

tests. In either case, the additional evidence on $\eta_{t(m)}$ suggests that $\xi_{t(m)}$ is able to capture all the Fed information effect in interest rate surprises.

3.2 Revisions of Private Sector Forecasts

This section tests for the second prediction: if the market responds to an FOMC announcement as if ξ_t is the revealed Fed information, one would expect the private sector to disproportionally revise up their economic outlook following an announcement with a positive ξ_t. The opposite holds for the identified monetary shock, η_t.

Similarly to the previous section, I use the Blue Chip forecasts to measure the private sector's belief about the state of the economy. For an announcement in Month m, a one-

Table 4: Predictability of GB-BC forecast differences for monetary shock η_t

h (quarter)	Real GDP (1)	Real PCE (2)	Industrial Production (3)	Unemp. Rate (4)	Consumer Price Index (5)	GDP Price Index (6)
0	-0.33	0.03	-0.10	-1.48	-0.21	0.13
	(0.37)	(0.23)	(0.10)	(2.14)	(0.23)	(0.30)
1	-0.42	**-0.69****	0.07	-0.11	-0.07	0.31
	(0.54)	(0.31)	(0.14)	(0.15)	(0.28)	(0.65)
2	-0.29	-0.15	-0.20	-0.08	0.21	1.45
	(0.48)	(0.33)	(0.20)	(1.29)	(0.57)	(1.00)
3	-0.34	-0.49	0.03	0.36	1.11	0.97
	(0.56)	(0.36)	(0.19)	(1.04)	(0.90)	(0.83)
4	-0.28	-0.37	0.30	0.27	0.48	0.07
	(0.57)	(0.59)	(0.24)	(0.92)	(0.89)	(0.53)
5	0.61	0.26	0.42	1.11	0.05	-0.24
	(0.49)	(0.54)	(0.27)	(0.81)	(1.05)	(0.51)
6	0.52	0.02	-0.03	**1.47***	0.37	**-0.24*****
	(0.64)	(0.83)	(0.32)	(0.87)	(1.26)	(0.03)
7	-0.20	-0.82	-0.60	1.59	1.65	1.47
	(1.11)	(1.18)	(1.04)	(1.63)	(1.63)	(0.87)

Each cell presents a coefficient, ϕ_ξ^h, from a separate regression: $\eta_{t(m)} = \phi_0^h + \phi_\eta^h(EI_{GB,t(m)}^h - EI_{BC,m}^h) + e_{t(m)}^h$, using one economic indicator (EI) for one horizon at a time. $EI_{GB,t(m)}^h$ is the Greenbook forecast of the h-quarter-ahead EI prepared for the FOMC meeting on Day t of Month m, $EI_{BC,m}^h$ is the Blue Chip forecast of the same variable at the beginning of Month m. The sample goes from 1991m7 to 2008m12. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

month change in the consensus forecast from the beginning of Month m to Month $m+1$ indicates the revision of private sector's expectation following that announcement. For each economic indicator, Table 5 lists the expected direction of change in expectations in response to the two shocks.

Before looking at the identified shocks, let us first look at how Blue Chip forecasters respond to an FOMC announcement overall. I summarize the information in an announcement on Day $t(m)$ with the first principal component of y_t, denoted by $PC_{t(m)}$ and normalized so that a unit increase in it increases $FF4$ by 1% across all the announcement windows over the sample. I then regress the Blue Chip forecast revisions on that information:

$$\Delta EI_{BC,m+1}^h = \alpha_0^h + \alpha_{PC}^h PC_{t(m)} + e_{t(m)}^h \tag{4}$$

Table 5: Expected directions of private sector forecast revisions in response to shocks in FOMC announcements

Economic indicator	information shock $\xi_t > 0$	monetary shock $\eta_t > 0$
Pro-cyclical variables		
Industrial production	$\uparrow$	$\downarrow$
Real GDP	$\uparrow$	$\downarrow$
GDP Price Index	$\uparrow$	$\downarrow$
CPI	$\uparrow$	$\downarrow$
PPI	$\uparrow$	$\downarrow$
Counter-cyclical variable		
Unemployment rate	$\downarrow$	$\uparrow$

where $\Delta EI^h_{BC,m+1} = EI^h_{BC,m+1} - EI^h_{BC,m}$ is the change in the Blue Chip consensus forecast of EI in h quarters from the beginning of Month m to that of Month $m+1$.

The columns labeled "PC" in Table 6 and 7 present the estimated α^h_{PC} using the sample from 1991m7 to 2008m12. Table 6 focuses on real variables, and Table 7 on price variables. These columns show that, following positive interest rate surprises, professional forecasters tended to revise up their economic outlook for two to three quarters into the future. For a tightening announcement that would increase FF4 by 1%, they would significantly increase the consensus forecast of industrial production for the contemporaneous quarter by 2.6% and for the following quarter by 1.3%. The upward revision declined greatly for longer horizons. Expectations of real GDP display a similar pattern. A better economic outlook can also be witnessed from the significant decreases in projected unemployment rates in the current and the third quarters. Furthermore, the tightening announcement would also lead the private sector to raise their projection of the current-quarter PPI by 2.8% on average, as shown in Table 7.

These results confirm the concerns raised by Campbell *et al.* (2012) and Nakamura and Steinsson (2018) about using the high-frequency approach directly to measure monetary shocks. An exogenous policy tightening is supposed to dampen the economy and reduce inflation based on standard macroeconomic models. To understand why we find the opposite, I replace the regressor in Equation (4) by the Fed information shock and the monetary shock identified with my approach:

$$\Delta EI^h_{BC,m+1} = \alpha^h_0 + \alpha^h_\xi \xi_{t(m)} + \alpha^h_\eta \eta_{t(m)} + e^h_{t(m)} \tag{5}$$

The rest of the columns in Table 6 and 7 report the estimated α^h_ξ and α^h_η. Looking at the columns labeled "ξ_t", I find that the information shock plays a dominant role in driving the revisions of Blue Chip forecasts. The estimated α^h_ξ's are generally larger than the α^h_{PC}'s in absolute value, have signs largely consistent with Table 5 and share similar dynamics across horizons with the α^h_{PC}'s. To highlight a few significant responses at the 5% level, a positive information shock that raises $FF4$ by 1% is associated with an upward forecast revision of (1) industrial production in the current and the next quarter by 3.0% and 1.5%, respectively; (2) real GDP in the next quarter by 0.9%; and (3) current PPI by 3.4%. On the other hand, they lowered their expected unemployment rate for the third quarter by 0.4%. These variables and horizons, along with those of 10% significance, largely match the ones for which Greenbook projections significantly differ from Blue Chip's in Section 3.1. These results suggest that the information shock successfully captures the market's learning of new information about economic fundamentals from FOMC announcements.

Table 6: Blue Chip regressions - real variables

	(a) Industrial Production			(b) Real GDP			(c) Unemployment Rate		
h	PC	ξ	η	PC	ξ_t	η_t	PC	ξ_t	η_t
0	**2.62***	**3.04****	0.74	0.66	0.79	0.63	**-0.17***	**-0.20***	-0.24
	(1.42)	(1.51)	(2.44)	(0.64)	(0.70)	(1.31)	(0.09)	(0.10)	(0.22)
1	**1.34****	**1.51****	0.88	**0.75****	**0.90****	0.48	0.00	-0.06	0.05
	(0.64)	(0.68)	(1.56)	(0.37)	(0.39)	(0.98)	(0.25)	(0.25)	(0.34)
2	0.37	0.47	-0.28	0.10	0.19	-0.50	**-0.34***	**-0.38****	-0.40
	(0.34)	(0.37)	(0.85)	(0.26)	(0.27)	(0.52)	(0.18)	(0.18)	(0.42)
3	0.28	0.40	-0.69	0.11	0.15	-0.35	-0.30	**-0.37***	-0.11
	(0.33)	(0.36)	(0.56)	(0.22)	(0.24)	(0.32)	(0.19)	(0.19)	(0.45)
4	0.13	0.25	**-1.10***	0.21	0.25	0.23	-0.06	-0.12	0.41
	(0.23)	(0.23)	(0.58)	(0.16)	(0.18)	(0.42)	(0.19)	(0.19)	(0.75)
5	0.30	0.35	-0.60	0.18	0.21	-0.42	-0.24	-0.27	-0.21
	(0.24)	(0.24)	(0.50)	(0.15)	(0.15)	(0.41)	(0.15)	(0.17)	(0.52)

Each cell in the columns labeled "PC" presents a coefficient, α^h_{PC}, from a separate regression: $\Delta EI^h_{t(m)} = \alpha^h_0 + \alpha^h_{PC} PC_{t(m)} + e^h_{t(m)}$. Each row in the columns labeled "ξ_t" and "η_t" presents a pair of coefficients, α^h_ξ and α^h_η, from a separate regression: $\Delta EI^h_{t(m)} = \alpha^h_0 + \alpha^h_\xi \xi_{t(m)} + \alpha^h_\eta \eta_{t(m)} + e^h_{t(m)}$. The sample is from 1991m7 to 2008m12, excluding the announcement in 2001m9 and those made in the first three business days of a month before 2000m12 and three business days in and after 2000m12. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Again, does ξ_t capture all the Fed information? Once the information shock is accounted for, the monetary shock is associated with insignificant changes in Blue Chip forecasts for most indicators and horizons, as the columns labeled "η_t" show. There are a few exceptions. Expectations for industrial production in four quarters got adjusted downward significantly by 1.1% at the 10% level and PPI in five quarters by almost 1.0% at the 5% level. The signs

Table 7: Blue Chip regressions - price variables

(a) CPI

h	PC	ξ_t	η_t
0	1.20	**1.60***	-1.13
	(0.87)	(0.96)	(1.59)
1	0.00	-0.11	0.37
	(0.57)	(0.74)	(1.74)
2	0.04	0.04	**0.35***
	(0.12)	(0.13)	(0.20)
3	0.12	0.11	0.13
	(0.12)	(0.14)	(0.22)
4	0.09	0.11	0.03
	(0.12)	(0.14)	(0.25)
5	0.14	0.18	0.08
	(0.21)	(0.23)	(0.38)

(b) PPI

PC	ξ_t	η_t
2.83*	**3.44****	-0.38
(1.48)	(1.67)	(2.67)
0.43	0.59	-1.03
(0.37)	(0.43)	(0.85)
-0.05	-0.04	-0.33
(0.21)	(0.24)	(0.40)
0.19	0.21	-0.41
(0.25)	(0.28)	(0.28)
0.05	0.09	-0.24
(0.20)	(0.22)	(0.59)
0.14	0.18	**-0.97****
(0.22)	(0.19)	(0.43)

(c) GDP Price Index

PC	ξ_t	η_t
0.13	0.15	0.15
(0.30)	(0.34)	(0.38)
0.14	0.15	0.13
(0.17)	(0.18)	(0.26)
0.00	0.01	-0.02
(0.16)	(0.19)	(0.24)
0.09	0.13	-0.28
(0.14)	(0.16)	(0.27)
-0.05	-0.06	-0.19
(0.14)	(0.16)	(0.30)
2.34	2.94	-8.31
(2.32)	(2.85)	(8.48)

Each cell in the columns labeled "PC" presents a coefficient, α^h_{PC}, from a separate regression: $\Delta EI^h_{t(m)} = \alpha^h_0 + \alpha^h_{PC} PC_{t(m)} + e^h_{t(m)}$. Each row in the columns labeled "ξ_t" and "η_t" presents a pair of coefficients, α^h_ξ and α^h_η, from a separate regression: $\Delta EI^h_{t(m)} = \alpha^h_0 + \alpha^h_\xi \xi_{t(m)} + \alpha^h_\eta \eta_{t(m)} + e^h_{t(m)}$. The sample goes from 1991m7 to 2008m12, excluding the announcement in 2001m9 and those made in the first three business days of a month before 2000m12 and three business days in and after 2000m12. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

of the effects are consistent with our predictions in Table 5. The coefficient associated with CPI in two quarters looks puzzling but should not be much of a concern given the consistent performance of the shocks for the other variables. It can result from the size of the test by construction.

Combining the analysis above with that of Section 3.1, one would find the argument for the Fed information effect complete: (1) market participants did expect a stronger economy than they would otherwise have predicted after an announcement surprised them with a tightening of interest rates; (2) the surprise tightening is a result of the Fed foreseeing a stronger growth of economy or a higher inflation than the private sector; and (3) ξ_t captures precisely that information gap.

3.3 Reconciliation with Bauer and Swanson (2022)

This section investigates how the previous results relate to the "Fed response to news" channel recently proposed by Bauer and Swanson (2022). First, I explain this channel by replicating the key results in Bauer and Swanson (2022). Then, I examine whether taking their evidence into account changes my results.

Bauer and Swanson (2022) challenge specifications like Equation (4) which previous studies have used to provide supporting evidence for the Fed information effect. Campbell *et al.* (2012), as a leading example of those studies, study the response of private sector's expectations to a FOMC announcement in a set-up similar to Equation (4). Specifically, they estimate the following regression over a sample from 1990m2 to 2007m12:

$$\Delta EI^h_{BC,m+1} = \alpha^h_0 + \alpha^h_{Target} Target_m + \alpha^h_{Path} Path_m + e^h_m \tag{6}$$

where $Target_m$ and $Path_m$, constructed based on Gürkaynak *et al.* (2005b), are two monetary shocks induced by the FOMC announcement in Month m that reflect the market surprise at the current policy rate and at its future path. They find the signs of α^h_{Target} and α^h_{Path} the opposite of what one would expect for the effect of a monetary shock. Nakamura and Steinsson (2018) as another example estimate the following equation over a sample from 1995m1 to 2014m3.

$$\Delta EI^h_{BC,m+1} = \alpha^h_0 + \alpha^h_P Policy_m + e^h_m \tag{7}$$

where $Policy_m$ is another construction of monetary shock associated with the FOMC announcement in Month m, measured as the first principal component of the 30-minute rate changes in five interest rate futures around the event. They also find the signs of the α^h_P's puzzling, just as shown in the "PC" columns of Table 6 and 7.[8]

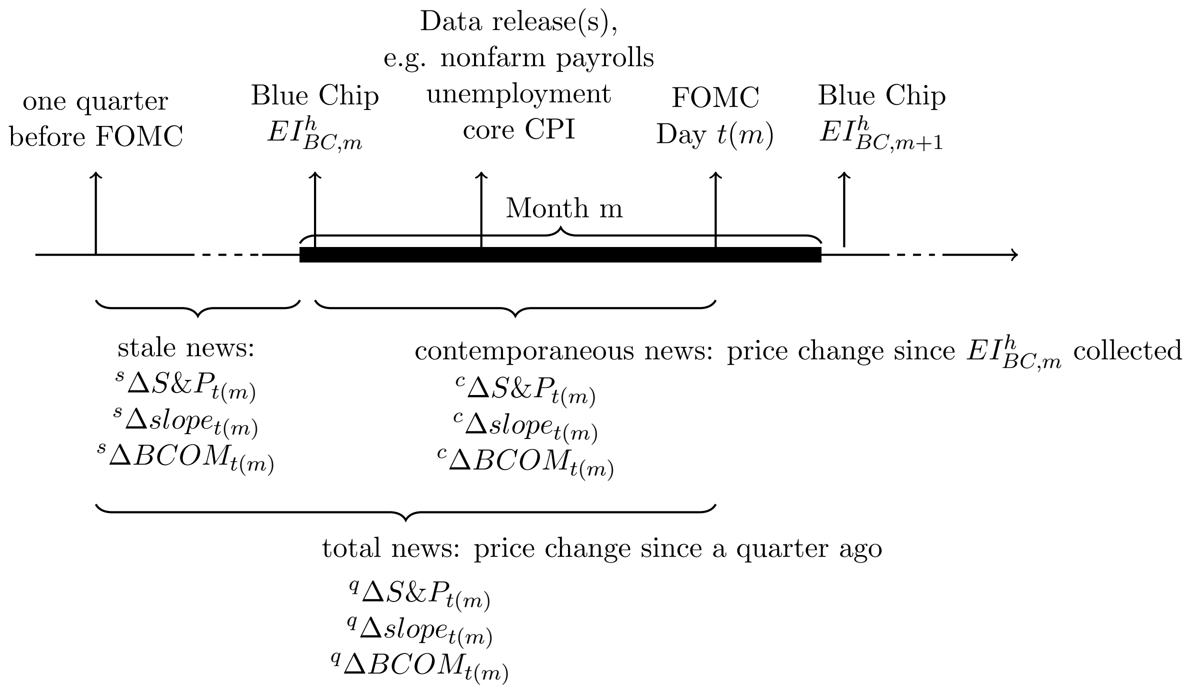
Figure 4 illustrates Bauer and Swanson (2022)'s concern about these specifications. If an unsatisfactory employment report got released between the FOMC announcement in Month m and the Blue Chip survey at the beginning of the month, it may have simultaneously led the Fed to cut the federal funds rate more than publicly expected and caused Blue Chip forecasters to revise down their economic outlook. Thus, what previous studies claim to be the Fed information effect could simply be a result of an omitted variable bias in Equation (6) and (7).[9]

In order to take this concern into account, I re-estimate Equation (4) by controlling for the *contemporaneous* public news that arrives between the Blue Chip survey at the beginning of Month m and the FOMC announcement in Month m. Along the lines of Bauer and

[8] I replicate the results of Campbell *et al.* (2012) and Nakamura and Steinsson (2018) in Table A1. For completeness, I extend their analyses to a full range of economic indicators and horizons available in the Blue Chip survey. I estimate the regressions at the meeting frequency. It is possible for a month to have two FOMC announcements, with one of them being unscheduled. When that happens, I use the same one-month change in Blue Chip forecasts for either announcement. Aggregating the monetary shocks to the month level and running the regressions at the monthly frequency makes negligible difference to the results.

[9] I replicate the results of Bauer and Swanson (2022) in Table A2.

Figure 4: Timeline of actions around an FOMC announcement



Swanson (2022), I collect two types of proxies for such news. The first group, denoted by $X_{t(m)}$, contains market surprises at the nonfarm payrolls, the unemployment rate, and the CPI inflation rate on release days that fall into the window. The second group, denoted by $F^c_{t(m)} = ({}^{c}\Delta S\&P_{t(m)},\ {}^{c}\Delta slope_{t(m)}$ and ${}^{c}\Delta BCOM_{t(m)})'$, contains the cumulative changes in the S&P 500 price index, the slope of the yield curve, and the Bloomberg commodity price index (BCOM) from the first day after the Blue Chip survey is conducted to the last day before the FOMC announcement in Month m (see Figure 4 for the timeline).

$$\Delta EI^h_{BC,m+1} = \alpha^h_0 + \alpha^h_\xi \xi_{t(m)} + \alpha^h_\eta \eta_{t(m)} + \alpha^{h\prime}_X X_{t(m)} + \alpha^{h\prime}_F F^c_{t(m)} + e^h_{t(m)} \tag{8}$$

The first two columns of Table 8 and 9 show the estimated α^h_ξ and α^h_η from Equation (8). Not only do the effects of an information shock on Blue Chip forecasts remain, they become even stronger than without the controls. The variables with significance become even more consistent with the ones for which the Greenbook differs the most from the Blue Chip in the previous section.

In fact, Bauer and Swanson (2022) propose to control for a larger set of variables in Equation (6) and (7). They include (i) lagged macroeconomic indicators, (ii) a time trend, (iii) lagged Blue Chip forecast revisions, (iv) the market surprise at GDP in the release in Month $m-1$, (v) the Brave-Butters-Kelley Index (Brave *et al.*, 2019), and (vi) the

Table 8: Robustness to the Fed response to economic news channel - real variables

EI	h	ξ_t	η_t	ξ_t	η_t	ξ_t	η_t
Industrial Production	0	**2.99****	-0.47	**2.58***	-3.38	-0.14	-3.84
		(1.39)	(2.18)	(1.32)	(2.05)	(1.91)	(2.62)
	1	**1.49****	-0.23	1.06	-1.05	-0.66	-1.06
		(0.61)	(1.06)	(0.89)	(1.20)	(1.01)	(1.38)
	2	0.44	-0.83	0.47	-0.21	**-1.20****	-0.28
		(0.40)	(0.65)	(0.48)	(0.63)	(0.54)	(0.63)
	3	0.44	-0.86	**0.98****	-0.01	-0.21	0.00
		(0.40)	(0.54)	(0.40)	(0.49)	(0.40)	(0.43)
	4	0.30	**-1.20***	**0.81****	-1.04	0.34	-1.10
		(0.27)	(0.70)	(0.38)	(0.87)	(0.38)	(0.96)
	5	0.38	**-1.13***	**0.92****	**-1.49***	0.56	-1.22
		(0.29)	(0.57)	(0.42)	(0.77)	(0.43)	(0.86)
Real GDP	0	0.67	-0.62	0.19	-0.60	-1.10	-0.76
		(0.66)	(1.03)	(0.68)	(0.94)	(0.66)	(0.97)
	1	**0.77***	-0.26	0.47	-0.05	-0.59	0.18
		(0.39)	(0.65)	(0.45)	(0.58)	(0.43)	(0.61)
	2	0.17	-0.44	0.16	-0.24	**-0.73****	-0.11
		(0.31)	(0.47)	(0.29)	(0.44)	(0.33)	(0.38)
	3	0.12	-0.42	**0.45***	-0.23	-0.26	-0.23
		(0.26)	(0.30)	(0.26)	(0.27)	(0.28)	(0.22)
	4	0.30	0.22	**0.53****	0.50	-0.19	0.35
		(0.18)	(0.40)	(0.23)	(0.48)	(0.22)	(0.48)
	5	0.21	-0.55	0.40	0.69	0.23	0.53
		(0.20)	(0.48)	(0.35)	(0.59)	(0.32)	(0.51)
Unemployment Rate	0	**-0.24*****	-0.10	**-0.23***	0.00	0.16	0.07
		(0.09)	(0.21)	(0.13)	(0.19)	(0.12)	(0.17)
	1	-0.15	0.38	-0.16	**0.42***	0.33	**0.47***
		(0.17)	(0.24)	(0.19)	(0.24)	(0.20)	(0.25)
	2	**-0.39****	-0.04	-0.24	0.02	0.36	0.04
		(0.16)	(0.27)	(0.22)	(0.29)	(0.22)	(0.31)
	3	**-0.37****	0.29	-0.17	0.34	**0.51****	0.42
		(0.18)	(0.32)	(0.19)	(0.33)	(0.23)	(0.28)
	4	-0.15	**0.87***	-0.11	**1.73****	**0.62****	**1.39*****
		(0.19)	(0.49)	(0.27)	(0.75)	(0.25)	(0.45)
	5	-0.20	**0.53***	-0.34	**0.90*****	0.05	0.61
		(0.13)	(0.30)	(0.22)	(0.33)	(0.24)	(0.47)
data releases		✓		✓		✓	
$^c\Delta$ in S&P, slope, BCOM		✓		✓			
time trend				✓		✓	
lagged BC revision				✓		✓	
lagged macro indicators				✓		✓	
GDP surprise				✓		✓	
$^q\Delta$ in S&P, slope, BCOM						✓	
BBK Index						✓	

Estimated α_ξ^h and α_η^h from regression: $\Delta EI_{t(m)}^h = \alpha_0^h + \alpha_\xi^h \xi_{t(m)} + \alpha_\eta^h \eta_{t(m)} + \alpha_c^{h'} control_{t(m)} + e_{t(m)}^h$, where $control_{t(m)}$ is a vector of controls varying across panels as listed in the lower panel. See the main text and Figure 4 for detailed definitions. The sample is from 1991m7 to 2008m12, excluding the announcement in 2001m9 and those made in the first three business days of a month before 2000m12 and three business days in and after 2000m12. Robust standard errors are in parentheses.

Table 9: Robustness to the Fed response to economic news channel - price variables

EI	h	ξ_t	η_t	ξ_t	η_t	ξ_t	η_t
CPI	0	**1.84****	-1.44	1.12	**-2.82****	**-1.39***	**-2.20***
		(0.87)	(1.35)	(0.72)	(1.27)	(0.75)	(1.14)
	1	-1.00	0.89	-1.75	0.14	**4.05***	0.04
		(0.99)	(1.59)	(2.46)	(2.05)	(2.20)	(2.20)
	2	0.02	**0.42***	-0.04	**0.40***	-0.14	**0.39***
		(0.14)	(0.23)	(0.16)	(0.23)	(0.19)	(0.20)
	3	0.12	0.25	0.13	0.11	-0.03	0.10
		(0.14)	(0.26)	(0.15)	(0.33)	(0.18)	(0.34)
	4	0.12	0.14	0.00	-0.05	-0.07	0.08
		(0.14)	(0.29)	(0.17)	(0.32)	(0.17)	(0.25)
	5	0.17	0.07	0.14	-0.90	0.02	-0.75
		(0.22)	(0.43)	(0.28)	(0.60)	(0.36)	(0.64)
PPI	0	**4.72*****	-0.83	**3.90****	-1.94	**-3.38***	-1.43
		(1.53)	(2.03)	(1.81)	(2.19)	(1.84)	(1.94)
	1	**0.98****	-1.11	1.41	-1.09	**-1.77***	-0.98
		(0.45)	(0.69)	(0.85)	(1.18)	(1.04)	(1.01)
	2	0.13	-0.24	0.24	0.22	-0.64	0.18
		(0.27)	(0.40)	(0.42)	(0.56)	(0.48)	(0.57)
	3	0.37	-0.30	0.42	-0.44	**0.58***	-0.32
		(0.28)	(0.32)	(0.37)	(0.49)	(0.34)	(0.44)
	4	0.02	-0.25	-0.39	0.23	0.15	0.35
		(0.24)	(0.62)	(0.32)	(0.83)	(0.29)	(0.77)
	5	0.17	**-1.17*****	0.15	-1.20	0.13	**-1.24***
		(0.19)	(0.39)	(0.35)	(0.77)	(0.40)	(0.64)
GDP Price Index	0	0.14	0.18	0.08	-0.53	-0.32	-0.34
		(0.33)	(0.39)	(0.38)	(0.46)	(0.33)	(0.39)
	1	0.18	0.10	0.12	-0.10	-0.17	-0.09
		(0.17)	(0.25)	(0.21)	(0.29)	(0.20)	(0.28)
	2	0.04	0.08	0.02	-0.13	-0.23	-0.09
		(0.19)	(0.21)	(0.22)	(0.24)	(0.21)	(0.24)
	3	0.17	-0.16	0.03	-0.44	-0.21	-0.43
		(0.16)	(0.26)	(0.22)	(0.29)	(0.19)	(0.30)
	4	-0.07	-0.24	-0.19	-0.07	-0.34	-0.10
		(0.16)	(0.29)	(0.27)	(0.41)	(0.24)	(0.39)
	5	3.93	-12.62	6.02	-1.98	6.84	1.78
		(3.53)	(11.68)	(6.34)	(7.87)	(7.76)	(10.91)
data releases		✓		✓		✓	
$^c\Delta$ in S&P, slope, BCOM		✓		✓			
time trend				✓		✓	
lagged BC revision				✓		✓	
lagged macro indicators				✓		✓	
GDP surprise				✓		✓	
$^q\Delta$ in S&P, slope, BCOM						✓	
BBK Index						✓	

Estimated α_ξ^h and α_η^h from regression: $\Delta EI_{t(m)}^h = \alpha_0^h + \alpha_\xi^h \xi_{t(m)} + \alpha_\eta^h \eta_{t(m)} + \alpha_c^{h'} control_{t(m)} + e_{t(m)}^h$, where $control_{t(m)}$ is a vector of controls varying across panels as listed in the lower panel. See the main text and Figure 4 for detailed definitions. The sample is from 1991m7 to 2008m12, excluding the announcement in 2001m9 and those made in the first three business days of a month before 2000m12 and three business days in and after 2000m12. Robust standard errors are in parentheses.

changes in the S&P 500 price index, the yield curve slope and BCOM over the entire quarter prior to the FOMC announcement on Day $t(m)$ (denoted by ${}^q\Delta S\&P_{t(m)}$, ${}^q\Delta slope_{t(m)}$, and ${}^q\Delta BCOM_{t(m)}$ in Figure 4). To investigate how these variables would affect my results, I re-estimate Equation (8) by adding them incrementally to the vector $C_{t(m)}$ in Equation (9).

$$\Delta EI^h_{BC,m+1} = \alpha^h_0 + \alpha^h_\xi \xi_{t(m)} + \alpha^h_\eta \eta_{t(m)} + \alpha^{h'}_X X_{t(m)} + \alpha^{h'}_F F^c_{t(m)} + \alpha^{h'}_c C_{t(m)} + e^h_{t(m)} \tag{9}$$

The coefficients remain to have their expected signs when the list of controls are added from (i) up to (iv). The middle panels of Table 8 and 9 show the estimated α^h_ξ and α^h_η when (i) - (iv) are all controlled for besides the contemporaneous news in data releases and in the financial variables. Even though their significance levels change slightly from the first panels, a positive information shock is still associated with upward revisions of economic outlook and inflation expectations, and vice versa for a positive monetary shock.

It is when I replace contemporaneous news $F^c_{t(m)}$ by (vi) and add the BBK Index in Equation (9) that the signs of the estimated α^h_ξ's reverse, as is shown in the last panels of Table 8 and 9. The sign reversion suggests that the identified information shock is positively correlated with stale news and not with contemporaneous news. This correlation stems from the behavior of the five interest rates from which the information shock is constructed. To see this, I take the change in the S&P500 price index only over *previous* months as a measure of stale news and label it with ${}^s\Delta S\&P_{t(m)}$ where s stands for "stale". I regress each of the five interest rates the public news that arrives in each of the three windows:

$$y_{t(m)} = \phi_0 + \phi_{SP}\, {}^i\Delta S\&P_{t(m)} + \phi_X X_{t(m)} + u_{t(m)}, \qquad i = q, c, s \tag{10}$$

Table 10 reports the estimated coefficients ϕ_{SP}. As the first two rows show, stale news as measured by ${}^s\Delta S\&P_{t(m)}$ dominates the positive correlations between quarterly news and the interest rate changes. Holding surprises at data releases constant, a 1% decline in the stock price in previous months driven by bad news strongly predicts that the market would be surprised at a rate cut during the contemporaneous announcement and adjust down their expected interest rates in various horizons by between 0.18% and 0.39%. The finding is consistent with the "Fed put" pattern documented in Cieslak and Vissing-Jorgensen (2020) where they conduct a text analysis of FOMC documents and show that the Fed has reacted to negative intermeeting stock returns with an accommodative policy since the mid-1990s. By contrast, the third row shows that contemporaneous news as measured by ${}^c\Delta S\&P_{t(m)}$ has no significant effect on these interest rates.

Stale news is relevant for the high-frequency responses of bond markets to FOMC announcements for two possible reasons. First, the Fed may read more into the stale news as to what the news means for the economy than the private sector. That is, given the same decline in the stock market, the Fed may form a more pessimistic view of the economy than the private sector. Second, given that the Fed and the private sector interpret the stale news in the same way, the Fed may react more aggressively than publicly believed. To the extent that the Blue Chip survey at the beginning of a month has already captured the private sector's reading of any stale news and to the extent that the Blue Chip forecasts responded to the information shock with the expected signs, I find the first explanation more plausible. In fact, one can check this by regressing the difference in projections by the Fed and by the Blue Chip on the stale news:

$$EI^h_{GB,t(m)} - EI^h_{BC,m} = \alpha^h_0 + \alpha^h_{SP}\, {}^s\Delta S\&P_{t(m)} + \alpha^h_X X_{t(m)} + e^h_{t(m)} \tag{11}$$

Table A4 reports the estimated α^h_{SP} from Equation (11). It shows that the Greenbook did tend to project a worse economy than the private sector following stock market declines. Since large rate cuts indeed tend to precede a recession, as Figure 1 showed earlier, I view Table 10 and A4 as suggestive evidence that the Fed was better at figuring out what stale news meant for the economy than the private sector. This way of interpreting the Fed information is also shared by the theoretical model in Miranda-Agrippino and Rico (2021) and reconciles Bauer and Swanson (2022) with the literature arguing for the existence of a Fed information effect.

Table 10: Predictability for interest rate surprises by changes in S&P500 price index over different windows

	FF4	ED2	ED3	ED4	2-year T yield
${}^q\Delta S\&P_{t(m)}$	**0.15***	**0.26****	**0.32*****	**0.32*****	**0.20****
	(0.08)	(0.12)	(0.12)	(0.12)	(0.08)
${}^s\Delta S\&P_{t(m)}$	**0.18***	**0.31****	**0.39*****	**0.39*****	**0.25*****
	(0.10)	(0.13)	(0.13)	(0.14)	(0.08)
${}^c\Delta S\&P_{t(m)}$	0.00	0.04	0.05	0.05	0.02
	(0.15)	(0.14)	(0.18)	(0.21)	(0.14)

Each cell reports a coefficient, ϕ_{SP}, from a separate regression: $y_{t(m)} = \phi_0 + \phi_{SP}\, {}^i\Delta S\&P_{t(m)} + \phi_X X_{t(m)} + u_{t(m)}$ $(i = q, s, c)$, where $y_{t(m)}$ is the surprise change in one of the five interest rates within a 30-minute window around an FOMC announcement, and $X_{t(m)}$ is a (3×1) vector containing the market surprises at the released numbers of non-farm payrolls, the unemployment rate, and the CPI inflation rate in Month m. The windows over which changes in the S&P500 price index are taken, as denoted by ${}^q\Delta$, ${}^s\Delta$ and ${}^c\Delta$, are illustrated in Figure 4.

Table 11: Predictability for GB-BC forecast differences by stale news

h (quarter)	Real GDP (1)	Real PCE (2)	Industrial Production (3)	Unemp. Rate (4)	Consumer Price Index (5)
0	**1.20***	1.19	1.83	-0.10	1.69
	(1.68)	(1.05)	(0.73)	(-0.87)	(1.02)
1	**3.70*****	**3.05*****	**8.15*****	**-0.62*****	1.78
	(4.14)	(2.97)	(4.22)	(-3.34)	(1.31)
2	**2.95*****	**2.66*****	**3.73****	**-0.81*****	-0.27
	(4.61)	(2.66)	(2.23)	(-4.02)	(-0.32)
3	**2.92*****	**3.39*****	**3.51*****	**-1.07*****	-0.35
	(3.31)	(4.22)	(2.82)	(-3.51)	(-0.97)
4	**2.63*****	**2.86*****	**1.78****	**-1.24*****	-0.15
	(3.28)	(4.10)	(2.08)	(-3.63)	(-0.48)
5	**2.24****	**3.72*****	1.50	**-1.47*****	-0.73
	(2.17)	(5.00)	(1.28)	(-3.68)	(-1.64)
6	**2.99****	**4.36*****	**2.80***	**-2.16*****	-0.96
	(2.17)	(3.75)	(1.70)	(-3.59)	(-1.05)
7	**3.94****	**3.51****	1.81	**-3.39*****	-0.97
	(2.69)	(2.29)	(1.20)	(-3.83)	(-0.80)

Each cell reports a coefficient, ϕ_{SP}, from a separate regression: $EI^h_{GB,t(m)} - EI^h_{BC,m} = \phi_0 + \phi_{SP}\, {}^s\Delta S\&P_{t(m)} + \phi_X X_{t(m)} + u_{t(m)}$, where ${}^s\Delta SP_{t(m)}$ is the change in the S&P500 price index from one quarter before the FOMC announcement on Day t of Month m to the last day of the Blue Chip survey at the beginning of Month m. $X_{t(m)}$ is a (3×1) vector containing the market surprises at the releases of non-farm payrolls, the unemployment rate, and the CPI inflation rate in Month m if the releases occurred between the Blue Chip survey and the FOMC announcement in Month m (filled with zero otherwise).

4 Composite Shock Measures From 1991m7 to 2019m3

This section extends the series of Fed information shocks and monetary shocks to 2019m3. Due to the zero lower bound (ZLB), the parameters in my model may have changed since the end of 2008. In order to deal with possible structural breaks in the model parameters, I re-estimate the model separately for the ZLB period from 2009m1 to 2016m12 and for the post-ZLB period from 2017m1 to 2019m3. Combining the estimated series from these later samples with the original one from my baseline sample yields two composite measures, one of the Fed information shock and the other of the monetary shock, for all the FOMC announcements from 1991m7 to 2019m3.[10]

[10] The estimated series is normalized to raise FF4 by 1% in each subsample for consistency.

Key intuition and results in Section 2 and 3 remain to hold for the composite measures. Table 12 shows that one factor continues to be sufficient for capturing the market response to various types of data releases in early 2009. Table 13 and 14 relate the composite measures to the forecast differences between the Greenbook and the Blue Chip. They confirm the results in Section 3.1; the composite Fed information shock fully captures the information asymmetry between the Fed and the private sector as measured by the difference in forecasts between the Greenbook and the Blue Chip. Most evidently, the Fed and the Blue Chip disagreed the most on output growth and inflation in the very near future. I also repeat the Blue Chip regressions in Section 3.2 with the composite measures, controlling for news between the Blue Chip survey and the FOMC announcement. Table 15 highlights the results for three economic indicators and confirms my findings in Section 3.2. An information shock identified to lower FF4 is associated with Blue Chip forecasters (1) revising down their expectations on real GDP for the next quarter and PPI for the current quarter. It also led the unemployment forecasts to drop for a set of horizons. For a more complete set of variables and specifications of control variables that showed up in Section 3.2, see Appendix A.4.

Table 12: Wright (2012)'s test for the number of news shocks

	Sample period	Dimension of $\tilde{\xi}_t$ ($N_{\tilde{\xi}}$)	p-value
ZLB	2009m1 - 2016m12	1	0.631
post-ZLB	2017m1 - 2019m3	1	0.462

The null hypothesis is that $\Sigma^D - \Sigma_{\tilde{u}} = \tilde{\gamma}\tilde{\gamma}'$, where $\tilde{\gamma}$ is an $N \times N_{\tilde{\xi}}$ matrix, Σ^D is the covariance matrix of daily interest rate changes on a day with a major data release (defined in Table 1 with a "Yes"), and $\Sigma_{\tilde{u}}$ is the covariance matrix on a day without any major data releases.

5 Effects of monetary policy on output and inflation

One of the goals of properly identifying monetary shocks is to understand their effects on the macro economy. In this section, I embed the estimated series of η_t in a vector-autoregressive model to evaluate their impact on output and inflation.

My baseline model takes the exogenous variable approach (Pascal, 2020) and estimate the following system of equations:

$$Y_t = B_0 + \sum_{i=1}^{p} B_i Y_{t-i} + \nu\eta_t + e_t \tag{12}$$

Table 13: Predictability of GB-BC forecast differences for Fed information shock ξ_t

h (quarter)	Real GDP (1)	Real PCE (2)	Industrial Production (3)	Unemp. Rate (4)	Consumer Price Index (5)	GDP Price Index (6)
0	**1.48*****	0.52	**0.35****	-0.21	**1.16****	-0.20
	(0.44)	(0.45)	(0.16)	(4.16)	(0.46)	(0.53)
1	**1.82****	**1.11****	**0.41***	-0.18	0.48	-0.96
	(0.84)	(0.48)	(0.21)	(0.38)	(0.53)	(0.94)
2	**1.18****	0.44	0.15	-1.85	-0.62	-0.91
	(0.60)	(0.37)	(0.24)	(1.86)	(0.92)	(1.31)
3	0.73	0.65	0.14	-1.59	-0.03	-1.29
	(0.63)	(0.51)	(0.39)	(1.41)	(1.04)	(1.03)
4	0.93	**1.24****	0.36	-1.62	0.89	0.01
	(0.60)	(0.63)	(0.40)	(1.31)	(1.06)	(0.83)
5	0.65	**1.50****	0.24	-1.75	0.53	-0.27
	(0.64)	(0.73)	(0.50)	(1.37)	(1.23)	(1.04)
6	0.59	1.23	0.50	-1.73	0.13	0.16
	(0.83)	(1.16)	(0.68)	(1.74)	(1.39)	(0.16)
7	0.47	1.68	-0.25	-1.91	-0.42	-1.61
	(0.84)	(1.19)	(0.83)	(1.84)	(1.77)	(1.82)

Each cell reports a coefficient, ϕ_ξ^h, from a separate regression: $\xi_{t(m)} = \phi_0^h + \phi_\xi^h(EI_{GB,t(m)}^h - EI_{BC,m}^h) + e_{t(m)}^h$, where $EI_{GB,t(m)}^h$ is the Greenbook forecast of the h-quarter-ahead economic indicator (EI) prepared by the Fed staff for the FOMC meeting on Day t of Month m, $EI_{BC,m}^h$ is the Blue Chip forecast of the same variable at the beginning of Month m. The sample is from 1991m7 to 2013m12. Robust standard errors are in parentheses.

where Y_t is a vector of endogenous variables, including log industrial production, log CPI and excess bond premium in the baseline specification. The sample for both Y_t and η_t spans from 1991m7 to 2019m3. The impulse response function of Y_t to η_t is computed by forward iteration with estimated ν and $\{B_i\}_{i=1}^p$.[11]

Figure 5 plots the dynamic responses of these endogenous variables to a positive shock η_t that raises FF4 by 1% around an announcement. Industrial production drops on impact by roughly 1% although the effect is hardly significant. The decline, however, continues and becomes significant 5 months after the shock. In 10 months, output declined by as much as 4% in comparison to its original level. Risk premium in the bond market seems to play an important role for the slowdown of the economy. As the third figure shows, the excess bond

[11] Pascal (2020) proves that the exogenous variable approach delivers numerically equivalent impulse response functions as the external instrument approach (Gertler and Karadi (2015)) under normal assumptions.

Table 14: Predictability of GB-BC forecast differences for monetary shock η_t

h (quarter)	Real GDP (1)	Real PCE (2)	Industrial Production (3)	Unemp. Rate (4)	Consumer Price Index (5)	GDP Price Index (6)
0	-0.21	0.02	-0.05	-1.27	-0.19	0.09
	(0.29)	(0.19)	(0.07)	(1.63)	(0.21)	(0.23)
1	-0.49	**-0.64****	0.03	-0.07	-0.09	0.20
	(0.46)	(0.27)	(0.10)	(0.14)	(0.22)	(0.48)
2	-0.33	-0.15	-0.18	0.18	0.14	1.02
	(0.42)	(0.30)	(0.16)	(1.08)	(0.44)	(0.82)
3	-0.36	-0.51	0.00	0.60	0.99	0.98
	(0.45)	(0.33)	(0.16)	(0.83)	(0.70)	(0.64)
4	-0.31	-0.42	0.21	0.48	0.66	0.17
	(0.42)	(0.49)	(0.20)	(0.72)	(0.60)	(0.50)
5	0.30	0.09	0.23	**1.06***	0.27	-0.18
	(0.31)	(0.42)	(0.21)	(0.63)	(0.67)	(0.48)
6	0.24	-0.05	-0.06	**1.16***	0.37	-0.08
	(0.33)	(0.51)	(0.20)	(0.61)	(0.67)	(0.11)
7	-0.02	-0.39	-0.21	0.96	1.26	**1.41***
	(0.36)	(0.57)	(0.35)	(0.96)	(1.05)	(0.74)

Each cell reports a coefficient, ϕ^h_η, from a separate regression: $\eta_{t(m)} = \phi^h_0 + \phi^h_\eta(EI^h_{GB,t(m)} - EI^h_{BC,m}) + e^h_{t(m)}$, where $EI^h_{GB,t(m)}$ is the Greenbook forecast of the h-quarter-ahead economic indicator (EI) by the Fed staff for the FOMC meeting on Day t of Month m, $EI^h_{BC,m}$ is the Blue Chip forecast of the same variable at the beginning of Month m. The sample is from 1991m7 to 2013m12. Robust standard errors are in parentheses.

premium jumps up immediately and significantly by nearly 1.3% and does not return to its original level until 10 months later. CPI adjusts fairly quickly within the first half of the year after the shock. It eventually shifts down by nearly 1.5% in the long run.

To show how controlling for the Fed information effect improves our understanding of the transmission of monetary policy, I compare the impulse responses to η_t with those to a shock in the high-frequency literature that does not adjust for the information effect. A popular benchmark is the VAR specification of Gertler and Karadi (2015) along with their preferred policy instrument, denoted in this paper with $FF4^{GK}$. This instrument is a monthly aggregate of changes in the three-month federal funds future rate across all FOMC announcement windows during the month. I apply Gertler and Karadi (2015)'s aggregation procedure and extend their shock series to 2019m3. Figure 6 plots the dynamic responses of industrial production and CPI to a positive $FF4^{GK}$ shock in red and to a positive η_t shock

Table 15: Blue Chip regressions controlling for news, 1991m7 - 2019m3

	(a) Real GDP			(b) Unemployment Rate			(c) PPI		
h	PC	ξ_t	η_t	PC	ξ_t	η_t	PC	ξ_t	η_t
0	0.53	0.62	-0.35	**-0.20****	**-0.22****	-0.15	**4.07*****	**4.49*****	-0.50
	(0.62)	(0.61)	(1.03)	(0.08)	(0.09)	(0.21)	(1.41)	(1.45)	(2.03)
1	**0.62***	**0.73****	-0.32	-0.06	-0.13	0.42	**0.83****	**0.75***	-1.01
	(0.36)	(0.35)	(0.65)	(0.19)	(0.18)	(0.27)	(0.42)	(0.39)	(0.67)
2	0.10	0.15	-0.50	**-0.33****	**-0.36****	-0.04	0.12	0.12	-0.25
	(0.29)	(0.29)	(0.45)	(0.15)	(0.16)	(0.25)	(0.24)	(0.26)	(0.41)
3	0.09	0.09	-0.43	**-0.28***	**-0.36****	0.26	0.34	0.36	-0.45
	(0.23)	(0.25)	(0.28)	(0.16)	(0.17)	(0.31)	(0.24)	(0.29)	(0.33)
4	0.25	0.28	0.11	-0.08	-0.13	**0.87***	0.00	0.05	-0.48
	(0.17)	(0.17)	(0.36)	(0.17)	(0.17)	(0.47)	(0.22)	(0.22)	(0.53)
5	0.19	0.26	-0.50	-0.15	-0.16	**0.54***	0.14	0.22	**-1.33*****
	(0.20)	(0.17)	(0.49)	(0.13)	(0.14)	(0.32)	(0.23)	(0.18)	(0.34)

Each cell in the columns labeled "PC" presents a coefficient, α^h_{PC}, from a separate regression: $\Delta EI^h_{t(m)} = \alpha^h_0 + \alpha^h_{PC} PC_{t(m)} + \alpha^{h'}_X X_{t(m)} + \alpha^{h'}_F F^c_{t(m)} + e^h_{t(m)}$. Each row in the columns labeled "ξ_t" and "η_t" presents a pair of coefficients, α^h_ξ and α^h_η, from a separate regression: $\Delta EI^h_{t(m)} = \alpha^h_0 + \alpha^h_\xi \xi_{t(m)} + \alpha^h_\eta \eta_{t(m)} + \alpha^{h'}_X X_{t(m)} + \alpha^{h'}_F F^c_{t(m)} + e^h_{t(m)}$. $X_{t(m)}$ is a (3×1) vector containing the market surprises at the released numbers of the non-farm payrolls, the unemployment rate and the CPI inflation rate if they occurred between the Blue Chip survey and the FOMC announcement in Month m (filled with zero otherwise). $F^c_{t(m)}$ is a (3×1) vector containing the changes in the S&P500 price index, the yield curve slope and the BCOM index between the Blue Chip survey at the beginning of Month m and the FOMC announcement in Month m. The sample is from 1991m7 to 2019m3, excluding the announcement in 2001m9 and those made in the first three business days of a month before 2000m12 and three business days in and after 2000m12. Robust standard errors are in parentheses.

in blue for a sample from 1979m7 to 2019m3. For comparison, I normalize both shocks to raise the one-year Treasury bond rate by 1% on impact.

Relative to $FF4^{GK}$, the responses of the macro economy to η_t display no output puzzle and are evidently larger in magnitude in all horizons. At the trough, industrial production decreases by more than 4% in response to a positive η_t shock. In contrast, $FF4^{GK}$ has a significantly positive effect on industrial production shortly after its realization, and its impact remains close to zero for any horizon within the first three years. CPI also declines more quickly and shifts down more dramatically following a positive η_t shock than following a positive $FF4^{GK}$ shock.

The Fed information effect can potentially explain Gertler and Karadi (2015)'s underestimation of impulse responses. As Section 3.2 illustrates, a rise in $FF4$ during an announcement window contains a Fed information component that leads the Blue Chip professionals to increase their forecasts for CPI, industrial production and real GDP significantly in the near future. Derived from such daily measures, $FF4^{GK}$ likely display a similar feature. Either if changes in market expectations upon announcements have self-fulfilling real effects or if the Fed information predicts the economy well, the estimated effects of monetary shocks on output and inflation would be biased upward if one were to use $FF4^{GK}$ directly in a VAR model. This is precisely what we see in Figure 6.

For a robustness check, I estimate the impulse responses of industrial production and CPI to η_t without incorporating the excess bond risk premium into the VAR model. This choice of specification is motivated by a recent finding of Miranda-Agrippino and Rico (2021) that the behavior of Gertler and Karadi (2015)'s $FF4^{GK}$ is sensitive to including the excess bond premium. In particular, including this very variable is key to avoiding an output puzzle in their dynamic responses. I show in Figure 7 that deleting this variable from my baseline specification does not qualitatively change my results. Not surprisingly, the 90% confidence intervals widens as the level of precision for estimating ν and B drops.

In summary, studying the transmissions of monetary policy with η_t, I find that an exogenous, contractionary monetary shock has a larger negative impact on output and inflation than one would observe with high-frequency monetary instruments themselves. The deviation potentially comes from the fact that existing monetary instruments are confounded by the Fed information effect. The estimated impulse response functions are robust to alternative specifications.

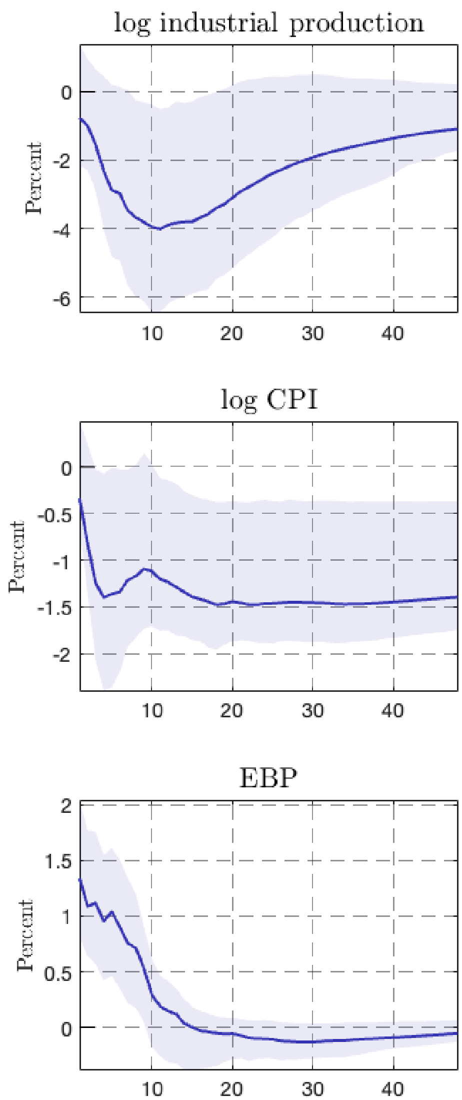
6 A comparison with existing monetary instruments

A number of previous studies have proposed alternative measures of monetary shocks. In this section, I compare η_t proposed in this paper with a number of popular ones.

6.1 Overview

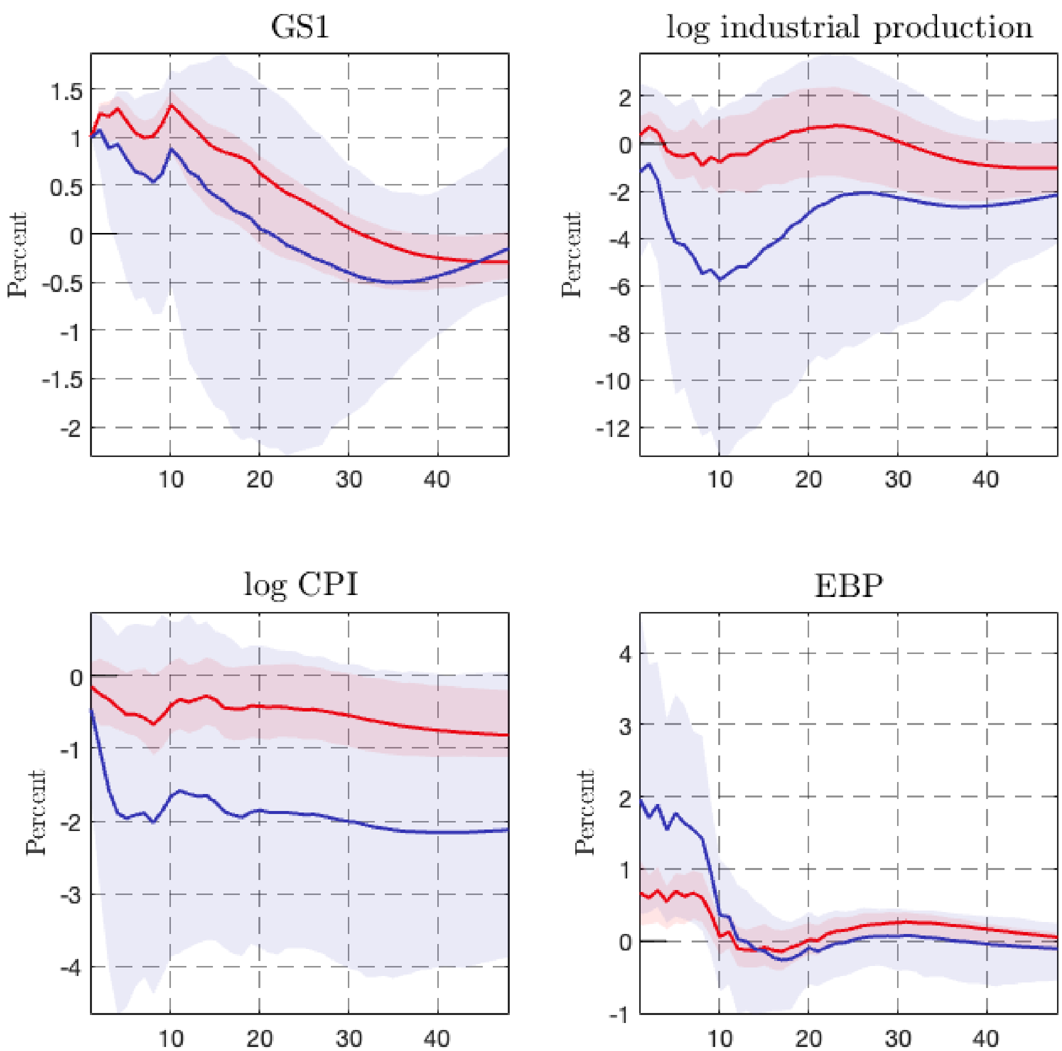
The first two columns of Table 16 list the sources and abbreviations of the shocks considered in the comparison. Some of them are daily measures. They take non-zero values only on Fed announcement days. For this category, I consider Gürkaynak *et al.* (2005b)'s target and path factors, Nakamura and Steinsson (2018)'s policy news shock, Zhang (2019)'s daily measure and Bu *et al.* (2020)'s BRW shock. The rest are monthly measures. They either construct the shocks with monthly data from the very beginning, such as the Romer and Romer (2000) shock, or aggregate daily shocks from FOMC days into monthly measures for a month with multiple announcements, such as Gertler and Karadi (2015)'s $FF4^{GK}$, Miranda-Agrippino and Rico (2021)'s information-robust shock, Zhang (2019)'s monthly measure and Jarociński

Figure 5: Dynamic responses to a monetary tightening shock - baseline



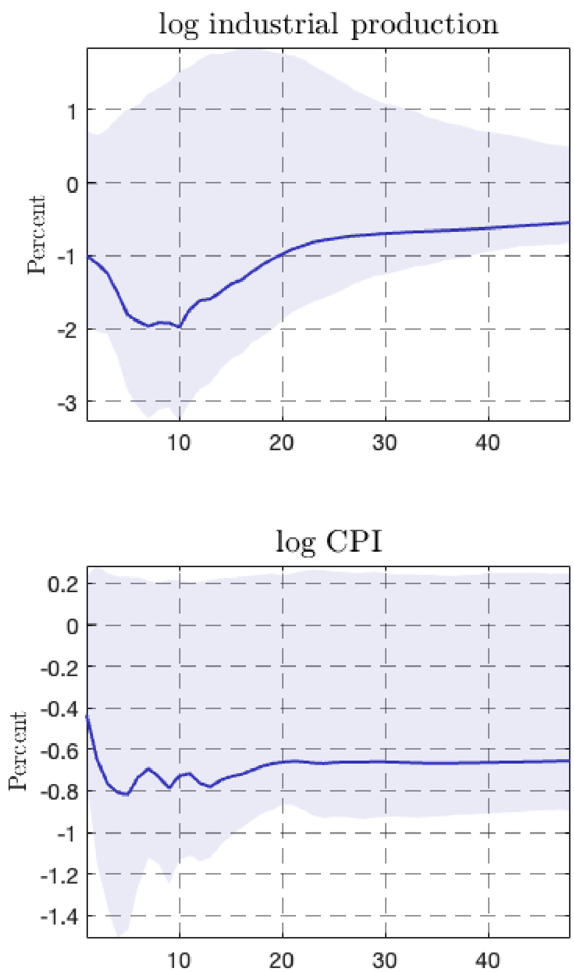
Impulse response functions from the baseline VAR model, $Y_t = B_0 + \sum_{i=1}^{p} Y_{t-i} + \nu\eta_t + e_t$. Endogenous variables Y_t include log industrial production, log CPI and excess bond premium. The shock η_t is normalized to raise FF4 by 1% on average. The sample for both Y_t and η_t goes from 1991m7 to 2019m3. The number of lags is 12 months. Shaded areas are 90% confidence interval constructed by a moving-block bootstrap.

Figure 6: Dynamic responses to a monetary tightening shock - a comparison with Gertler and Karadi (2015)



The red curves show the impulse responses to Gertler and Karadi (2015)'s policy instrument $FF4^{GK}$, while the blue ones show those to η_t. The sample for both endogenous variables and the shock series runs from 1991m7 to 2019m3.

Figure 7: Dynamic responses to a monetary tightening shock - a robustness check



Impulse response functions from a VAR model that differs from my baseline only by not having the excess bond risk premium in Y_t. See notes under Figure 5 for detailed specifications.

and Karadi (2020)'s monetary shock. For comparison with the latter category, I also create a monthly version of η_t by aggregating my daily values by month and treating the shock as zero for those months with no FOMC announcements.

Table 16 also shows the correlation coefficients of η_t with these alternative constructions. As one might expect from my earlier discussions, η_t largely co-moves with the ones that are also identified to remove the Fed information effect, such as Miranda-Agrippino and Rico (2021), Zhang (2019) and Jarociński and Karadi (2020). Even though η_t also has a nontrivially positive correlation with $FF4^{GK}$ and with $Target$, they display drastically different behavior in terms of their relations to business cycles, as I show in the next section.

Table 16: Overview of monetary shocks in the literature

Shock	Abbrev.	Corr. w/ η_t	Availability
Monthly			
Romer and Romer (2000)	RR	0.12	1969m3 - 2007m12
Gertler and Karadi (2015)	$FF4^{GK}$	0.29	1990m1 - 2012m6
Miranda-Agrippino and Rico (2021)	MAR	0.42	1991m2 - 2010m1
Zhang (2019)	Zhang	0.22	1988m3 - 2013m12
Jarociński and Karadi (2020)	JK	0.41	1990m2 - 2015m12
η_t, this paper	η_t	n.a.	1991m7 - 2019m3
Daily			
Path, Gürkaynak *et al.* (2005b)	Path	-0.50	1990m2 - 2004m12
Target, Gürkaynak *et al.* (2005b)	Target	0.57	1990m2 - 2004m12
Nakamura and Steinsson (2018)	NS	0.19	1995m2 - 2014m3
Zhang (2019)	Zhang	0.22	1988m3 - 2013m12
Bu *et al.* (2020)	BRW	-0.05	1994m2 - 2019m9
η_t, this paper	η_t	n.a.	1991m7 - 2019m3

6.2 Cyclicality

Exogenous monetary shocks ought to display no patterns of cyclicality with business cycles. If a series tends to be negative during and before a recession, it is likely a response of policymakers to their understanding of the state of the economy. I check if the shocks listed above are exogenous in this sense by running the following Probit regression.

$$IsRecession_t^h = \kappa_0^h + \kappa^h Shock_t + e_t^h \tag{13}$$

where $IsRecession_t^h$ is binary, taking the value of 1 if the economy is in an NBER recession h quarters following the shock and zero otherwise. I consider $h = 0, \ldots, 6$.

Table 17 shows that the target factor, the NS shock, the RR shock and the GK shock tend to precede a recession by 0-3 quarters when they take negative values. It indicates that they have captured some Fed information on bad economic fundamentals. In contrast, the proposed shock here along with the others that take care of the Fed information effect do not significantly predict recessions.

Notably, when I replace the regressor in Equation (13) with my constructed information shock, I show in Table 18 that it significantly predicts a recession in the current quarter or the next at the 5% level. This again proves the success of my decomposition.

6.3 Revisions of Blue Chip forecasts

For comparison, I repeat my exercise in Section 3.2 for all of the monetary shocks considered here. If a monetary shock is well identified to be expansionary, it should revise up Blue Chip forecasts for pro-cyclical variables. For each shock, I use the raw series as posted on the authors' websites and filter the data in the same way as Bauer and Swanson (2022) when running the regressions. Contemporaneous news as reflected in market surprises at data releases and in the financial variables are added in the regressions to control for the Fed response to news channel.

Table 19, 20 and 21 repeat the results for each of the proposed monetary shocks along with η_t. I highlight in red the coefficients that are statistically significantly different from zero but of the wrong sign. The first three columns confirm the findings in the literature (Campbell *et al.*, 2012; Nakamura and Steinsson, 2018). A shock that is constructed to be contractionary leads Blue Chip forecasters to significantly predict higher CPI, higher PPI, higher industrial production, higher real GDP or lower employment rate for at least one quarter in the future. These three shocks yield the most puzzling results because they do not control for the Fed information effect at all. Miranda-Agrippino and Rico (2021)'s information-robust shock performs slightly better in the sense that it results in fewer significant, incorrectly-signed coefficients. However, the shock is significantly correlated with an upward change in the forecasts for CPI and PPI in the third quarter. This suggests that the shock may still contain some remaining Fed information.

On the other hand, there is no overwhelming evidence for remaining Fed information in Jarociński and Karadi (2020) and Zhang (2019). The responses of Blue Chip forecasts are mostly insignificant. The desirable behavior of these proposals points out the importance of using asset prices of multiple dimensions and explicitly disentangling the Fed information

Table 17: Predictability of monetary shocks for NBER recessions

h (quarters)	0	1	2	3	4	5	6
Path	-0.69	-0.68	0.29	1.20	**2.35****	**2.00****	**4.01*****
	(0.89)	(1.15)	(1.15)	(1.29)	(0.96)	(0.91)	(1.50)
Target	**-3.00****	-2.12	-2.33	-0.50	2.03	1.91	2.29
	(1.28)	(1.65)	(1.53)	(2.03)	(1.32)	(1.68)	(2.87)
NS	**-7.18*****	**-8.13*****	**-5.31****	-2.16	0.05	0.09	2.04
	(2.78)	(3.06)	(2.65)	(2.59)	(2.68)	(2.66)	(3.33)
Zhang	-0.07	-0.93	0.09	0.66	-0.21	-2.07	-0.69
	(3.26)	(3.41)	(3.29)	(2.63)	(2.28)	(2.00)	(1.95)
BRW	-1.80	-0.87	1.44	0.69	1.34	0.83	1.42
	(4.47)	(4.07)	(3.48)	(2.96)	(3.07)	(2.73)	(2.60)
η_t (pre-ZLB)	0.54	-1.49	-1.58	-1.28	0.48	1.23	-1.16
	(7.93)	(8.48)	(7.74)	(7.39)	(6.78)	(6.60)	(3.37)
η_t (full sample)	0.39	-1.36	-1.43	-1.10	0.88	1.73	-0.97
	(9.79)	(11.23)	(10.60)	(10.08)	(9.10)	(8.77)	(4.38)
RR	**-0.41***	**-0.44***	-0.29	-0.08	-0.09	-0.13	0.05
	(0.22)	(0.24)	(0.21)	(0.17)	(0.17)	(0.16)	(0.18)
$FF4^{GK}$	**-6.41*****	**-4.85****	**-3.78****	0.08	0.75	0.83	4.15
	(2.01)	(1.94)	(1.86)	(2.16)	(2.29)	(2.42)	(2.66)
MAR	-0.45	-0.54	-1.68	1.67	1.05	0.43	1.09
	(3.02)	(3.22)	(2.81)	(3.06)	(2.63)	(2.43)	(1.71)
Zhang (monthly)	0.80	-0.52	-1.69	1.35	0.46	-0.47	0.25
	(4.41)	(3.96)	(3.48)	(3.16)	(2.90)	(2.78)	(2.23)
JK	-3.24	-2.91	-1.85	0.73	2.03	1.98	2.76
	(2.61)	(2.70)	(2.90)	(3.26)	(3.07)	(3.18)	(3.00)
η_t (monthly, pre-ZLB)	0.33	-1.27	-1.67	0.11	0.82	1.37	5.14
	(8.71)	(8.55)	(7.98)	(7.12)	(6.80)	(6.64)	(4.12)
η_t (monthly, full sample)	0.01	-1.41	-1.58	0.43	1.25	1.88	6.57
	(10.16)	(10.98)	(11.11)	(9.88)	(9.39)	(9.11)	(5.02)

Each cell reports a coefficient, κ^h, from a separate Probit regression: $IsRecession_t^h = \kappa_0^h + \kappa^h Shock_t + e_t^h$, where $IsRecession_t^h$ is one if the economy was in an NBER recession h quarters following Day t and zero otherwise, and $Shock_t$ is a monetary shock listed in the left-most column, taken directly from the original study that proposed it. Robust standard errors are in parentheses.

Table 18: Information shock ξ_t predicts near-future recessions

h (quarters)	0	1	2	3	4	5	6
Pre-ZLB	**-5.53****	**-5.21****	-2.38	-0.13	0.79	0.15	1.98
	(2.45)	(2.51)	(2.23)	(2.00)	(2.19)	(1.99)	(2.42)
Full sample	**-6.08****	**-5.89****	-2.76	-0.07	1.10	0.29	2.66
	(2.68)	(2.93)	(2.77)	(2.61)	(2.99)	(2.63)	(3.47)

Each cell reports a coefficient, κ_ξ^h, from a separate Probit regression: $IsRecession_t^h = \kappa_0^h + \kappa_\xi^h \xi_t + e_t^h$, where $IsRecession_t^h$ is one if the economy was in an NBER recession h quarters following Day t and zero otherwise. Robust standard errors are in parentheses.

effect for the identification of monetary policy.

To summarize the findings in this section, I conclude that the series proposed in this paper display expected features of monetary shocks. My approach is further desirable in its real-time availability and its point-identified feature.

Table 19: Blue Chip forecast revisions in response to various shocks

Panel (a): Industrial Production

h	Path	Target	NS	Zhang	BRW	MAR	JK	η_t
0	0.13	1.60	**3.54***	0.41	**2.36****	1.57	2.02	-0.22
	(0.73)	(1.32)	(1.85)	(1.63)	(0.99)	(1.21)	(1.30)	(2.16)
1	0.10	0.30	**1.98****	0.60	0.36	0.94	0.42	-0.44
	(0.30)	(0.55)	(0.81)	(0.69)	(0.63)	(0.71)	(0.62)	(1.07)
2	0.13	-0.02	0.72	0.28	-0.34	0.43	-0.32	-0.97
	(0.18)	(0.25)	(0.46)	(0.42)	(0.43)	(0.51)	(0.44)	(0.63)
3	0.17	-0.03	0.71	0.37	0.25	0.34	-0.41	**-0.95***
	(0.18)	(0.26)	(0.47)	(0.40)	(0.31)	(0.44)	(0.37)	(0.49)
4	0.15	-0.12	0.19	0.13	0.06	0.18	**-0.32***	**-1.22***
	(0.15)	(0.15)	(0.30)	(0.27)	(0.23)	(0.24)	(0.19)	(0.64)
5	0.17	-0.05	0.16	0.28	0.35	0.15	-0.20	**-1.09****
	(0.14)	(0.16)	(0.38)	(0.27)	(0.31)	(0.24)	(0.23)	(0.53)

Panel (b): Real GDP

h	Path	Target	NS	Zhang	BRW	MAR	JK	η_t
0	-0.06	0.15	**1.30***	0.16	0.33	0.46	0.12	-0.35
	(0.29)	(0.71)	(0.78)	(0.71)	(0.65)	(0.60)	(0.71)	(1.03)
1	0.18	0.31	**1.07****	0.29	0.22	0.33	-0.01	-0.32
	(0.14)	(0.31)	(0.44)	(0.39)	(0.43)	(0.48)	(0.42)	(0.65)
2	0.02	0.15	0.44	0.00	-0.09	0.19	-0.18	-0.50
	(0.11)	(0.15)	(0.37)	(0.33)	(0.32)	(0.39)	(0.30)	(0.45)
3	0.11	0.14	0.29	0.03	0.13	0.26	-0.10	-0.43
	(0.09)	(0.11)	(0.29)	(0.22)	(0.17)	(0.22)	(0.17)	(0.28)
4	0.13	0.06	0.31	0.15	**0.40*****	0.16	-0.08	0.11
	(0.08)	(0.11)	(0.23)	(0.18)	(0.15)	(0.20)	(0.17)	(0.36)
5	**0.28*****	-0.13	0.05	0.14	0.08	-0.06	-0.14	-0.50
	(0.10)	(0.17)	(0.32)	(0.23)	(0.15)	(0.16)	(0.24)	(0.49)

Table 20: Blue Chip forecast revisions in response to various shocks (cont.)

Panel (c): Unemployment Rate

h	Path	Target	NS	Zhang	BRW	MAR	JK	η_t
0	-0.05	**-0.13***	**-0.22****	-0.03	**-0.38****	-0.05	**-0.18***	-0.15
	(0.05)	(0.07)	(0.11)	(0.13)	(0.17)	(0.11)	(0.10)	(0.21)
1	**-0.23****	0.21	-0.17	0.11	-0.31	0.91	0.00	0.42
	(0.09)	(0.25)	(0.16)	(0.14)	(0.23)	(0.91)	(0.15)	(0.27)
2	-0.12	**-0.14***	**-0.32***	-0.06	-0.32	-0.11	-0.14	-0.04
	(0.08)	(0.08)	(0.19)	(0.15)	(0.21)	(0.16)	(0.14)	(0.25)
3	-0.09	-0.09	-0.36	0.08	**-0.51****	-0.01	-0.10	0.26
	(0.07)	(0.09)	(0.22)	(0.16)	(0.25)	(0.21)	(0.17)	(0.31)
4	-0.07	0.01	-0.18	0.25	-0.45	0.08	0.09	**0.87***
	(0.08)	(0.08)	(0.21)	(0.16)	(0.29)	(0.24)	(0.17)	(0.47)
5	**-0.16****	0.01	-0.23	0.22	**-0.74****	0.14	-0.07	**0.54***
	(0.07)	(0.08)	(0.19)	(0.16)	(0.31)	(0.18)	(0.15)	(0.32)

Panel (d): CPI

h	Path	Target	NS	Zhang	BRW	MAR	JK	η_t
0	0.31	0.08	**1.92***	0.75	-0.14	0.37	0.06	-1.02
	(0.26)	(0.30)	(1.16)	(0.71)	(0.95)	(0.91)	(0.64)	(1.32)
1	-0.04	**0.28****	-1.89	-0.64	-1.85	-1.70	0.97	0.75
	(0.09)	(0.14)	(1.45)	(0.78)	(1.47)	(1.55)	(0.81)	(1.51)
2	0.00	0.06	0.12	0.07	0.30	0.02	0.09	**0.38***
	(0.08)	(0.07)	(0.17)	(0.14)	(0.21)	(0.13)	(0.12)	(0.20)
3	-0.09	0.12	**0.27***	0.01	0.13	**0.28****	0.11	0.21
	(0.09)	(0.07)	(0.14)	(0.15)	(0.21)	(0.11)	(0.10)	(0.27)
4	0.05	-0.03	0.13	-0.03	-0.03	0.02	-0.04	0.05
	(0.09)	(0.08)	(0.16)	(0.14)	(0.21)	(0.11)	(0.12)	(0.29)
5	0.12	0.03	0.20	0.07	0.17	-0.02	0.14	-0.13
	(0.09)	(0.12)	(0.29)	(0.20)	(0.20)	(0.20)	(0.17)	(0.43)

Table 21: Blue Chip forecast revisions in response to various shocks (cont.)

Panel (e): PPI

h	Path	Target	NS	Zhang	BRW	MAR	JK	η_t
0	**0.93***	0.67	**5.62*****	**2.69****	**3.23***	2.09	1.59	-0.50
	(0.51)	(0.74)	(2.14)	(1.35)	(1.91)	(1.65)	(1.35)	(2.03)
1	-0.08	0.21	1.02	0.66	1.06	0.49	-0.03	-1.01
	(0.15)	(0.22)	(0.62)	(0.47)	(0.72)	(0.71)	(0.45)	(0.67)
2	0.00	-0.11	0.31	0.03	0.40	0.12	-0.20	-0.25
	(0.11)	(0.15)	(0.34)	(0.29)	(0.31)	(0.26)	(0.23)	(0.41)
3	**0.18****	-0.04	0.36	0.00	0.46	**0.50*****	0.19	-0.45
	(0.08)	(0.10)	(0.32)	(0.28)	(0.31)	(0.18)	(0.20)	(0.33)
4	0.11	-0.06	0.06	-0.27	-0.26	-0.12	-0.01	-0.48
	(0.12)	(0.12)	(0.27)	(0.23)	(0.40)	(0.24)	(0.18)	(0.53)
5	0.10	-0.07	0.26	0.07	0.54	-0.03	0.03	**-1.33*****
	(0.13)	(0.12)	(0.30)	(0.19)	(0.33)	(0.18)	(0.17)	(0.34)

Panel (f): GDP Price Index

h	Path	Target	NS	Zhang	BRW	MAR	JK	η_t
0	-0.15	0.00	0.15	-0.08	-0.43	0.01	-0.12	0.26
	(0.11)	(0.15)	(0.37)	(0.28)	(0.30)	(0.25)	(0.24)	(0.37)
1	0.04	0.02	0.17	0.02	0.14	0.04	0.07	0.10
	(0.08)	(0.14)	(0.19)	(0.18)	(0.21)	(0.19)	(0.16)	(0.25)
2	0.01	-0.08	0.08	-0.14	0.16	0.04	0.09	0.03
	(0.12)	(0.09)	(0.22)	(0.18)	(0.17)	(0.16)	(0.12)	(0.21)
3	0.00	0.06	0.14	0.00	**0.31****	0.06	0.15	-0.21
	(0.09)	(0.12)	(0.20)	(0.16)	(0.14)	(0.13)	(0.13)	(0.26)
4	-0.04	-0.10	-0.13	-0.12	0.09	-0.10	-0.11	-0.20
	(0.08)	(0.09)	(0.18)	(0.16)	(0.12)	(0.14)	(0.11)	(0.29)
5	3.53	-1.85	2.22	1.80	1.14	2.08	0.31	-10.40
	(3.04)	(1.91)	(2.40)	(1.89)	(1.06)	(2.15)	(0.95)	(9.96)

Each cell reports a predictive coefficient, α^h, from a separate OLS regression: $\Delta EI^h_{BC,m+1} = \alpha^h_0 + \alpha^h_S Shock_{t(m)} + \alpha^{h'}_F F^c_{t(m)} + \alpha^{h'}_X X_{t(m)} + e^h_{t(m)}$, where $\Delta EI^h_{BC,m+1}$ is the change in the Blue Chip forecast of the h-quarter-ahead economic indicator (EI) from Month m to Month $m+1$ and $Shock_{t(m)}$ is a monetary shock listed in the head row of each panel, taken directly from the original study that proposes it. $F^c_{t(m)}$ and $X_{t(m)}$ are vectors containing two sets of controls measuring contemporaneous news detailed in Section 3.2. In the rightmost column, the estimates repeat those in Column "η_t" in Table 15 and A5. Highlighted in red are coefficients for which the forecast revision responds to a monetary shocks with a significantly wrong sign. Robust standard errors are in parentheses.

7 Conclusion

As the FOMC announcements in the past three decades have increasingly accompanied policy decisions with discussions about economic fundamentals, it is reasonable to say that the Fed would want to sync its non-monetary information with the market through announcements. It is an empirical question to ask how much of what it discusses is new to the market, or equivalently whether or not there is a Fed information effect in the language of the literature. This paper proposes a novel approach to answering this question with limited point-identifying assumptions and the requirement of only public data. From a sample from late 1990 to early 2019, I decompose the high-frequency interest rate surprises around FOMC announcements into a Fed information shock and a monetary shock. With the decomposed Fed information shock, I am able to explain private forecast revisions for a variety of economic indicators after an announcement. The information shock captures the market's learning of industrial production, CPI and PPI in the current quarter and real GDP in the fifth quarter from an FOMC announcement. Reconciliating this result with those of Bauer and Swanson (2022), this paper suggests that the information asymmetry may come from the FOMC's better judgment of public news instead of its better access to information per se. Without the confounding effect of non-monetary news, the resulting monetary shock delivers theoretically-consistent dynamic responses of industrial production and CPI that are more pronounced and long-lasting than those without adjusting for the Fed information effect.

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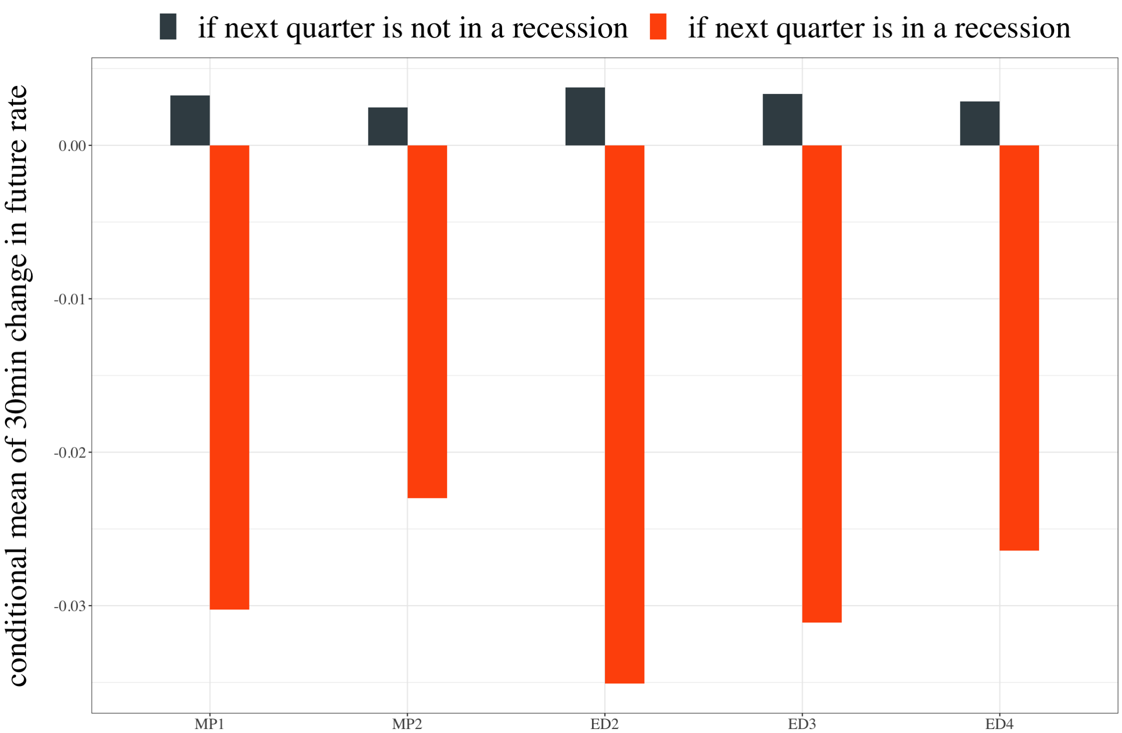
Appendices

A.1 Figure(s)

Figure A1: Easing policy consistently surprised interest rate futures market before recession



Listed on the x-axis are five assets reflecting market expectations of interest rates for various horizons. Y-axis plots the average change in the rate of each asset during a 30-minute window around an FOMC announcement across two samples. MP1 and MP2: federal funds future contracts to be settled at the end of the current month and the third month after the FOMC announcement. ED2, ED3 and ED4: Eurodollar future contracts to be settled at the end of the second, third and fourth quarter. The figure differs from Figure 1 only in that here all series are demeaned before being split into subsamples.

A.2 Estimation Procedure

The model in Section 2 is governed by the following parameter vector.

$$\Theta = (\tilde{\gamma}, \gamma, \beta, \sigma_\xi, \text{vech}(\Sigma_{\tilde{u}})', \text{diag}(\Sigma_u)')'$$

I estimate the parameters with maximum likelihood. The log-likelihood function for Day t depends on the type of event taking place on that day. Given data $y_t = (y_{1,t}, \ldots, y_{N,t})'$ or $\tilde{y}_t = (\tilde{y}_{1,t}, \ldots, \tilde{y}_{N,t})$ as defined in the main text, the model implies the following log-likelihood for Day t,

$$\begin{aligned} l\left(\Theta; y_t, \tilde{y}_t\right) = & \left(-\frac{N}{2}log(2\pi) - \frac{1}{2}log|\Sigma^F| - \frac{1}{2}y_t'(\Sigma^F)^{-1}y_t\right) d_t \\ & + \left(-\frac{N}{2}log(2\pi) - \frac{1}{2}log|\Sigma^D| - \frac{1}{2}\tilde{y}_t'(\Sigma^D)^{-1}\tilde{y}_t\right) \tilde{d}_t \left(1 - d_t\right) \\ & + \left(-\frac{N}{2}log(2\pi) - \frac{1}{2}log|\Sigma_{\tilde{u}}| - \frac{1}{2}\tilde{y}_t'\Sigma_0^{-1}\tilde{y}_t\right) \left(1 - \tilde{d}_t\right) \left(1 - d_t\right) \end{aligned}$$

where

$$\begin{aligned} d_t &= \begin{cases} 1, & \text{if Day t has an FOMC announcement} \\ 0, & \text{otherwise} \end{cases} \\ \tilde{d}_t &= \begin{cases} 1, & \text{if Day t has a major data release as determined in Table 1} \\ 0, & \text{otherwise} \end{cases} \end{aligned},$$

$\Sigma_{\tilde{u}}$ is the covariance matrix of $\tilde{y}_t$ if Day t has neither major data release nor an FOMC announcement. Σ^D is the covariance matrix of $\tilde{y}_t$ if Day t has a major data release and no FOMC announcements. Given the factor structure, we have

$$\Sigma^D = \tilde{\gamma}\tilde{\gamma}' + \Sigma_{\tilde{u}}$$

Σ^F is the covariance matrix of y_t if Day t has an FOMC announcement, i.e.

$$\Sigma^F = \gamma\sigma_\xi^2\gamma' + \beta\beta' + \Sigma_u.$$

The parameters are then estimated to maximize the log-likelihood function defined below for all days subject to constraints implied by the identifying assumptions.

$$\min_{\Theta} \quad L\left(\Theta; \{y_t, \tilde{y}_t\}_{t=1}^{T}\right) = \sum_{t=1}^{T} l\left(\Theta; y_t, \tilde{y}_t\right) \tag{A1}$$

$$s.t. \quad \gamma = \tilde{\gamma} \tag{A2}$$

$$\sum_{t=1}^{T} d_t \hat{\xi}_t \hat{\eta}_t = 0 \tag{A3}$$

I numerically solve this problem by using a function called *constrOptim.nl* in the *alabama* R package.

A.3 Replication of Evidence For/Against Fed Information Effect

Table A1: Replication of Campbell *et al.* (2012) and Nakamura and Steinsson (2018)

(a) Real variables

EI	h	Campbell et al. (2012) Target	Campbell et al. (2012) Path	NS (2018) Policy
Industrial Production	0	**2.24***	-0.13	**3.71***
		(1.29)	(0.84)	(2.19)
	1	0.39	-0.20	**2.07***
		(0.52)	(0.44)	(1.08)
	2	-0.19	-0.39	0.73
		(0.26)	(0.43)	(0.47)
	3	-0.34	-0.16	0.66
		(0.24)	(0.24)	(0.43)
	4	**-0.35***	0.18	0.06
		(0.18)	(0.15)	(0.28)
	5	-0.13	**0.37****	0.09
		(0.17)	(0.16)	(0.32)
Real GDP	0	0.54	-0.21	1.48
		(0.59)	(0.37)	(0.90)
	1	**0.41***	0.04	**1.16****
		(0.24)	(0.18)	(0.53)
	2	0.09	-0.01	0.39
		(0.14)	(0.12)	(0.34)
	3	0.07	0.12	0.26
		(0.12)	(0.10)	(0.27)
	4	-0.01	**0.23****	0.22
		(0.09)	(0.09)	(0.22)
	5	-0.16	**0.26*****	0.01
		(0.15)	(0.09)	(0.26)
Unemployment Rate	0	**-0.16****	-0.04	-0.20
		(0.07)	(0.06)	(0.14)
	1	0.13	-0.09	-0.23
		(0.27)	(0.08)	(0.22)
	2	**-0.23****	-0.07	-0.36
		(0.09)	(0.08)	(0.26)
	3	**-0.18***	-0.01	-0.39
		(0.09)	(0.09)	(0.29)
	4	-0.05	0.01	-0.17
		(0.07)	(0.08)	(0.29)
	5	-0.06	-0.06	-0.33
		(0.08)	(0.10)	(0.23)

(b) Price variables

EI	h	Campbell et al. (2012) Target	Campbell et al. (2012) Path	NS (2018) Policy
CPI	0	0.09	0.61	1.86
		(0.33)	(0.40)	(1.26)
	1	**0.31****	0.33	-1.07
		(0.14)	(0.30)	(1.09)
	2	0.07	-0.07	0.09
		(0.07)	(0.10)	(0.16)
	3	0.09	-0.12	0.20
		(0.07)	(0.09)	(0.15)
	4	-0.01	0.07	0.10
		(0.08)	(0.08)	(0.15)
	5	0.01	0.10	0.24
		(0.12)	(0.10)	(0.30)
PPI	0	0.82	**1.52****	**4.49****
		(0.74)	(0.67)	(2.27)
	1	0.20	0.43	0.61
		(0.25)	(0.42)	(0.60)
	2	-0.10	-0.06	-0.02
		(0.16)	(0.13)	(0.28)
	3	-0.05	0.10	0.08
		(0.10)	(0.12)	(0.31)
	4	0.05	-0.03	0.02
		(0.13)	(0.14)	(0.25)
	5	-0.05	0.06	0.13
		(0.12)	(0.17)	(0.30)
GDP Price Index	0	-0.03	0.05	0.22
		(0.16)	(0.18)	(0.39)
	1	0.11	0.10	0.12
		(0.12)	(0.18)	(0.21)
	2	0.01	0.02	0.05
		(0.08)	(0.13)	(0.21)
	3	0.08	0.06	0.08
		(0.12)	(0.10)	(0.21)
	4	-0.10	-0.02	-0.09
		(0.07)	(0.08)	(0.17)
	5	-0.44	0.70	2.22
		(0.54)	(0.65)	(2.34)

Each row in the columns labeled "Campbell et al. (2012)" presents a pair of coefficients, α^h_{Target} and α^h_{Path}, from a separate regression: $\Delta EI^h_{t(m)} = \alpha^h_0 + \alpha^h_{Target} Target_{t(m)} + \alpha^h_{Path} Path_{t(m)} + e^h_{t(m)}$ on a sample from 1990m2 to 2007m6, where $Target_{t(m)}$ and $Path_{t(m)}$ are replicated following the authors' procedure. Each cell in the columns labeled "NS (2018)" presents a coefficient, α^h_P, from a separate regression: $\Delta EI^h_{t(m)} = \alpha^h_0 + \alpha^h_P Policy_{t(m)} + e^h_{t(m)}$ on a sample from 1995m1 to 2014m4, where $Policy_{t(m)}$ is taken from authors' website. The samples for both regressions exclude the announcement in 2001m9, those made in the first three business days of a month before 2000m12 and in the first two business days in and after 2000m12. Robust standard errors are in parentheses.

Table A2: Replication of Bauer and Swanson (2022)

(a) Real variables

EI	h	Campbell et al. (2012)		NS (2018)
		Target	Path	Policy
Industrial Production	0	-0.09	0.27	0.06
		(1.55)	(0.96)	(1.78)
	1	-0.24	-0.25	-0.53
		(0.75)	(0.56)	(0.86)
	2	-0.37	-0.65	**-0.90****
		(0.23)	(0.41)	(0.43)
	3	-0.13	-0.08	-0.19
		(0.18)	(0.29)	(0.31)
	4	-0.20	0.31	-0.02
		(0.19)	(0.26)	(0.28)
	5	-0.22	0.47	0.08
		(0.14)	(0.29)	(0.30)
Real GDP	0	-0.38	-0.53	-0.83
		(0.49)	(0.46)	(0.56)
	1	-0.30	-0.42	**-0.67***
		(0.31)	(0.29)	(0.39)
	2	**-0.34****	**-0.46****	**-0.69****
		(0.16)	(0.23)	(0.27)
	3	-0.12	-0.26	-0.32
		(0.10)	(0.19)	(0.21)
	4	-0.10	-0.03	-0.13
		(0.13)	(0.14)	(0.17)
	5	0.08	0.10	0.21
		(0.12)	(0.16)	(0.19)
Unemployment Rate	0	0.07	0.06	0.12
		(0.08)	(0.09)	(0.10)
	1	**0.26****	-0.02	**0.28***
		(0.11)	(0.10)	(0.16)
	2	0.21	0.11	**0.31***
		(0.13)	(0.11)	(0.18)
	3	**0.29****	0.07	**0.37***
		(0.14)	(0.13)	(0.20)
	4	**0.50*****	-0.01	**0.58*****
		(0.13)	(0.17)	(0.17)
	5	**0.27*****	-0.06	0.28
		(0.09)	(0.15)	(0.18)

(b) Price variables

EI	h	Campbell et al. (2012)		NS (2018)
		Target	Path	Policy
CPI	0	**-0.84****	-0.07	**-0.94***
		(0.37)	(0.51)	(0.56)
	1	0.31	**2.57***	2.20
		(0.78)	(1.38)	(1.37)
	2	-0.01	-0.15	-0.14
		(0.10)	(0.11)	(0.15)
	3	0.12	**-0.19***	-0.01
		(0.08)	(0.11)	(0.13)
	4	-0.01	0.04	0.04
		(0.08)	(0.13)	(0.12)
	5	**-0.40*****	0.25	-0.25
		(0.12)	(0.18)	(0.24)
PPI	0	-0.59	-1.27	-1.50
		(0.68)	(1.30)	(1.18)
	1	-0.26	-0.89	-0.95
		(0.36)	(0.61)	(0.63)
	2	0.04	**-0.55***	-0.41
		(0.21)	(0.29)	(0.36)
	3	**0.26***	0.07	0.34
		(0.15)	(0.25)	(0.24)
	4	0.07	-0.09	0.04
		(0.20)	(0.23)	(0.22)
	5	**-0.30***	0.25	-0.15
		(0.15)	(0.24)	(0.30)
GDP Price Index	0	-0.22	-0.12	-0.32
		(0.19)	(0.18)	(0.26)
	1	0.01	-0.14	-0.12
		(0.12)	(0.12)	(0.16)
	2	-0.04	-0.12	-0.14
		(0.09)	(0.13)	(0.14)
	3	-0.08	-0.04	-0.11
		(0.13)	(0.14)	(0.15)
	4	-0.14	-0.12	**-0.25***
		(0.12)	(0.14)	(0.15)
	5	-1.22	6.17	3.21
		(1.52)	(5.67)	(3.68)

Each row in the columns labeled "Campbell et al. (2012)" presents a pair of coefficients, α^h_{Target} and α^h_{Path}, from a separate regression: $\Delta EI^h_{t(m)} = \alpha^h_0 + \alpha^h_{Target} Target_{t(m)} + \alpha^h_{Path} Path_{t(m)} + \alpha^{h\prime}_c control_{t(m)} + e^h_{t(m)}$, where $Target_{t(m)}$ and $Path_{t(m)}$ are constructed based on Gürkaynak *et al.* (2005b). Each cell in the columns labeled "NS (2018)" presents a coefficient, α^h_P, from a separate regression: $\Delta EI^h_{t(m)} = \alpha^h_0 + \alpha^h_P Policy_{t(m)} + \alpha^{h\prime}_X X_{t(m)} + \alpha^{h\prime}_c control_{t(m)} + e^h_{t(m)}$, where $Policy_{t(m)}$ is constructed based on Nakamura and Steinsson (2018). $control_{t(m)}$ is a vector of controls containing variables in (i)-(v) in the main text. For all columns the sample goes from 1991m7 to 2019m3, excluding the announcement in 2001m9, those in the first three business days of a month before 2000m12 and in the first two business days in and after 2000m12. Robust standard errors are shown in parentheses.

Table A3: Predictability for interest rate surprises by the Bloomberg commodity price index over different windows

	FF4	ED2	ED3	ED4	2-year T yield
${}^{q}\Delta BCOM_{t(m)}$	0.13	**0.22***	**0.26****	**0.28****	**0.16****
	(0.09)	(0.12)	(0.12)	(0.11)	(0.08)
${}^{s}\Delta BCOM_{t(m)}$	**0.19***	**0.33****	**0.38*****	**0.40*****	**0.25*****
	(0.10)	(0.13)	(0.13)	(0.12)	(0.08)
${}^{c}\Delta BCOM_{t(m)}$	-0.03	-0.08	-0.04	-0.04	-0.10
	(0.14)	(0.16)	(0.19)	(0.20)	(0.15)

Each cell reports a coefficient, ϕ_{bcom}, from a separate regression: $y_{t(m)} = \phi_0 + \phi_{bcom}\,{}^{i}\Delta BCOM_{t(m)} + \phi_X X_{t(m)} + u_{t(m)}$ $(i = q, s, c)$, where $y_{t(m)}$ is the surprise change in one of the five interest rates within a 30-minute window around an FOMC announcement, $BCOM$ is the Bloomberg commodity price index, and $X_{t(m)}$ contains the market surprises at the released nonfarm payrolls, the unemployment rate, and the CPI inflation rate in Month m. The windows over which changes in BCOM are taken, as denoted by ${}^{q}\Delta$, ${}^{s}\Delta$ and ${}^{c}\Delta$, are illustrated in Figure 4.

Table A4: Predictability for GB-BC forecast differences by stale news

h (quarter)	Real GDP (1)	Real PCE (2)	Industrial Production (3)	Unemp. Rate (4)	Consumer Price Index (5)
0	0.65	-0.96	**4.36***	0.05	**8.21*****
	(1.02)	(-0.90)	(1.92)	(0.42)	(5.36)
1	**2.33***	1.24	2.97	-0.03	**5.39*****
	(1.86)	(1.48)	(1.34)	(-0.15)	(5.41)
2	**2.10****	-1.03	-0.16	0.00	**-1.95*****
	(2.51)	(-1.16)	(-0.10)	(0.02)	(-3.39)
3	**2.58****	0.46	1.23	-0.09	**-1.10****
	(2.48)	(0.40)	(1.00)	(-0.40)	(-2.42)
4	**3.75*****	**2.22*****	**2.28*****	-0.38	-0.33
	(4.57)	(3.05)	(2.80)	(-1.44)	(-0.99)
5	**3.39*****	**1.88****	**2.84****	-0.61	-0.17
	(3.98)	(2.10)	(2.12)	(-1.38)	(-0.30)
6	**3.43*****	1.41	**5.08*****	**-1.20***	0.36
	(2.68)	(1.14)	(3.52)	(-1.83)	(0.46)
7	**5.66*****	2.60	2.15	-2.12	0.11
	(3.18)	(1.46)	(1.17)	(-1.64)	(0.09)

Each cell reports a coefficient, ϕ_{bcom}, from a separate regression: $EI^{h}_{GB,t(m)} - EI^{h}_{BC,m} = \phi_0 + \phi_{bcom}\,{}^{s}\Delta BCOM_{t(m)} + \phi_X X_{t(m)} + u_{t(m)}$, where ${}^{s}\Delta BCOM_{t(m)}$ is the change in the BCOM price index from one quarter before the FOMC announcement on Day t of Month m to the last day of the Blue Chip survey at the beginning of Month m. $X_{t(m)}$ is a (3×1) vector containing the market surprises at the releases of non-farm payrolls, the unemployment rate, and the CPI inflation rate in Month m if the releases occurred between the Blue Chip survey and the FOMC announcement in Month m (filled with zero otherwise).

A.4 Additional Corroborating Evidence on Composite Measures

Table A5: Blue Chip regressions controlling for news, 1991m7 - 2019m3

(a) Industrial Production

h	PC	ξ_t	η_t
0	**2.57***	**2.64***	-0.22
	(1.32)	(1.34)	(2.16)
1	**1.28****	**1.36****	-0.44
	(0.57)	(0.56)	(1.07)
2	0.32	0.40	-0.97
	(0.36)	(0.36)	(0.63)
3	0.32	0.40	**-0.95***
	(0.38)	(0.37)	(0.49)
4	0.17	0.35	**-1.22***
	(0.25)	(0.25)	(0.64)
5	0.31	0.43	**-1.09****
	(0.29)	(0.27)	(0.53)

(b) CPI

PC	ξ_t	η_t
1.44*	**1.77****	-1.02
(0.81)	(0.87)	(1.32)
-0.89	-0.55	0.75
(0.92)	(0.76)	(1.51)
0.03	0.04	**0.38***
(0.13)	(0.13)	(0.20)
0.13	0.11	0.21
(0.13)	(0.14)	(0.27)
0.10	0.14	0.05
(0.12)	(0.14)	(0.29)
0.13	0.17	-0.13
(0.20)	(0.22)	(0.43)

(c) GDP Price Index

PC	ξ_t	η_t
0.12	0.12	0.26
(0.30)	(0.33)	(0.37)
0.16	0.15	0.10
(0.16)	(0.17)	(0.25)
0.04	0.05	0.03
(0.17)	(0.19)	(0.21)
0.14	0.17	-0.21
(0.14)	(0.16)	(0.26)
-0.06	-0.06	-0.20
(0.14)	(0.16)	(0.29)
3.16	3.44	-10.40
(2.98)	(3.13)	(9.96)

Each cell in the columns labeled "PC" presents a coefficient, α^h_{PC}, from a separate regression: $\Delta EI^h_{t(m)} = \alpha^h_0 + \alpha^h_{PC} PC_{t(m)} + \alpha^{h'}_X X_{t(m)} + \alpha^{h'}_F F^c_{t(m)} + e^h_{t(m)}$. Each row in the columns labeled "ξ_t" and "η_t" presents a pair of coefficients, α^h_ξ and α^h_η, from a separate regression: $\Delta EI^h_{t(m)} = \alpha^h_0 + \alpha^h_\xi \xi_{t(m)} + \alpha^h_\eta \eta_{t(m)} + \alpha^{h'}_X X_{t(m)} + \alpha^{h'}_F F^c_{t(m)} + e^h_{t(m)}$. $X_{t(m)}$ is a (3×1) vector containing the market surprises at the released numbers of the non-farm payrolls, the unemployment rate and the CPI inflation rate if they occurred between the Blue Chip survey and the FOMC announcement in Month m (filled with zero otherwise). $F^c_{t(m)}$ is a (3×1) vector containing the changes in the S&P500 price index, the yield curve slope and the BCOM index between the Blue Chip survey at the beginning of Month m and the FOMC announcement in Month m. The sample is from 1991m7 to 2019m3, excluding the announcement in 2001m9 and those made in the first three business days of a month before 2000m12 and three business days in and after 2000m12. Robust standard errors are in parentheses.

Table A6: Robustness to the Fed Response to Economic News Channel - Real Variables

EI	h	ξ_t	η_t	ξ_t	η_t	ξ_t	η_t
Industrial Production	0	**3.08****	0.66	**2.19***	-3.05	0.19	-3.56
		(1.46)	(2.41)	(1.30)	(2.15)	(1.69)	(2.48)
	1	**1.50****	0.56	0.81	-1.10	-0.54	-1.21
		(0.64)	(1.55)	(0.78)	(1.15)	(0.93)	(1.30)
	2	0.47	-0.45	0.07	-0.49	**-1.16****	-0.70
		(0.36)	(0.85)	(0.46)	(0.59)	(0.57)	(0.60)
	3	0.41	-0.74	**0.58***	-0.33	-0.25	-0.39
		(0.35)	(0.55)	(0.34)	(0.41)	(0.41)	(0.41)
	4	0.25	**-1.18****	**0.67****	**-1.35***	0.16	-1.03
		(0.23)	(0.57)	(0.33)	(0.81)	(0.33)	(0.82)
	5	0.37	-0.62	**0.76****	**-1.66****	0.28	**-1.30***
		(0.25)	(0.50)	(0.34)	(0.66)	(0.32)	(0.71)
Real GDP	0	0.81	0.44	0.19	-0.45	**-1.08***	-0.67
		(0.68)	(1.30)	(0.53)	(0.86)	(0.62)	(0.95)
	1	**0.88****	0.26	0.01	-0.39	**-0.80***	-0.37
		(0.37)	(0.98)	(0.37)	(0.60)	(0.46)	(0.61)
	2	0.19	-0.57	-0.16	-0.36	**-0.89****	-0.37
		(0.27)	(0.51)	(0.31)	(0.43)	(0.34)	(0.38)
	3	0.13	-0.38	0.12	-0.32	-0.40	-0.38
		(0.24)	(0.31)	(0.26)	(0.25)	(0.28)	(0.24)
	4	0.25	0.19	0.36	0.47	-0.17	0.20
		(0.18)	(0.41)	(0.24)	(0.41)	(0.22)	(0.45)
	5	0.22	-0.41	0.32	0.58	0.17	0.54
		(0.15)	(0.41)	(0.25)	(0.47)	(0.23)	(0.44)
Unemployment Rate	0	**-0.20****	-0.26	-0.14	-0.06	0.14	0.04
		(0.10)	(0.23)	(0.12)	(0.20)	(0.11)	(0.16)
	1	-0.08	0.10	-0.13	0.35	0.24	**0.42***
		(0.23)	(0.34)	(0.17)	(0.23)	(0.18)	(0.23)
	2	**-0.38****	-0.34	-0.11	0.06	0.33	0.14
		(0.18)	(0.42)	(0.19)	(0.28)	(0.20)	(0.31)
	3	**-0.39****	-0.07	-0.14	0.36	**0.41***	0.47
		(0.19)	(0.46)	(0.18)	(0.32)	(0.22)	(0.28)
	4	-0.14	0.45	0.01	**1.39****	**0.56*****	**1.23*****
		(0.19)	(0.75)	(0.24)	(0.69)	(0.20)	(0.46)
	5	-0.27	-0.21	-0.18	**0.73***	0.21	0.51
		(0.16)	(0.52)	(0.18)	(0.39)	(0.22)	(0.44)
data releases				✓		✓	
$^c\Delta$ in S&P, Slope, BCOM				✓			
time trend				✓		✓	
lagged BC revision				✓		✓	
lagged macro indicators				✓		✓	
GDP surprise				✓		✓	
BBK Index						✓	
$^q\Delta$ in S&P, Slope, BCOM						✓	

Estimated α^h_ξ and α^h_η from regression: $\Delta EI^h_{t(m)} = \alpha^h_0 + \alpha^h_\xi \xi_{t(m)} + \alpha^h_\eta \eta_{t(m)} + \alpha^{h\prime}_c control_{t(m)} + e^h_{t(m)}$, where $control_{t(m)}$ is a vector of controls varying across panels as listed in the lower panel. See the main text and Figure 4 for detailed definitions. The sample is from 1991m7 to 2019m3, excluding the announcement in 2001m9 and those made in the first three business days of a month before 2000m12 and three business days in and after 2000m12. Robust standard errors are in parentheses.

Table A7: Robustness to the Fed Response to Economic News Channel - Price Variables

EI	h	ξ_t	η_t	ξ_t	η_t	ξ_t	η_t
CPI	0	**1.63***	-1.08	**1.19***	**-2.49***	-0.96	**-1.95****
		(0.95)	(1.57)	(0.70)	(1.35)	(0.65)	(0.95)
	1	-0.15	0.44	0.10	0.07	**3.50***	0.22
		(0.73)	(1.71)	(1.53)	(1.60)	(1.88)	(1.92)
	2	0.04	**0.33***	0.00	**0.38***	-0.18	**0.37***
		(0.13)	(0.20)	(0.15)	(0.21)	(0.17)	(0.20)
	3	0.10	0.09	0.13	0.04	-0.06	0.04
		(0.14)	(0.21)	(0.14)	(0.32)	(0.17)	(0.34)
	4	0.12	-0.06	0.15	-0.26	0.01	-0.23
		(0.14)	(0.26)	(0.17)	(0.30)	(0.17)	(0.29)
	5	0.19	0.02	0.12	**-0.93***	-0.20	-0.77
		(0.22)	(0.39)	(0.24)	(0.51)	(0.27)	(0.56)
PPI	0	**3.54****	-0.49	**2.93****	-1.83	-2.13	-1.28
		(1.65)	(2.66)	(1.46)	(1.93)	(1.62)	(1.68)
	1	0.58	-1.02	0.84	-1.07	-1.28	-1.11
		(0.42)	(0.84)	(0.62)	(0.93)	(0.86)	(0.96)
	2	-0.03	-0.39	0.20	0.24	-0.60	0.16
		(0.24)	(0.40)	(0.39)	(0.49)	(0.44)	(0.49)
	3	0.18	-0.45	0.33	-0.41	0.50	-0.34
		(0.28)	(0.28)	(0.39)	(0.41)	(0.33)	(0.37)
	4	0.04	-0.37	-0.19	-0.16	0.15	-0.16
		(0.21)	(0.58)	(0.32)	(0.82)	(0.27)	(0.80)
	5	0.19	**-1.00****	0.14	-0.93	-0.04	-0.80
		(0.18)	(0.42)	(0.29)	(0.66)	(0.33)	(0.68)
GDP Price Index	0	0.15	0.13	0.08	-0.50	-0.31	-0.36
		(0.33)	(0.38)	(0.38)	(0.46)	(0.32)	(0.35)
	1	0.14	0.09	0.09	-0.13	-0.10	-0.12
		(0.18)	(0.26)	(0.19)	(0.27)	(0.19)	(0.25)
	2	0.03	-0.07	0.03	-0.15	-0.19	-0.13
		(0.19)	(0.23)	(0.20)	(0.21)	(0.19)	(0.23)
	3	0.15	-0.30	0.05	-0.45	-0.16	-0.44
		(0.16)	(0.26)	(0.20)	(0.28)	(0.18)	(0.30)
	4	-0.05	-0.18	-0.16	-0.16	**-0.34***	-0.11
		(0.16)	(0.29)	(0.23)	(0.37)	(0.20)	(0.35)
	5	2.84	-8.21	5.11	-14.28	6.19	-13.74
		(2.72)	(8.30)	(4.78)	(13.30)	(6.11)	(13.85)
data releases				✓		✓	
$^c\Delta$ in S&P, Slope, BCOM				✓			
time trend				✓		✓	
lagged BC revision				✓		✓	
lagged macro indicators				✓		✓	
GDP surprise				✓		✓	
BBK Index						✓	
$^q\Delta$ in S&P, Slope, BCOM						✓	

Estimated α_ξ^h and α_η^h from regression: $\Delta EI_{t(m)}^h = \alpha_0^h + \alpha_\xi^h \xi_{t(m)} + \alpha_\eta^h \eta_{t(m)} + \alpha_c^{h'} control_{t(m)} + e_{t(m)}^h$, where $control_{t(m)}$ is a vector of controls varying across panels as listed in the lower panel. See the main text and Figure 4 for detailed definitions. The sample is from 1991m7 to 2019m3, excluding the announcement in 2001m9 and those made in the first three business days of a month before 2000m12 and three business days in and after 2000m12. Robust standard errors are in parentheses.