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: E50, G10, C10

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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 resulted 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 isolates the contribution of the revelation of Fed information to rate responses from that of a policy shock in

[1] One may notice that for each asset the *unconditional* mean of the rate change is also negative. This may reflect the secular downward trend in the interest rates over the sample period. Instead of looking for the driving forces behind the trend, this paper focuses on the potential revelation of Fed information on business cycles. Figure A1 in Appendix A.1 plots a version of the graph where the unconditional mean is subtracted from the whole sample.

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.

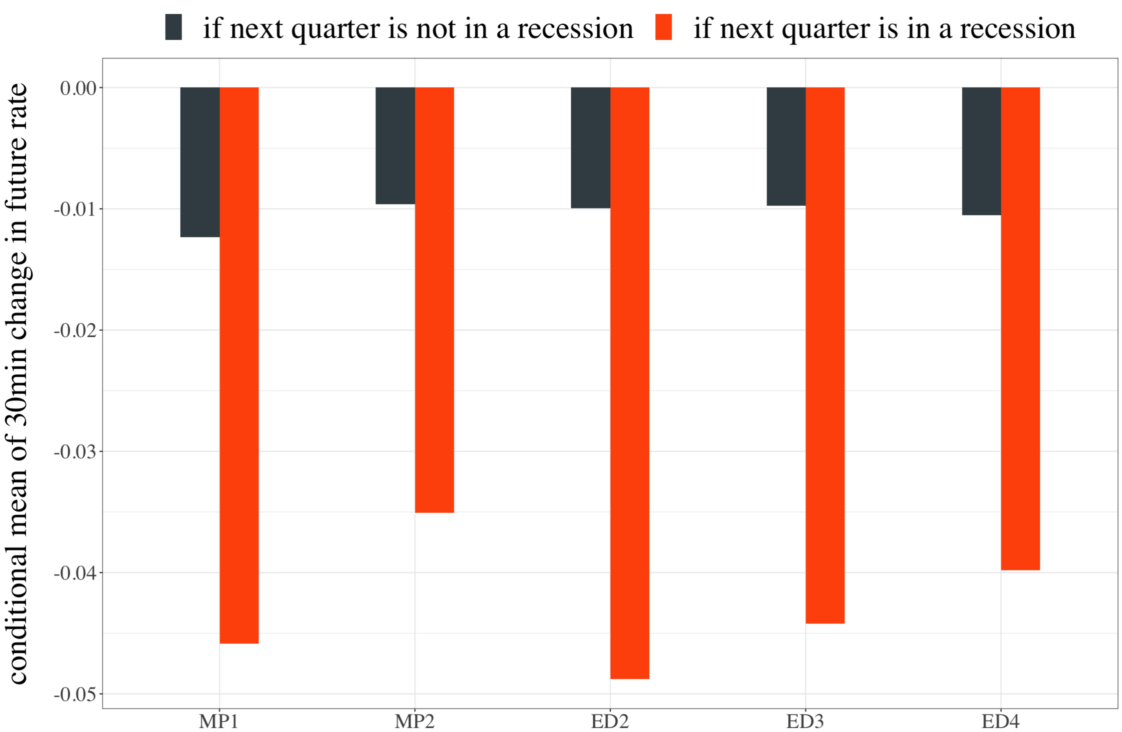


Figure 1: Easing policy consistently surprised interest rate futures market before recession

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 to an FOMC announcement during the 30-minute window; (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 revisions 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 Ricco (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 information shock to be the macro news revealed by *an FOMC announcement* instead of a data release. My framework estimates different realizations of the macro news for these two types of events in the same period whereas they do not. After all, market participants may learn a lot from an FOMC announcement even if they do not learn much from a data release. 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 5.0% in 10 months. It causes CPI to adjust quickly and shift down by nearly 2.0% 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 Ricco (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 further argue for 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 revelation 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 measures of monetary shocks 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 sufficient 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 (FF4), the two-, three-, and four-quarter-ahead eurodollar futures contracts (ED2, ED3, ED4) 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]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.

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, $\tilde{\xi}_t \sim \text{iid}\,(0,1)$, which elicits responses of the N interest rates 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, $\tilde{u}_t \sim \text{iid}\,(0, \Sigma_{\tilde{u}})$, 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 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.

Equation (1) uses the factor structure in the interest rates to identify macro news in a data release. The estimated factor captures not only the market surprise at the headline number, as is usually the focus of the literature and proxied by the difference between the released number and the market expectation for it, but also news in all other aspects of the release. The latter is difficult to measure directly but essential for accounting for the market response to the event (Gürkaynak *et al.*, 2018).

In general, one may use more than one latent factor to capture news in different types of data releases. However, I find that one factor is sufficient to do so over the sample from 1990m1 to

[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 data release?
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 fourth column indicates whether the Type-k release is determined to be a major one.

2008m12. To see this, I conduct another bootstrapped χ^2-test proposed by Wright (2012). Let Σ^D denote the covariance of $\tilde{y}_t$ on all the release days regardless of the release type. The null hypothesis is the restriction imposed by Equation (1): $\Sigma^D - \Sigma_{\tilde{u}} = \tilde{\gamma}\tilde{\gamma}'$ for $\tilde{\gamma}$ an $(N \times 1)$ vector.[4] Based on the p-value of 0.08 for this test in Table 2, one cannot reject the null at the 5% level that a single factor summarizes well the movements of short-term interest rates around different types of releases.[5] This implies that the bond market consistently perceived and cared about only one dimension of economic news as reflected in those interest rates.

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

	Sample period	p-value
pre-ZLB	1990m1 - 2008m12	0.079

The null hypothesis is that $\Sigma^D - \Sigma_{\tilde{u}} = \tilde{\gamma}\tilde{\gamma}'$, where $\tilde{\gamma}$ is an $(N \times 1)$ 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. The test statistic is $\chi^2 = [\mathrm{vech}(\hat{\Sigma}^D - \hat{\Sigma}_{\tilde{u}}) - \mathrm{vech}(\hat{\tilde{\gamma}}\hat{\tilde{\gamma}}')]'(\hat{V}^D + \hat{V}_{\tilde{u}})^{-1}[\mathrm{vech}(\hat{\Sigma}^D - \hat{\Sigma}_{\tilde{u}}) - \mathrm{vech}(\hat{\tilde{\gamma}}\hat{\tilde{\gamma}}')]$, where $\hat{V}^D$ and $\hat{V}_{\tilde{u}}$ are the estimated covariances of $\mathrm{vech}(\hat{\Sigma}^D)$ and $\mathrm{vech}(\hat{\Sigma}_{\tilde{u}})$, respectively. The p-value is constructed by comparing χ^2 against a distribution of its boostrapped analogs.

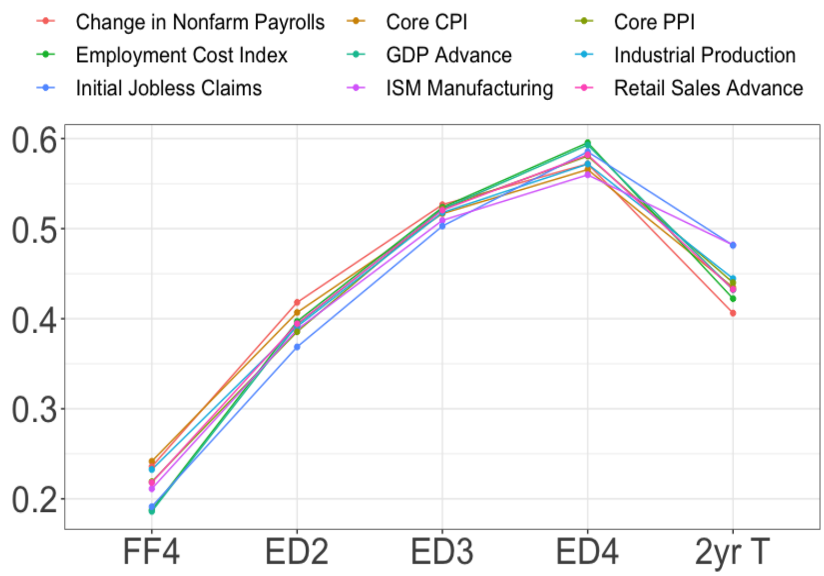
The one-factor specification implies similar responses of the short end of the yield curve to different data releases. To visualize this in the data, Figure 2 plots the estimated eigenvector

[4] In Equation (1), the unconditional variance of $\tilde{\xi}_t$ has been normalized to 1 to separately identify $\tilde{\gamma}$ and $\tilde{\xi}_t$. This does not restrict the variance of $\tilde{\xi}_t$ conditional on the type of release; the releases that have historically elicited a bigger response in $\tilde{y}_t$ will show up as having large realizations of $\tilde{\xi}_t$.

[5] 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.

associated with the first principal component of the covariance matrix of $\tilde{y}_t$ for each type of release. Strikingly, no matter which economic indicator got released, the interest rates responded in the same hump-shaped manner even though the overall magnitude of the response could vary with release type as reflected by the release-specific eigenvalues. In the next two subsections, I will use this insight to model the rate responses to FOMC announcements.

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 is from 1990m1 to 2008m12.

2.2 Interest rates around FOMC announcements

This section models the responses of interest rates to an FOMC 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. I use a latent factor model to summarize the various reasons why the interest rates may move in this window:[6]

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

where $\xi_t \sim \text{iid}\ (0, \sigma_\xi^2)$ is a Fed information shock, $\eta_t \sim \text{iid}\ (0,1)$ is an exogenous monetary shock, and $u_t \sim \text{iid}\ (0, \Sigma_u)$ is an $(N \times 1)$ vector of white noises capturing the idiosyncratic movements in

[6]Note the difference in the notations between y_t and $\tilde{y}_t$. They correspond to the rate changes in different windows around the event. Section 2.3 discusses how I handle the difference.

y_t.

Fed information shock, ξ_t. This 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 a rate cut bigger than 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 factor accounts for the changes of interest rates due to the Fed announcing an unexpected course of policy commitments. Because the factor is extracted from interest rates of a range of maturities, it captures the Fed's commitment to changing the federal funds rate not only in the current month but also in the future.[7] 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).

2.3 Identifying assumptions

The key to isolating η_t from ξ_t in Equation (2) is to think of an FOMC announcement as a sum of a major macro data release and a purely monetary announcement. Assumption 1 below formalizes the partial resemblance of FOMC announcements to data releases by connecting the factor loadings in Equation (1) and (2).

Assumption 1: $\gamma = \tilde{\gamma}$, with the first element of $\tilde{\gamma}$ being positive and $\sigma_\xi^2 = \text{var}(\xi_t)$ a free parameter.

The assumption requires 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 in data releases, $\tilde{\xi}_t$. Note that the size and the sign of ξ_t and $\tilde{\xi}_t$ are estimated to be different for every date t, meaning that the model-implied rate movements change from event to event as is the case in the data.

The average 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, which would show up as having a different sample variance on FOMC announcement days compared to data release days. To recognize this, I allow the variance of ξ_t to be different from one which is

[7]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.

the normalized variance of $\tilde{\xi}_t$. In other words, Assumption 1 only requires that interest rates of various maturities respond to economic news always in the same proportions. It does not restrict the absolute magnitude of the responses to FOMC announcements.

The free parameter σ_{ξ}^2 also flexibly accommodates the difference in the window width chosen for an FOMC announcement versus a data release. In this paper, I use a 30-minute window to compute the rate changes around FOMC announcements and a daily window for data releases (hence the difference in notations between $\tilde{y}_t$ and y_t). Although the choice of the window width is dictated by data availability, it should not raise any concern about the validity of the strategy. On the one hand, daily changes have been shown to capture the market response to data releases better than intraday changes. For example, Altavilla *et al.* (2017) find that macro data releases have a persistent effect on nominal bond yields. Bauer (2015a) argues that the delayed response of real bond yields to such events is likely to be missed by intraday windows. On the other hand, the yield curve tends to respond to an FOMC announcement fairly quickly within the 20 minutes after the event (Gürkaynak *et al.*, 2005b). Using a daily window instead would introduce unnecessary noise into the data (Nakamura and Steinsson, 2018).

The partial resemblance of FOMC announcements to data releases also motivates my choice for the dimension of ξ_t. Since economic news in data releases can be summarized by a scalar $\tilde{\xi}_t$, it is natural to assume a single factor for the Fed information component in y_t. One concern that researchers may have about this 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 separate the monetary shock from the Fed information shock, it is important to rule out the knife-edge case where the two shocks change the short-term interest rate in exactly the same proportions:

Assumption 2: There exists no constant $c \in \mathscr{R}$ such that $\beta = c\gamma$.[8]

Finally, I impose an orthogonality condition in Assumption 3 in order for η_t to be interpreted as a monetary shock. A monetary shock is usually defined as the deviation of the policy rate from where it would be if the Fed were to follow a policy rule. It is by construction orthogonal to any fundamentals that the Fed would react to. In our context, the Fed information shock is part of those fundamentals. The orthogonality condition also helps with the interpretations of results in the next section.

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

[8]To see why, suppose that $\beta = c\gamma$ for some $c \in \mathscr{R}$. Equation (2) becomes $y_t = \gamma(\xi_t + c\eta_t) + u_t + \theta_0$. It is equivalent to $y_t = \gamma(\xi_t^* + c\eta_t^*) + u_t + \theta_0$ where $\xi_t^* = \xi_t + ca$ and $\eta_t^* = \eta_t - a$. Only the sum $\xi_t + c\eta_t$ is identified but not ξ_t or η_t individually.

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 produced by the Fed and the other by the private sector. Section 3.1 shows that when the information shock is estimated to have raised 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

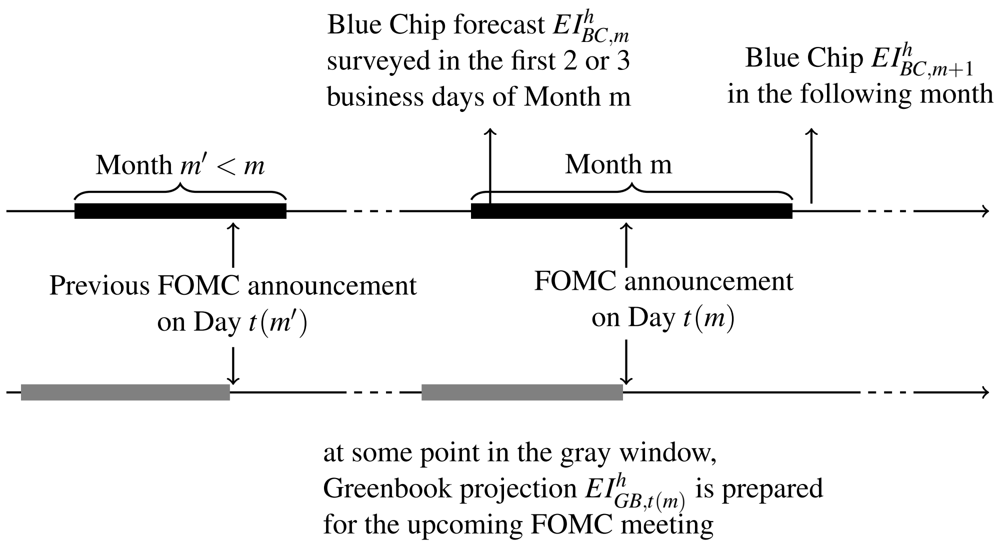
If the information component indeed captured the Fed information effect, one would expect it to be disproportionately positive when the Fed was more optimistic about the economy than the private sector. To test this prediction, I use two sets of forecast data below.

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 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 Ricco, 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, Blue Chip solicits projections for key macroeconomic variables from about fifty professional forecasters.[9] 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 a month to gauge the market expectation of it before the FOMC announcement in that month. Figure 3 sketches the timeline of the two sets of projections relative to a typical FOMC announcement.

[9]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 every month.

Figure 3: Timeline of actions around an FOMC announcement



Conveniently, six variables are commonly predicted in the Greenbook and the Blue Chip. For each of them and for each horizon, I look at the difference between their predictions and regress the estimated 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 Day t in Month m when an FOMC announcement took place, $EI^h_{GB,t(m)}$ is the Greenbook forecast of the h-quarter-ahead EI (economic indicator) prepared for that announcement, $EI^h_{BC,m}$ 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 $\xi_{t(m)}$ on average raises the three-month-ahead federal funds future rate by 1%.[10]

Table 3 shows the OLS estimates of ϕ_ξ^h from Equation (3), using one economic indicator for one horizon at a time. Column (1)-(3) present the results for real GDP, real personal consumption expenditures and industrial production. For such procyclical variables, a positive forecast difference on the right-hand side of Equation (3) suggests that the Fed expected a stronger economy than the private sector prior to the FOMC announcement on Day $t(m)$. In this case, one would expect $\xi_{t(m)}$ to be positive, reflecting a rise in interest rates due to the market learning of the Fed's more optimistic view. The consistently positive coefficients in Column (1)-(3) confirm this prediction. In particular, a positive $\xi_{t(m)}$ is strongly associated with the Fed projecting a higher real GDP growth than professional forecasters for two quarters into the future and a higher growth rate of industrial

[10]For all the regressions involving the Greenbook forecasts in this paper, only *scheduled* FOMC announcements can be studied because the forecasts were not prepared for unscheduled announcements. Historically, there has been no more than one scheduled FOMC announcement in a given month.

production for the current quarter.

Column (5) and (6) show the estimated ϕ_{ξ}^{h} for two measures of inflation, the GDP Price Index and the CPI. At the 5% level, the coefficient on CPI for the current quarter and that on GDP Price Index in six quarters are significantly positive, again consistent with what one would expect for a procyclical indicator.

By contrast, one would expect $\phi_{\xi}^{h} < 0$ for a countercyclical variable such as unemployment. If interest rates went up because market participants revised up their economic outlook, it was likely that the Fed had 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 forecast horizons despite the fact that none of the coefficients is significant.

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

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

Each cell reports a coefficient, ϕ_{ξ}^{h}, from a separate regression: $\xi_{t(m)} = \phi_0^h + \phi_{\xi}^{h}(EI_{GB,t(m)}^{h} - EI_{BC,m}^{h}) + e_{t(m)}^{h}$, 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.

The exercise above confirms the prediction that the information shock tends to be positive when the Fed was more optimistic about the economy than the market. It suggests that the shock does capture some Fed information that was not known to the market. However, does it capture all that information? The answer is yes. I check this by replacing the dependent variable in Equation (3) with the estimated 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. Predictability in this direction can arise for two reasons. First, the staff of the Fed might have been better informed of what monetary shock to expect for each meeting and thus been more able to factor in its effect in their projections. Second, the significant coefficients could arise as false positives due to the size of the 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 another prediction of my decomposition: if the market responded to an FOMC announcement as if ξ_t were 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.

Like in 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-month change in the consensus forecast from the beginning of Month m to the beginning of 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 expectation in response to the two shocks.

Before looking at the individual shocks, let us first look at how Blue Chip forecasters responded to an FOMC announcement as a whole. 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 $PC_{t(m)}$ increases $FF4$ by 1% on average. I then regress the Blue Chip forecast revision on an indicator for a given horizon on that information:

$$\Delta EI^h_{BC,m+1} = \alpha^h_0 + \alpha^h_{PC} PC_{t(m)} + e^h_{t(m)} \tag{4}$$

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 the h-quarter-ahead EI from the beginning of Month m to that of Month $m+1$.

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

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_η^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.

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 $\eta_t > 0$
Procyclical variables		
Industrial production	↑	↓
Real GDP	↑	↓
GDP Price Index	↑	↓
CPI	↑	↓
PPI	↑	↓
Countercyclical variable		
Unemployment rate	↓	↑

The columns labeled "PC" in Table 6 and 7 present the estimated α_{PC}^h's using one indicator and one horizon at a time. The coefficients suggest that following positive interest rate surprises, professional forecasters tended to revise up their near-term economic outlook. For example, after a tightening announcement that increased FF4 by 1%, the consensus forecasts of the next-quarter industrial production growth and the next-quarter real GDP growth would rise by 1.34% and 0.75%, respectively. Both rises are significant at the 5% level. The tightening would also lead to moderate decreases in the projected unemployment rate for the current and the third quarters and a moderate increase in the projected PPI for the current quarter.

These results confirm the concerns raised by Campbell *et al.* (2012) and Nakamura and Steinsson (2018) about using high-frequency rate changes directly as instruments for monetary shocks. According to standard macroeconomic models, an exogenous policy tightening is supposed to dampen the economy and reduce inflation. To understand why we find the opposite, I replace the regressor in Equation (4) by my estimated Fed information shock and monetary shock jointly to study how they each changed market expectations:

$$\Delta EI_{BC,m+1}^h = \alpha_0^h + \alpha_\xi^h \xi_{t(m)} + \alpha_\eta^h \eta_{t(m)} + e_{t(m)}^h \tag{5}$$

The rest of Table 6 and 7 report the estimated α_ξ^h and α_η^h using one economic indicator and one horizon at a time. Clearly, the information shock played a dominant role in driving the revisions of Blue Chip forecasts following FOMC announcements. For almost every dependent variable $\Delta EI_{BC,m+1}^h$, the coefficient $\hat{\alpha}_\xi^h$ is close to the previously studied $\hat{\alpha}_{PC}^h$ in both numerical value and significance level, whereas the coefficient on the monetary shock, $\hat{\alpha}_\eta^h$, is insignificant.

Let us look at the coefficients on the information shock in the columns labeled "ξ" in detail. In almost all regressions, the sign of $\hat{\alpha}_\xi^h$ is consistent with the prediction in Table 5, suggesting what $\xi_{t(m)}$ captures is indeed the economic news, not the monetary news, of an FOMC announcement.

By economic news, it was mainly the near-term economic outlook that market participants would update after an FOMC announcement. This can be seen from the indicators and the horizons for which $\hat{\alpha}_\xi^h$ is the most significant. Specifically, following a positive $\xi_{t(m)}$ that raised the $FF4$ by 1%, the Blue Chip forecast would be revised up for the current-quarter industrial production by 3.04%, the current-quarter PPI by 3.44%, the next-quarter industrial production by 1.51%, the-next-quarter real GDP growth by 0.90%, and revised down for the-third-quarter unemployment by 038%. All these revisions are significant at the 5% level and pertain to economic performances within three quarters from the time of the forecasts.

Remarkably, the variables for which $\xi_{t(m)}$ led to the most significant revisions also match the ones for which the forecasts of Greenbook and Blue Chip differed the most, which were recovered by $\xi_{t(m)}$ in Table 3. In other words, $\xi_{t(m)}$ manages to pick up consistent information in different sets of forecast data. This is not by coincidence, but strong evidence that $\xi_{t(m)}$ successfully captures the market's learning of economic news from FOMC announcements.

With Regression (5), one could ask again the question of whether a single shock $\xi_{t(m)}$ captured *all* the Fed information about the economy. If it did, the coefficients on $\eta_{t(m)}$ would not have the same signs as $\hat{\alpha}^h_{\xi}$'s. The columns labeled "η" show it is indeed the case. While the $\hat{\alpha}^h_{\eta}$'s are insignificant for most indicators and horizons, a positive $\eta_{t(m)}$ that raised FF4 by 1% was followed by the Blue Chip forecasts being revised down for the four-quarter-ahead industrial production by 1.10% and for the five-quarter-ahead PPI by almost 1.00%. Both revisions are significant at at least the 10% level, and the signs are consistent with what Table 5 predicts. The only exception is the coefficient associated with the two-quarter-ahead CPI, which has a wrong sign but is only marginally significant. I argue that it is not worth much concern as it might be a false positive due to the size of the test.

To summarize, the analysis with forecast data in this section and Section 3.1 corroborates the labeling of $\xi_{t(m)}$ as the Fed information shock and $\eta_{t(m)}$ as the monetary shock. The information shock captures the information gap between the Fed and market participants regarding the near-term economic prospect prior to each FOMC announcement. It explains why market participants tended to expect a stronger economy than they would otherwise have predicted after a surprise policy tightening.

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 channel into account changes my results.

Bauer and Swanson (2022) challenge specifications like Equation (4) which have widely been used by researchers to support the Fed information effect. For example, Campbell *et al.* (2012) study the response of private sector's expectations to an FOMC announcement with the following regression:

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

where $Target_m$ and $Path_m$ are two monetary shocks reflecting the market surprise at the current policy rate and at the path of future rates, respectively, during the announcement in Month m (Gürkaynak *et al.*, 2005b). Using data from 1990m2 to 2007m12, the study finds that the signs of $\hat{\alpha}^h_{Target}$ and $\hat{\alpha}^h_{Path}$ are the opposite to what one would expect for the effect of a monetary shock.

Table 6: Blue Chip regressions - real variables

	(a) Industrial Production			(b) Real GDP			(c) Unemployment Rate		
h	PC	ξ	η	PC	ξ	η	PC	ξ	η
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" and "η" 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.

Nakamura and Steinsson (2018) as another example estimate the following regression over a sample from 1995m1 to 2014m3:

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

where $Policy_m$ is their measure of monetary shock, constructed as the first principal component of the rate changes in five interest rate futures during a 30-minute window around the announcement in Month m. They also find the signs of the α^h_{Policy}'s puzzling, just like the $\hat{\alpha}^h_{PC}$'s in Table 6 and 7.[11]

Figure 4 illustrates Bauer and Swanson (2022)'s concern about these specifications. If an unsatisfactory employment report got released between the Blue Chip survey and the FOMC announcement in Month m, it may have simultaneously led the Fed to cut the federal funds rate more

[11] 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 for which Blue Chip forecasts are available. I estimate the regressions at the meeting frequency. When two meetings took place in the same month, I use the same Blue Chip forecast revision as the dependent variable for both observations. Aggregating the monetary shocks to the month level and running the regressions at the monthly frequency makes negligible difference to the results.

Table 7: Blue Chip regressions - price variables

h	(a) Consumer Price Index PC	(a) ξ	(a) η	(b) Producer Price Index PC	(b) ξ	(b) η	(c) GDP Price Index PC	(c) ξ	(c) η
0	1.20	**1.60**	-1.13	**2.83**	**3.44**	-0.38	0.13	0.15	0.15
	(0.87)	(0.96)	(1.59)	(1.48)	(1.67)	(2.67)	(0.30)	(0.34)	(0.38)
1	0.00	-0.11	0.37	0.43	0.59	-1.03	0.14	0.15	0.13
	(0.57)	(0.74)	(1.74)	(0.37)	(0.43)	(0.85)	(0.17)	(0.18)	(0.26)
2	0.04	0.04	**0.35**	-0.05	-0.04	-0.33	0.00	0.01	-0.02
	(0.12)	(0.13)	(0.20)	(0.21)	(0.24)	(0.40)	(0.16)	(0.19)	(0.24)
3	0.12	0.11	0.13	0.19	0.21	-0.41	0.09	0.13	-0.28
	(0.12)	(0.14)	(0.22)	(0.25)	(0.28)	(0.28)	(0.14)	(0.16)	(0.27)
4	0.09	0.11	0.03	0.05	0.09	-0.24	-0.05	-0.06	-0.19
	(0.12)	(0.14)	(0.25)	(0.20)	(0.22)	(0.59)	(0.14)	(0.16)	(0.30)
5	0.14	0.18	0.08	0.14	0.18	**-0.97**	2.34	2.94	-8.31
	(0.21)	(0.23)	(0.38)	(0.22)	(0.19)	(0.43)	(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" and "η" 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.

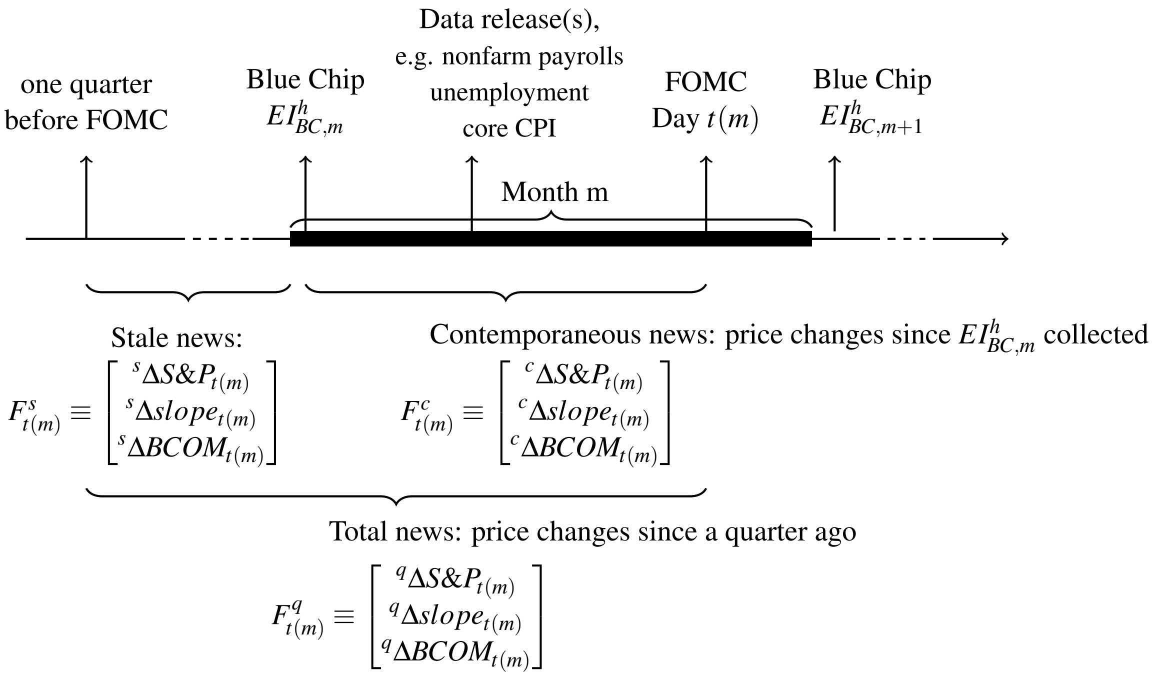
than publicly expected and caused Blue Chip forecasters to revise down their economic outlook. In other words, what previous studies claimed to be evidence for the Fed information effect may actually be caused by an omitted variable bias in Equation (6) and (7).[12]

In order to take their concern into account, I re-estimate Equation (4) controlling for the 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 Swanson (2022), I control for two groups 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 their release days if the days fit into the window.[13] The second group, denoted by $F^c_{t(m)} = ({}^c\Delta S\&P_{t(m)}, {}^c\Delta slope_{t(m)}, {}^c\Delta BCOM_{t(m)})'$ where c stands for "contemporaneous", 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 last day of the Blue Chip survey to the day before the FOMC announcement in Month m (see Figure 4

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

[13] If a release did not take place between the Blue Chip survey and the FOMC announcement in Month m, the corresponding element of $X_{t(m)}$ is set to zero.

Figure 4: Timeline of actions around an FOMC announcement



for the timeline).

$$\Delta EI^h_{BC,m+1} = \alpha^h_0 + \alpha^h_\xi \xi_{t(m)} + \alpha^h_\eta \eta_{t(m)} + \alpha^{h'}_X X_{t(m)} + \alpha^{h'}_F F^c_{t(m)} + e^h_{t(m)} \tag{8}$$

The first two columns of Table A3 and A4 show the estimated α^h_ξ and α^h_η from Equation (8). Not only do their signs remain the same as before, the coefficients become even more significant than without the controls. The variables for which professional forecasts changed significantly in response to $\xi_{t(m)}$ align even better with the variables for which the forecasts differed the most between the Fed and Blue Chip as I documented in the previous section.

In fact, Bauer and Swanson (2022) propose to control for a larger set of variables. They include (i) the market surprise at GDP in the release in Month $m-1$, (ii) lagged macroeconomic indicators, (iii) a time trend, (iv) lagged Blue Chip forecast revisions, (v) the Brave-Butters-Kelley News Index (Brave *et al.*, 2019), and (vi) the changes in the S&P 500 price index, the yield curve slope and BCOM over the entire quarter prior to the FOMC announcement (denoted by $F^q_{t(m)} = ({}^q\Delta S\&P_{t(m)}, {}^q\Delta slope_{t(m)}, {}^q\Delta BCOM_{t(m)})'$ in Figure 4). To see how these variables would affect my results, I add them incrementally as additional controls to Equation (8).[14]

The coefficients continue to have their expected signs when the variables from (i) to (iv) are controlled for in addition to the measures of contemporaneous news, as the middle panels of Table

[14]When controlling for $F^q_{t(m)}$, I use it to replaces $F^c_{t(m)}$ instead of adding it alongside $F^c_{t(m)}$.

A3 and A4 show. Even though the significance levels of α_{ξ}^{h} and α_{η}^{h} 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 control for (iv) the BBK Index and (v) $F_{t(m)}^{q}$ that the signs of $\hat{\alpha}_{\xi}^{h}$'s reverse, as shown in the last panels of Table A3 and A4. It turns out that the sign reversion is caused by the information shock being positively correlated with stale news, measured by the stock returns earned in *previous* months or in other words the difference between ${}^{q}\Delta S\&P_{t(m)}$ and ${}^{c}\Delta S\&P_{t(m)}$. I denote the difference with ${}^{s}\Delta S\&P_{t(m)}$, where s stands for "stale". The positive correlation stems from the positive correlations between ${}^{s}\Delta S\&P_{t(m)}$ and each of the five interest rates in $y_{t(m)}$. To see this, I regress each interest rate on ${}^{q}\Delta S\&P_{t(m)}$, ${}^{c}\Delta S\&P_{t(m)}$, or their difference ${}^{s}\Delta S\&P_{t(m)}$, using one regressor at a time and controlling for comporaneous news measured by $X_{t(m)}$:

$$y_{j,t(m)} = \phi_0 + \phi_{SP}\,{}^{i}\Delta S\&P_{t(m)} + \phi_X' X_{t(m)} + u_{t(m)}, \tag{9}$$

$$i = q,c,s \quad j = \text{FF4, ED2, ED3, ED4, 2-year Treasury yield} \tag{10}$$

Table A5 reports $\hat{\phi}_{SP}$ for different pairs of i and j. As the first two rows show, stale news measured by ${}^{s}\Delta S\&P_{t(m)}$ dominates the positive correlations between total news measured by ${}^{q}\Delta S\&P_{t(m)}$ and the interest rate changes. Holding surprises at data releases constant, a 1% decline in the stock price in previous months strongly predicts that the market would be surprised by a rate cut at the upcoming 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). In a text analysis of FOMC documents, they show that the Fed has reacted to negative intermeeting stock returns with an accommodative policy since the mid-1990s. By contrast, the third row of Table A5 shows that contemporaneous news measured by ${}^{c}\Delta S\&P_{t(m)}$ has no significant correlations with these interest rates.

Stale news might be relevant for the high-frequency rate responses to FOMC announcements for two 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, conditional on the Fed and the private sector interpreting the stale news in the same way, the Fed may react more aggressively than publicly believed to that interpretation. Given that the Blue Chip survey at the beginning of a month has already captured the private sector's reading of stale news and 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 A6 reports the estimated α^{h}_{SP} from Equation (11). It shows that the Fed indeed tended to project a worse economy than the private sector following stock market declines. Since large rate cuts did tend to precede a recession, as Figure 1 showed earlier, I view Table A5 and A6 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 empirical finding of Sastry (2021) and the theoretical model in Miranda-Agrippino and Ricco (2021). It reconciles Bauer and Swanson (2022) with the literature arguing for the Fed information effect.

4 Composite shock measures from 1991m7 to 2019m3

This section extends the series of Fed information shocks and monetary shocks to 2019m3, the last period for which I have available data.

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 each subsample yields two composite series, one for the Fed information shock and the other for the monetary shock, covering all the FOMC announcements from 1991m7 to 2019m3.[15]

Key intuition and results in Section 2 and 3 continue to hold for the composite series. Table 8 shows that one latent factor is still sufficient for capturing the market response to various types of data releases in the whole sample. Table 9 and 10 relate the composite series to the forecast differences between the Greenbook and 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. Most evidently, the Fed and 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 series, controlling for the news between the Blue Chip survey and the FOMC announcement. Table 11 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 significantly for a set of horizons at the 5% level. For results for the other three indicators and for specifications with different control

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

variables that showed up in Section 3.2, see Appendix A.4.

To further corroborate my method, I show that the information shock is fully responsible for the large rate cut surprises before recessions in Figure 1. I take the three-month-ahead federal funds future contract as a target of decomposition. Figure 5 plots the model-implied sample averages of the information shock ($\hat{\gamma}_j \hat{\xi}_t$) and of the monetary shock ($\hat{\beta}_j \hat{\eta}_t$) across all the FOMC announcements that preceded a recession by a quarter. Clearly, the information shock nicely captures the Fed's superior knowledge of a worsening economy while the monetary component displays no correlation with the occurrence of recessions. In Section 5, I will provide a formal test for the cyclicality of measures of monetary shock where I compare η_t with alternative proposals in the literature.

Table 8: Wright (2012)'s test for the number of news shocks

	Sample period	p-value
ZLB	2009m1 - 2016m12	0.631
post-ZLB	2017m1 - 2019m3	0.462

The null hypothesis is that $\Sigma^D - \Sigma_{\tilde{u}} = \tilde{\gamma}\tilde{\gamma}'$, where $\tilde{\gamma}$ is an $(N \times 1)$ 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 impact on the macroeconomy. In this section, I trace out the effects of monetary policy in a structural VAR using the composite series of η_t as an instrument for the policy shock.

For a baseline specification, I include four endogenous variables in the VAR. They are the one-year nominal Treasury bond yield, the log industrial production, the log CPI and the excess bond risk premium, all measured at a monthly frequency. To obtain a monthly instrument, I sum the monetary shocks by month in case more than one announcement took place in a month, i.e. $\eta_m = \sum_{j=1}^{n} \eta_{t_n(m)}$ for $\eta_{t_j(m)}$ the monetary shock associated with the j-th announcement in Month m on Day $t_j(m)$.[16] Let Y_m denote the (4×1) vector of endogenous variables. The VAR model can then be expressed as follows:

$$Y_m = B_0 + \sum_{i=1}^{p} B_i Y_{m-i} + \nu \eta_m + e_m, \tag{12}$$

[16] For a month without an FOMC announcement, η_m is simply set to zero.

Table 9: 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: $\xi_{t(m)} = \phi_0^h + \phi_\xi^h(EI^h_{GB,t(m)} - EI^h_{BC,m}) + e^h_{t(m)}$, where $EI^h_{GB,t(m)}$ is the Greenbook forecast of the h-quarter-ahead economic indicator (EI) prepared 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.

where ν is a (4×1) vector of coefficients capturing the immediate impact of η_m on Y_m, and B_i's are (4×4) coefficient matrices summarizing dynamic correlations between the elements of Y_m.

I estimate B_0, B_i's and ν in Equation (12) in one step by regressing each element of Y_m on $(1, Y_{m-1}, \ldots, Y_{m-p}, \eta_m)'$. In doing so, I treat η_m as an exogenous variable in the VAR. The impulse response functions are then calculated from $\hat{\nu}$ and $\{\hat{B}_i\}_{i=1}^p$. Pascal (2020) calls this procedure the exogenous variable approach, a simpler alternative to the external instrument approach to structural VAR (Gertler and Karadi, 2015). He shows that the two approaches deliver numerically equivalent relative impulse response functions under regularity conditions.

For a baseline implementation, I estimate Equation (12) using data from 1991m7 to 2019m3. Figure 6 plots in black the impulse response of Y_m to a positive monetary shock that is normalized to raise the one-year Treasury yield on impact by 1%. The first figure shows a hump-shaped contractionary effect of the shock on output. Although the drop in industrial production was initially

Table 10: 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_η^h, from a separate regression: $\eta_{t(m)} = \phi_0^h + \phi_\eta^h(EI^h_{GB,t(m)} - EI^h_{BC,m}) + e^h_{t(m)}$, 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.

indistinguishable from zero, it continued and became significant in five months. Ten months after the shock, output declined by over 5% relative to its original level. Risk premium in the bond market seems to play a big role in the slowdown of the economy. As the third figure shows, the excess bond premium jumped up immediately by nearly 2.0% in response to the shock. The heightened risk premium remained significant at the 10% level for ten months, by the end of which output also reached its lowest level. Meanwhile, the shock took its contractionary effect on inflation fairly quickly. CPI adjusted down by nearly 2.0% in the long-run, and the majority of that adjustment was achieved within six months after the shock.

These effects are much larger than previously documented in the VAR literature. For comparison, I estimate another set of impulse response functions using another instrument that is also high-frequency but unadjusted for the Fed information effect. For that purpose, I follow Gertler and Karadi (2015) and construct a monthly series that aggregates the surprises in the three-month

Table 11: Blue Chip regressions controlling for news, 1991m7 - 2019m3

	(a) Real GDP			(b) Unemployment Rate			(c) PPI		
h	PC	ξ	η	PC	ξ	η	PC	ξ	η
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)

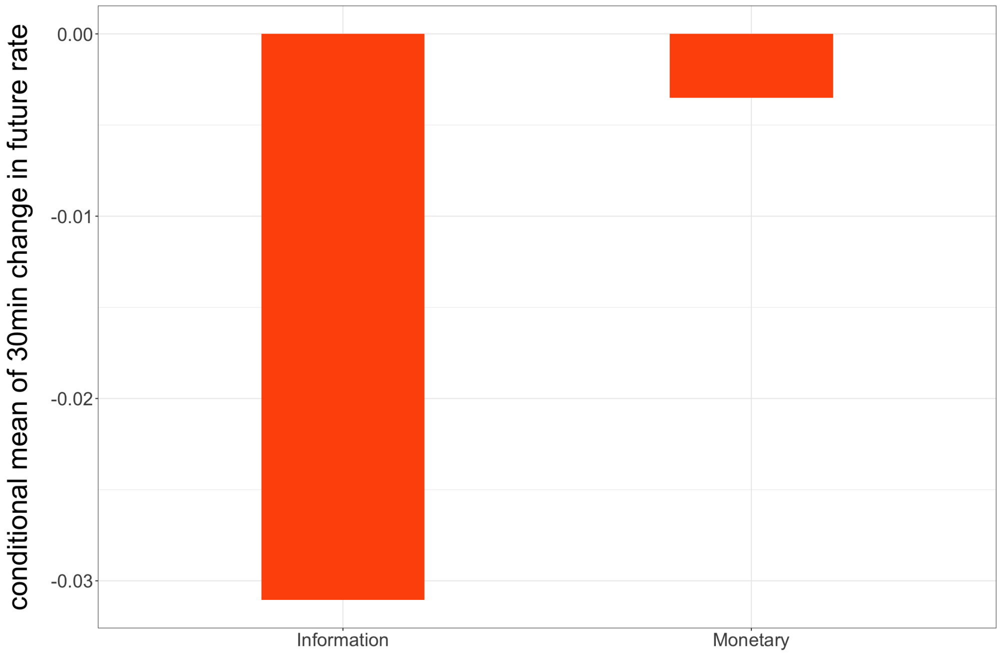
Each cell in the columns labeled "PC" presents a coefficient, α^h_{PC}, from a separate regression: $\Delta EI^h_{t(m)} = \alpha^h_0 + \alpha^h_{PC} PC_{t(m)} + \alpha^{h'}_X X_{t(m)} + \alpha^{h'}_F F^c_{t(m)} + e^h_{t(m)}$. Each row in the columns labeled "ξ" and "η" presents a pair of coefficients, 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.

ahead futures rate around FOMC announcements. The series, which I denote with FF4^{GK}, is a popular benchmark instrument in the literature for studying the transmission of monetary policy. I construct FF4^{GK} for the period from 1991m7 to 2019m3 and normalize it so that it raises the one-year Treasury yield by 1% on impact.

Figure 6 plots in red the impulse response of Y_m using FF4^{GK} as the instrument for the contractionary shock. The response of the macroeconomy was evidently smaller in all horizons than the finding with η_m. In particular, the shock had a significantly positive effect on industrial production shortly after its realization, a puzzling finding for monetary policy effectiveness. The effect remained close to zero for three years. CPI also declined more slowly and shifted down by less following a positive FF4^{GK} shock than following a positive η_m shock.

The Fed information effect can explain why η_m produces a more contractionary effect than FF4^{GK}. Figure 5 shows that the information shock is responsible for a nontrivial part of the high-frequency change in the three-month-ahead federal funds futures rate from which FF4^{GK} is constructed. In the next section, I will show that a negative Fed information shock historically

Figure 5: Decomposition of interest rates into identified shocks before recessions



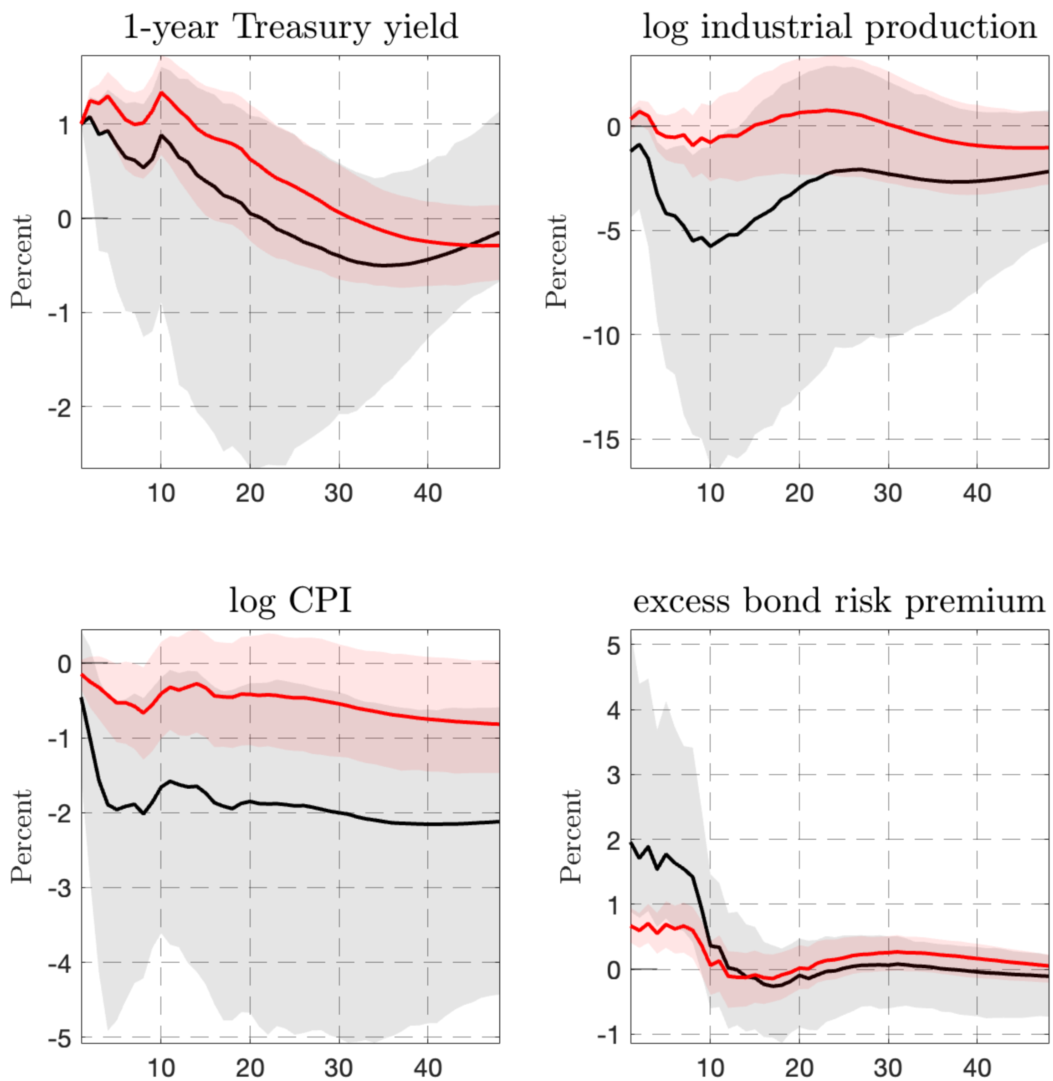
The figure shows the decomposition of the three-month-ahead federal funds futures rate (FF4) into the information shock and the monetary shock based on the approach proposed in this paper. For $j = FF4$, the left bar plots the sample mean of $\hat{\gamma}_j \hat{\xi}_t$ from $y_{j,t} = \hat{\theta}_{j,0} + \hat{\gamma}_j \hat{\xi}_t + \hat{\beta}_j \hat{\eta}_t + \hat{u}_{j,t}$, taken across FOMC announcement windows that preceded a recession by one quarter, and the right bar plots that of $\hat{\beta}_j \hat{\eta}_t$.

predicted recessions well. In other words, there was a positive correlation between the information shock and realized economic performances in following periods. As a result, the estimated effects of monetary shocks on output and inflation would be biased upward if one were to use FF4^{GK} as the instrument. This is precisely what we see in Figure 6.

For a robustness check, I drop the 1-year Treasury bond yield and the excess bond risk premium from the VAR, and estimate the impulse response functions with η_m again. This specification is motivated by a recent finding of Miranda-Agrippino and Ricco (2021) that the impulse responses constructed based on FF4^{GK} are sensitive to including the excess bond premium. In particular, including this very variable is key to avoiding an output puzzle for GK's original sample period. The specification also treats η_m as the policy shock itself instead of an instrument of the shock. I show in Figure 7 that dropping the variables from my baseline specification does not qualitatively change my results.

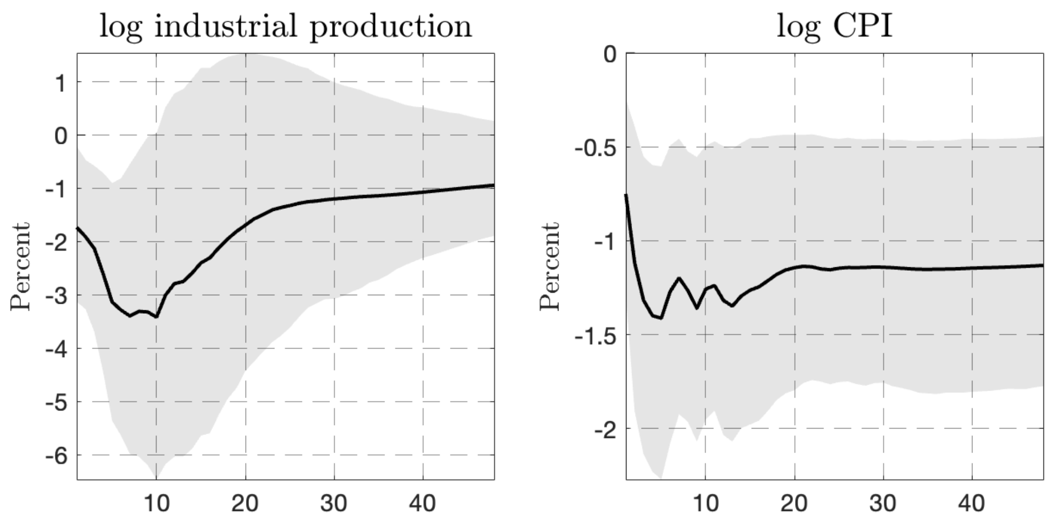
In summary, using my newly-constructed monetary factor as an instrument, I show robustly that an exogenous, contractionary monetary shock had a significantly negative impact on economic activity and aggregate price level. The impact on output was more pronounced and the impact on inflation was more immediate than one would find with raw high-frequency monetary surprises. The deviation can be explained by the confounding effect of the Fed information component in the surprises.

Figure 6: Dynamic responses to a monetary tightening shock



Impulse response functions to a contractionary monetary shock instrumented by (1) η_m proposed in this paper (black) and (2) Gertler and Karadi (2015)'s policy instrument FF4^{GK} (red). The VAR model is $Y_m = B_0 + \sum_{i=1}^{p} B_i Y_{m-i} + \nu Instrument_m + e_m$, where $Instrument_m = \eta_m$ or $FF4_m^{GK}$, Y_m includes the 1-year Treasury bond rate, the log industrial production, the log CPI, and the excess bond risk premium, and $p = 12$. Shaded areas are 90% confidence bands constructed from a wild bootstrap. 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 to a contractionary monetary shock measured by η_m, normalized to increase the 1-year Treasury bond rate by 1% contemporaneously. The VAR model is $Y_m = B_0 + \sum_{i=1}^{p} B_i Y_{m-i} + \nu\eta_m + e_m$, where Y_m includes the log industrial production and the log CPI, and $p = 12$. Shaded areas are 90% confidence bands constructed from a wild bootstrap. The sample for both endogenous variables and the shock series runs from 1991m7 to 2019m3.

6 A comparison with existing monetary instruments

To study the effect of monetary policy, numerous studies have proposed alternative measures of monetary shocks. In this section, I show the desirability of η_t compared to a number of popular choices.

6.1 Overview

The first two columns of Table 12 list the sources and the abbreviations of all the measures I consider in this comparison. Some of them are at the FOMC meeting frequency, taking a non-zero value for each FOMC announcement. 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. Others are available at a monthly frequency, aggregating values from each announcement to the month level. They include the Romer and Romer (2000) shock, Gertler and Karadi (2015)'s FF4^{GK}, Miranda-Agrippino and Ricco (2021)'s information-robust shock, Zhang (2019)'s monthly measure and Jarociński and Karadi (2020)'s monetary shock.

The third column of Table 12 reports the correlation coefficients between η_t (or η_m) and each of these measures. The correlation is higher with measures built from very short-maturity interest rates, such as the target factor, the FF4^{GK} shock, the MAR shock, and the JK shock. This is unsurprising given that η_t loads more heavily on FF4 than on other interest rates in y_t with longer maturities. That said, the level of the positive coefficients is at most modest, suggesting crucial differences between η_t and these alternatives.

Table 12: Overview of monetary shocks in the literature

Shock	Abbrev.	Correlation w/ η	Availability
Monthly			
Romer and Romer (2000)	RR	0.12	1969m3 - 2007m12
Gertler and Karadi (2015)	FF4^{GK}	0.29	1990m1 - 2012m6
Miranda-Agrippino and Ricco (2021)	MAR	0.42	1991m2 - 2010m1
Zhang (2019)	Zhang	0.22	1988m3 - 2013m12
Jarociński and Karadi (2020)	JK	0.41	1990m2 - 2015m12
η_m, this paper	η_m	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

The first criterion for a solid measure of monetary shock is how it relates to business cycles. Standard macro theories say that monetary policy easing should stimulate economic activity, thus decreasing the likelihood of a recession. If a measure instead was more likely to be followed by a recession when it was intended to capture policy easing, it must be confounded by policymakers' response to their anticipation of the recession. I check if this is the case for each of the measures with the following Probit regression:

$$Pr\left(IsRecession_t^h = 1|Shock_t\right) = \Phi\left(\kappa_0^h + \kappa_S^h Shock_t\right), \tag{13}$$

where $IsRecession_t^h$ takes the value of one if the economy is in an NBER recession h quarters after Day t and zero otherwise, and $Shock_t$ is a measure of policy shock coming from the announcement on Day t. The key parameter of interest is κ_S^h. Because every measure is normalized so that it takes a negative value for policy easing, a significantly negative $\hat{\kappa}_t^h$ indicates that the measure is contaminated by a policy reaction to the development of the economy.

Table 13 shows $\hat{\kappa}^h$ for different measures, looking at one horizon at a time. The target factor, the NS shock, the RR shock and the FF4^{GK} shock all tended to predict a recession by 0-3 quarters in advance when they were supposed to measure exogenous policy easing. These earlier constructs are endogenous to business cycles as they were not intended to control for the Fed information effect.

In contrast, no estimate is significantly negative for η_t and recent measures proposed by MAR, Zhang, JK and BRW, meaning that it is unlikely for them to be confounded by policy reactions to anticipated or realized recessions. This is unsurprising given that they all attempt to tease out monetary shocks from the Fed information effect. For this set, none of the estimates is significantly positive either due to limited variations of these measures and the small number of recessions in the sample period.

The confounding factor in those earlier constructs is well captured by the information shock. Table 14 shows $\hat{\kappa}^h$ when I replace the regressor by ξ_t. When policy easing was driven by a negative information shock, a recession would be more likely in the current quarter and in the next quarter, a correlation significant at the 5% level. This is further evidence that ξ_t measures how much of a rate surprise is due to a policy response to the state of the economy.

6.3 Revisions of Blue Chip forecasts

As Campbell *et al.* (2012) and Nakamura and Steinsson (2018) discuss, an obvious symptom of having a problematic measure of policy shock due to the Fed information effect is to find that professional forecasts of pro-cyclical variables tended to go down after the measure was supposed to indicate an expansionary monetary shock. I have verified in Section 3.2 that this is not the case for η_t. In this section, I check if the other measures can pass this test.

For every measure, I run regression (8) using the original series posted on the respective authors' website as the regressor. The regression controls for the contemporaneous news to minimize the impact of the Fed response to news channel. Table 15, 16 and 17 report the estimated coefficients on every measure. For comparison, I repeat the coefficients on η_t in the last column. Highlight in red are statistically significant estimates with a wrong sign.

With no attempt to control for the information asymmetry between the Fed and the market, the measures taken directly from interest rate surprises yield the most puzzling results. As the first three columns show, when the path factor, the target factor and the NS shock were supposed to measure an expansionary shock, the Blue Chip forecasters actually lowered their predictions of CPI, PPI, industrial production, real GDP growth and increased those of the unemployment rate for various horizons.[17]

Those measures that do attempt to tease out the Fed information effect generally perform better,

[17]The estimates in the first three columns of Table 15 - 17 are different from those in Table A1 because the regressions for the latter do not include any control variables.

Table 13: Predictability of monetary shocks for NBER recessions

h (quarter)	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_m (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_m (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_S^h, from a separate Probit regression: $IsRecession_t^h = \kappa_0^h + \kappa_S^h Shock_t + e_t^h$, 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 measure of policy shock listed in the left-most column, taken directly from the original study that proposed it. Robust standard errors are in parentheses.

Table 14: Information shock ξ_t strongly predicts near-future recessions

h (quarter)	0	1	2	3	4	5	6
ξ_t (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)
ξ_t (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.

expect the BRW shock. Miranda-Agrippino and Ricco (2021)'s information-robust shock yields only two significant coefficients with the wrong sign. One is significant at the 5% level for the forecast of the third-quarter-ahead CPI, and the other at the 1% level for PPI for the same horizon. Even better are the measures proposed by Jarociński and Karadi (2020) and Zhang (2019). They are associated with mostly insignificant forecast revisions. For comparison, an expansionary shock measured by η_t can explain significant upward revisions of industrial production and PPI, and the downward revision of unemployment in five quarters.

Overall, the shock series proposed in this paper, η_t, is a solid measure of exogenous monetary shock in that it is orthogonal to other developments of the economy and that it is consistent with the direction in which professional forecasters revised their economic prospect. Compared to the very few alternatives that also pass the tests above, my approach has two additional advantages. First, it allows the monetary shock to be constructed in real time as it relies solely on market-based interest rate data. Second, it is point-identified, allowing one to interpret the effect of monetary shocks in a standard VAR framework.

Table 15: 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 16: 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 17: 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_S^h, from a separate OLS regression: $\Delta EI^h_{BC,m+1} = \alpha_0^h + \alpha_S^h Shock_{t(m)} + \alpha_F^{h'} F^c_{t(m)} + \alpha_X^{h'} X_{t(m)} + e^h_{t(m)}$, 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 two vectors of control variables measuring the contemporaneous news. Details are in Section 3.2. The last column repeats Column "η" in Table 11 and A7. Highlighted in red are coefficients for which the forecast revision responds to a monetary shock 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 minimum 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 the economic outlook in the near future 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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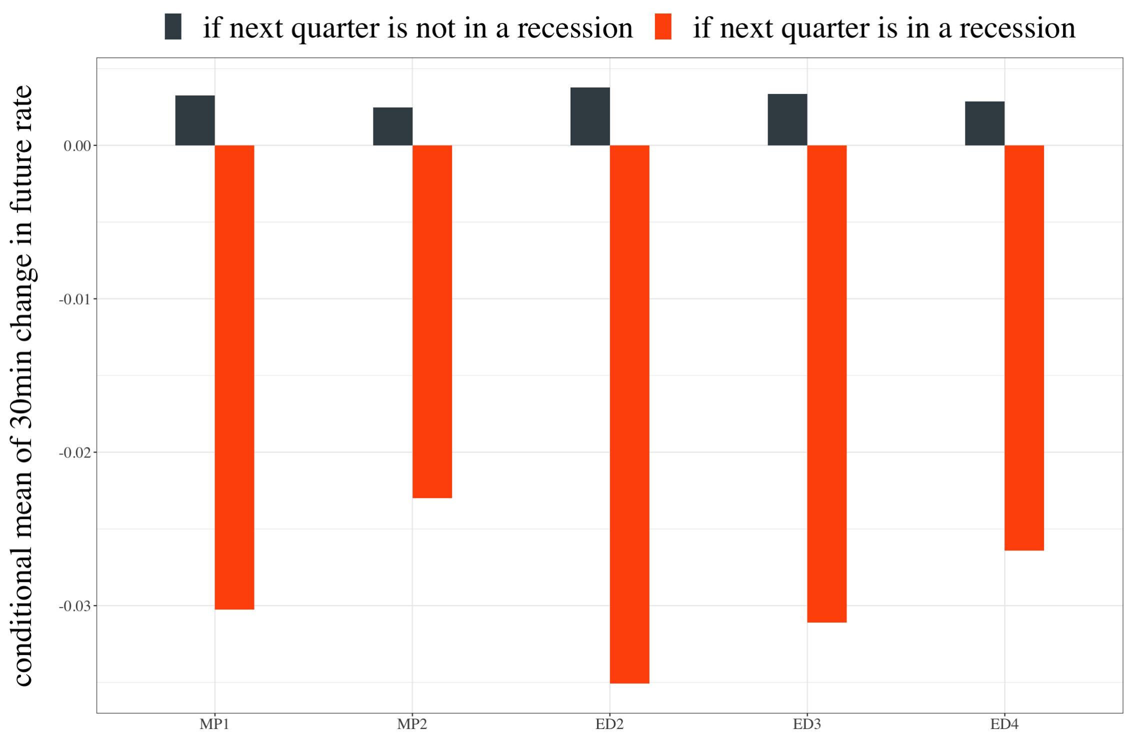
Appendices

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.

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

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

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

$\Sigma_{\tilde{u}}$ 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.

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

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

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

where $\hat{\xi}_t$ and $\hat{\eta}_t$ are smoothed estimates from Kalman filtering of the model. I numerically solve this problem by using a function called *constrOptim.nl* in the *alabama* R package.

A.3 Robustness to the Fed response to news channel

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_{Policy}, from a separate regression: $\Delta EI^h_{t(m)} = \alpha^h_0 + \alpha^h_{Policy} Policy_{t(m)} + e^h_{t(m)}$ 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) Target	Campbell et al. (2012) Path	NS (2018) 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) Target	Campbell et al. (2012) Path	NS (2018) 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_{Policy}, from a separate regression: $\Delta EI^h_{t(m)} = \alpha^h_0 + \alpha^h_{Policy} Policy_{t(m)} + \alpha^{h\prime}_X X_{t(m)} + \alpha^{h\prime}_c control_{t(m)} + e^h_{t(m)}$, 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: Robustness to the Fed response to economic news channel - real variables

EI	h	ξ	η	ξ	η	ξ	η
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: $\Delta EI^h_{t(m)} = \alpha_0^h + \alpha_\xi^h \xi_{t(m)} + \alpha_\eta^h \eta_{t(m)} + \alpha_c^{h'} control_{t(m)} + e^h_{t(m)}$, 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 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 A4: Robustness to the Fed response to economic news channel - price variables

EI	h	ξ	η	ξ	η	ξ	η
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: $\Delta EI^h_{t(m)} = \alpha_0^h + \alpha_\xi^h \xi_{t(m)} + \alpha_\eta^h \eta_{t(m)} + \alpha_c^{h'} control_{t(m)} + e^h_{t(m)}$, 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 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 A5: Predictability for interest rate surprises by changes in the S&P500 price index over different windows

	FF4	ED2	ED3	ED4	2yr 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 A6: Predictability for GB-BC forecast differences by stale news ${}^{s}\Delta S\&P_{t(m)}$

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).

A.4 Additional corroborating evidence on composite measures

Table A7: Blue Chip regressions controlling for news, 1991m7 - 2019m3

	(a) Industrial Production			(b) CPI			(c) GDP Price Index		
h	PC	ξ	η	PC	ξ	η	PC	ξ	η
0	**2.57**	**2.64**	-0.22	**1.44**	**1.77**	-1.02	0.12	0.12	0.26
	(1.32)	(1.34)	(2.16)	(0.81)	(0.87)	(1.32)	(0.30)	(0.33)	(0.37)
1	**1.28**	**1.36**	-0.44	-0.89	-0.55	0.75	0.16	0.15	0.10
	(0.57)	(0.56)	(1.07)	(0.92)	(0.76)	(1.51)	(0.16)	(0.17)	(0.25)
2	0.32	0.40	-0.97	0.03	0.04	**0.38**	0.04	0.05	0.03
	(0.36)	(0.36)	(0.63)	(0.13)	(0.13)	(0.20)	(0.17)	(0.19)	(0.21)
3	0.32	0.40	**-0.95**	0.13	0.11	0.21	0.14	0.17	-0.21
	(0.38)	(0.37)	(0.49)	(0.13)	(0.14)	(0.27)	(0.14)	(0.16)	(0.26)
4	0.17	0.35	**-1.22**	0.10	0.14	0.05	-0.06	-0.06	-0.20
	(0.25)	(0.25)	(0.64)	(0.12)	(0.14)	(0.29)	(0.14)	(0.16)	(0.29)
5	0.31	0.43	**-1.09**	0.13	0.17	-0.13	3.16	3.44	-10.40
	(0.29)	(0.27)	(0.53)	(0.20)	(0.22)	(0.43)	(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" and "η" 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 A8: Robustness to the Fed Response to Economic News Channel - Real Variables

EI	h	ξ	η	ξ	η	ξ	η
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_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.

Table A9: Robustness to the Fed Response to Economic News Channel - Price Variables

EI	h	ξ	η	ξ	η	ξ	η
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^h_ξ and α^h_η from regression: $\Delta EI^h_{t(m)} = \alpha^h_0 + \alpha^h_\xi \xi_{t(m)} + \alpha^h_\eta \eta_{t(m)} + \alpha^{h'}_c control_{t(m)} + e^h_{t(m)}$, 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.