Noisy Monetary Policy*

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Abstract

We introduce imperfect information in monetary policy (in the sense of imperfect central bank communications). Agents receive signals from the central bank revealing new information ("news") about the future evolution of the policy rate before changes in the rate actually take place. However, the signal is disturbed by noise. We employ a non-standard vector autoregression procedure to disentangle the economic and financial effects of news and noise in US monetary policy since the mid-1990s. Using survey- and market-based data on federal funds rate expectations, we find that the noisy signal plays a relatively important role for macroeconomic dynamics. A signal reporting news about a future policy tightening shifts policy rate expectations upwards and decreases output and prices. A sizable part of the signal is noise surrounding future monetary policy actions. The noise decreases output and prices and can explain up to 15% and 8% of their variations, respectively. Furthermore, it significantly increases the excess bond premium, the corporate spread and financial market volatility, and decreases stock prices.

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"The fundamental reason that communication is so important is that monetary policy is more appropriately viewed as the path of the policy rate, not simply the current rate. This is evident today as the markets seem highly attentive to signals regarding the future path of the funds rate not simply its current setting." Charles I. Plosser, 2014.

1 Introduction

The press pays close attention to the words of every member of the Federal Open Market Committee (FOMC) and, above all, to the words of the Federal Reserve's Chairman. Over the past decades, communicating its future intentions has become a monetary policy tool of the Federal Reserve in addition to the traditional tool of interest rates. While Federal Reserve communications included forward-looking language since the mid 1990s, especially with the federal (fed) funds rate stuck at the zero lower bound (ZLB) after the global financial crisis, so-called "forward guidance" has been the only way for the Federal Reserve to affect market expectations of future monetary policy.[1]

The FOMC's use of forward guidance gives reason to think, that monetary policy is inherent to a signal extraction problem (Figure 1). Agents receive signals from the central bank revealing new information ("news") about the future path of the policy rate well before changes in the rate actually occur and adjust their expectations accordingly. Signals can be transmitted to the public via statements, press releases or speeches, for example. However, the signal may be disturbed by noise in the sense that agents do not receive a clear signal and, thus, do not understand or interpret the news correctly. Therefore, agents observe only a noisy signal, which can be decomposed into a news shock and a noise shock. The news shock corresponds to a future or anticipated monetary policy shock reflecting policy changes that actually occur in the future. Noise in monetary policy reflects two key communication challenges. First, communication about future monetary policy by the central bank could be unclear; e.g., there could be ambiguity in words, sentences, or paragraphs (also known as semantic noise). Second, agents may interpret the signal from the central bank incorrectly due to their preconceived notions about the central bank's biases based on its track record, i.e., central bank credibility (psychological noise). As time passes, agents learn about past news shocks by looking at the realized policy rate and can disentangle the real news from noise.

This raises a few interesting questions: How do we identify news and noise in monetary policy? How noisy are signals about future monetary policy decisions? What are the economic and financial effects of anticipated (news) and noise shocks? Does noise in

[1] In addition, quantitative easing (QE) may also affect expectations about future policy rate decisions.

monetary policy matter? In this paper we address these questions by expanding the noise-news setting as in **?** to monetary policy. We provide a unified empirical framework that can disentangle the economic effects of news and noise in monetary policy when the signal about future monetary policy actions is noisy.[2] To reveal the signal, we use survey-based and market-based measures of fed funds rate expectations.[3]

The bulk of the empirical literature assessing the effects of monetary policy has focused mainly on the economic effects of unanticipated changes in the fed funds rate: the so-called "surprise." (See for example, **?**, **?**, **?**, and **?**, among many others.) There seems to be considerable agreement about the qualitative effects on the macroeconomy. After an unanticipated monetary tightening, i.e., an unexpected increase in the policy rate, short-term interest rates increase and economic aggregates such as investment, output and prices generally decrease.

A communicated commitment of future policy tightening made by the central bank should have similar contractionary effects on the economy. Indeed, this is in line with predictions of standard theoretical models with nominal rigidities (see, e.g., **?** and **?**). Moreover, **?** show that anticipated monetary policy shocks have a larger, delayed and more persistent effect than unanticipated shocks.

Further, there is empirical evidence showing that central bank communications affect financial markets via shifting market expectations of future interest rates (see, e.g., **?**, **?**, **?**). In addition, **?** separately identifies the effects on asset prices of Federal Reserve forward guidance and large-scale asset purchases during the ZLB period.

Empirical studies assessing the macroeconomic effect of news shocks in monetary policy are still scarce. There exist some early contributions regarding the role of monetary policy anticipation, for example, **?** and **?**. More recently, **?** and **?** take into account the anticipated component of monetary policy in vector autoregressions (VARs) using unexpected changes in future contracts around FOMC announcements as external instruments. Further, **?** show that the empirical effects of forward guidance shocks using these instruments directly in a VAR are consistent with the predictions of a standard theoretical model. Finally, **?** use a VAR including survey expectations directly to assess the effects of anticipated monetary policy.

However, so far, the literature has largely abstracted from noise. By doing so, one assumes that news always materializes as expected and, therefore, one ignores the commu-

[2] The recent finding of **?** that news and noise are observationally equivalent is not of applicability here since the signal (albeit not observed by the econometrician) can be extracted using a structural model (see **?**).

[3] In our setting, QE announcements could potentially be part of the news shock at the ZLB, as long as they affect policy rate expectations.

nication challenges inherent to monetary policy. A notable exception is the recent paper by **?** which introduces a theoretical model of imperfect central bank communication and shows that poor communications have been a source of macroeconomic volatility. Our paper introduces an empirical model which disentangles news and noise shocks in monetary policy. This allows us to study the role of imperfect central bank communications for macroeconomic outcomes as well as financial markets.

Modelling news and noise in monetary policy imposes a challenge for empirical analysis because standard VAR methods fail. Because agents cannot observe the current structural news shocks, current and past values of economic time series are not sufficient to recover such shocks (**?**). This implies that structural shocks are non-fundamental with respect to the agents' information set (see **?** and **??**).

Against this backdrop, we follow the approach originally proposed by Forni et al. (2017) and introduce a non-standard structural VAR framework for monetary policy that allows for estimation of the structural shocks when the signals are noisy. In particular, we use dynamic rotations of the VAR residuals to recover the structural shocks (**?**). Since agents cannot distinguish between the current news shock and the noise shock, combinations of current and past values of the VAR residuals do not identify the structural shocks. However, combinations of future values of such residuals identify the current news and noise shock because, as time passes, realized monetary policy actions reveal the noise component contained in the news shock. This approach has been successfully introduced to study stock market bubbles (**?**) and business cycle issues (**?**).

We find the following: first, the noisy signal, containing news about future monetary policy tightening, shifts policy rate expectations upwards, and decreases output and prices. Second, a sizable part of the signal is noise surrounding future monetary policy decisions. The noise shock decreases output and prices and can explain up to 15% and 8% of their variations, respectively. Further, the noise component of fed funds rate expectations shows cyclical variations but no apparent trend suggesting that communications (or agent's interpretations thereof) have not significantly improved over time.[4] Finally, financial markets react significantly to the noise surrounding future monetary policy. In particular, stock prices fall, and financial market volatility and the excess bond premium increase following a monetary policy noise shock. Our results are robust to controlling for non-anticipated monetary policy shocks as well as other news shocks. Therefore, noise seems to be an empirically relevant component of monetary policy as it can be economically costly and can disrupt financial markets.

[4] As will be discussed later in the paper, we use policy rate expectations at the 6-months-ahead horizon to reveal the signal in our benchmark model. As those expectations remained relatively flat at the ZLB, we cannot say much about communications at the ZLB.

The paper proceeds as follows. Section 2 documents monetary policy anticipation and presents a simple model of monetary policy with imperfect information (communication). Section 3 discusses the econometric implications and introduces the VAR identification strategy for the bivariate and multivariate case. Section 4 presents our empirical results for news and noise in monetary policy based on our benchmark specification. Section 5 discusses additional results and robustness. Section 6 concludes.

2 Anticipated Monetary Policy and Imperfect Information

2.1 Is Monetary Policy Anticipated?

We start by discussing whether monetary policy is actually anticipated and, thus, allows us to extract a signal revealing future monetary policy decisions.

Twenty-five years ago, the Federal Reserve did not announce its monetary policy decisions to the public. Markets were left to infer the FOMC's decision by watching the open market desk buying or selling securities in financial markets. However, since then, FOMC communication has changed radically. In February 1994, for the first time, the Federal Reserve started issuing a statement immediately after the FOMC, noting its decision to tighten. The Federal Reserve mentioned that the statement was issued "to avoid any misunderstanding of the committee's purposes, given the fact that this is the first firming of reserve market conditions by the committee since early 1989." Since then, the Federal Reserve has become more and more transparent in its policy deliberations. Today, when the FOMC makes monetary policy decisions, it releases a detailed statement outlining the rationale for its current decisions and providing guidance for future ones. The FOMC also releases minutes and quarterly projections and holds press conferences. Further, the Chairman and the FOMC members give numerous speeches and press interviews throughout the year to explain their thinking. These tools help the FOMC to communicate its beliefs about the likely stance of monetary policy over the coming months and quarters.

Given the history of Federal Reserve communication, it is hard to argue that monetary policy decisions were always anticipated. This is especially before 1994, when the only signal agents received about future policy decisions were changes in the fed funds rate per se. However, with the first release of a FOMC statement in 1994, the idea that monetary policy is partly anticipated has gained ground and is largely accepted nowadays. For example, **?** and **?** have demonstrated that monetary policy news (from FOMC statements) affects expectations about future monetary policy decisions. At the same time, **?** shows that since February 1994, policy decisions taken at regularly scheduled FOMC meetings, whether or not they have involved a federal funds target change, have generated relatively little surprise in the federal funds futures market. Such current decisions have been well anticipated by market participants. Moreover, **?** find an increase in the ability of financial markets and professional forecasters to predict subsequent interest rate changes after 1994. Similarly, **?** documents improved predictability of US monetary policy by both professional forecasters and fed funds futures after communications reforms (including the introduction of FOMC statements in 1994).

Figure 1 plots the fed funds target rate with its expectations, i.e., six-months-ahead fed funds rate forecasts (both survey and market based). Expectations follow the dynamics of the fed funds rate well, indicating that future target rate decisions are anticipated to some extent. However, anticipation is not perfect as there is generally a gap between expectations and the policy rate. Policy cycle turning points seem hard to predict. Further, in line with findings in the literature predictability of the fed funds rate seems to improve after 1994 as the gap between expectations and the fed fund rate gets smaller, especially during the 2001 and 2005 tightening cycles.

2.2 A Simple Model of Noisy Monetary Policy

We present a simple theoretical framework to illustrate the effects of anticipated monetary policy shocks in an environment of imperfect information (in the sense that there is imperfect central bank communication). The framework is a version of the one proposed in Forni et al. (2017) for news shock to total factor productivity (TFP), but adapted for the case of monetary policy.

Let us start from the assumption that there are two type of agents: the central bank, which has full information about the shocks hitting the economy, and the agents, who only have partial information in a sense that will be discussed and clarified below.[5] As a first step, let us consider the simplest case and assume that the interest rate is set by the bank according to

$$i_t = \varepsilon_{t-1}. \tag{1}$$

The shock ε_t affects the policy rate with a delay and defines the news or anticipated monetary policy shock.

We assume that agents form expectations rationally but information is limited. Agents receive news about the future path of interest rate, i.e., ε_t, in every period. We can think of the central bank announcing the future path of the interest rate. However, the announcement can be noisy in the sense that it does not fully reveal the future actual path of the interest rate.

[5]Note that in our setting, agents can observe other economic shocks fully.

This could be due to the lack of clear communication or lack of credibility by the central bank. As a result, in many cases market expectations might remain unfulfilled. We model this situation by assuming that the agents receive a signal, i.e., the communicated path of the interest rate,

$$s_t = \epsilon_t + \nu_t, \tag{2}$$

where ν_t is the noise shock that is uncorrelated with ϵ_t at all leads and lags and the variance of the signal is simply the sum of the variance of the shock and the noise $\sigma_s^2 = \sigma_\varepsilon^2 + \sigma_\nu^2$. The agents' information set, $\mathcal{I}_t$, consists of $\{i_{t-j}, s_{t-j}\}$ for $j \geq 0$. Now assume that agents make consumption decisions on the basis of the expected path of the interest rate, very simplistically $c_t = aE(i_{t+1}|\mathcal{I}_t)$. The expectation will coincide with the linear projection of ε_t onto s_t, $c_t = \gamma(\varepsilon_t + \nu_t)$, where $\gamma = \sigma_\varepsilon^2/\sigma_s^2$ is the linear projection coefficient. This means that the noise component can generate fluctuations in consumption. In general, under rational expectations and limited information, any variable that is the outcome of an agent's decisions and depends on the expected future interest rate will be affected by the noise component.

Now let us generalize the framework. First, we assume that there are other $n-2$ shocks ($n > 2$) driving the economy. All these additional shocks are observed both by the central bank and by the agents (and uncorrelated with news and noise shocks). Second, by definition of the news shock, we have a general impulse response function of the interest rate to the news/anticipated shock with a zero impact effect. Third, we assume that the central bank does not respond to the noise shock, that is, the bank will not react to fluctuations in the economy generated by the noise component. This is consistent with a monetary policy rule where monetary policy reacts only to the non-noise component of inflation and output, the component driven by genuine economic shocks. So, the equation for the interest rate becomes

$$i_t = c(L)\varepsilon_t + q(L)'w_t, \tag{3}$$

where $q(L)$ is a $n-2$-dimensional column vector of lag polynomials and w_t is $n-2$-dimensional vector of economic shocks. The vector might include the standard non-anticipated policy shock as well as other real or nominal shocks. As before, agents do not observe the news shock but receive only a noisy signal. The information set of the agents is now the set spanned by $\{i_{t-j}, s_{t-j}, w_{t-j}\}$, $j \geq 0$. As long as agents react to the expected path of current and future interest rates, the economy will be affected by the noise shock. We do not model the non-policy part of the economy as the empirical strategy does not require any additional assumptions other than those discussed above.

3 The Econometric Model

As is well known, in the model described above, standard VAR methods using i_t and s_t fail in correctly identifying the anticipated shock since agents themselves cannot distinguish between news and noise shocks. In other words, the information set of agents differs from the information set spanned by the structural shocks, implying that the VAR is non-fundamental. To identify the news and noise shock in monetary policy, we follow **?** and **?**. These papers propose a new identifying approach to recover the structural shocks in a noisy information setting based on dynamic rotations of future VAR residuals (see, e.g., **?**). Here we discuss the main features of the econometric approach and we refer the reader to the papers for details. For ease of explanation, we start by describing a bivariate specification and then move to a more general specification that includes output and prices.

3.1 Bivariate Specification

Suppose that the policy rate is driven only by the news shock affecting the policy rate with a delay, i.e.,

$$i_t = c(L)\epsilon_t, \tag{4}$$

where $c(L)$ is a rational function in the lag operator with $c(0) = 0$ and the monetary policy news shock, ϵ_t, is a white noise process. As before, at time t agents receive some information about ϵ_t, i.e., the announcement. More specifically, they observe the signal that is given by equation 2. Agents also observe the policy rate at time t so that the agent's information set is $I_t = \text{span}(i_{t-k}, s_{t-k}, k \geq 0)$. Then, the structural representation becomes

$$\begin{pmatrix} i_t \\ s_t \end{pmatrix} = \begin{pmatrix} c(L) & 0 \\ 1 & 1 \end{pmatrix} \begin{pmatrix} \epsilon_t \\ \nu_t \end{pmatrix}. \tag{5}$$

This representation is non-fundamental since the determinant of the MA matrix (i.e., $c(L)$) is zero at $L = 0$ by definition of the news shock. This implies that a VAR representation for i_t and s_t in the structural shocks does not exist, as present and past values of the observed series contain strictly less information than the present and past values of the structural shocks. However, we can find a fundamental representation with orthogonal innovations, i.e.,

$$\begin{pmatrix} i_t \\ s_t \end{pmatrix} = \begin{pmatrix} \frac{c(L)}{b(L)} & \frac{c(L)\sigma_\epsilon^2}{\sigma_s^2} \\ 0 & 1 \end{pmatrix} \begin{pmatrix} u_t \\ s_t \end{pmatrix}, \tag{6}$$

where

$$b(L) = \prod_{j=1}^{n} \frac{L - r_j}{1 - \bar{r}_j L} \tag{7}$$

with r_j, $j = 1, ..., n$, being the roots of $c(L)$ that are smaller than 1 in modulus and $\bar{r}_j$ being the complex conjugate of r_j. Moreover, u_t and s_t are orthogonal innovations for I_t, i.e., I_t =span$(u_{t-k}, s_{t-k}, k \geq 0)$ given by

$$\begin{pmatrix} u_t \\ s_t \end{pmatrix} = \begin{pmatrix} b(L)\frac{\sigma_\nu^2}{\sigma_s^2} & -b(L)\frac{\sigma_\epsilon^2}{\sigma_s^2} \\ 1 & 1 \end{pmatrix} \begin{pmatrix} \epsilon_t \\ \nu_t \end{pmatrix}. \tag{8}$$

The innovation u_t is the deviation of the realized policy rate from agents' expectations, that is, agents' new information due to the observation of i_t. Future realizations of the policy rate convey information about how noisy past signals were. This means that representation (8), although not invertible in the past, can be inverted in the future:

$$\begin{pmatrix} \epsilon_t \\ \nu_t \end{pmatrix} = \begin{pmatrix} b(F) & \frac{\sigma_\epsilon^2}{\sigma_s^2} \\ -b(F) & \frac{\sigma_\nu^2}{\sigma_s^2} \end{pmatrix} \begin{pmatrix} u_t \\ s_t \end{pmatrix}, \tag{9}$$

where F is the forward operator and $1/b(L) = b(F)$. The above equation shows that the news shock and noise shock are linear combinations of future and present values of u_t and s_t.

We further assume that the signal, s_t, is not observed by the econometrician but rather there is a variable z_t that reveals to the econometrician the information contained in the signal received by the agents. The signal-revealing series may depend on both u_t and s_t. Then, the representation in terms of the econometrician's information set (and with unit variance shocks) is given by

$$\begin{pmatrix} i_t \\ z_t \end{pmatrix} = \begin{pmatrix} a_{11}(L) & a_{12}(L) \\ a_{21}(L) & a_{22}(L) \end{pmatrix} \begin{pmatrix} u_t/\sigma_u \\ s_t/\sigma_s \end{pmatrix} = \begin{pmatrix} \frac{c(L)}{b(L)}\sigma_u & \frac{c(L)\sigma_\epsilon^2}{\sigma_s} \\ d(L)\sigma_u & f(L)\sigma_s \end{pmatrix} \begin{pmatrix} u_t/\sigma_u \\ s_t/\sigma_s \end{pmatrix}. \tag{10}$$

The mapping between the normalized innovations and the normalized structural shocks is

$$\begin{pmatrix} u_t/\sigma_u \\ s_t/\sigma_s \end{pmatrix} = \begin{pmatrix} b(L)\frac{\sigma_\nu}{\sigma_s} & -b(L)\frac{\sigma_\epsilon}{\sigma_s} \\ \frac{\sigma_\epsilon}{\sigma_s} & \frac{\sigma_\nu}{\sigma_s} \end{pmatrix} \begin{pmatrix} \epsilon_t/\sigma_\epsilon \\ \nu_t/\sigma_\nu \end{pmatrix}. \tag{11}$$

The structural representation is obtained by combining equations (10) and (11):

$$\begin{pmatrix} i_t \\ z_t \end{pmatrix} = \begin{pmatrix} c(L)\sigma_\epsilon & 0 \\ f(L)\sigma_\epsilon + b(L)d(L)\frac{\sigma_\nu^2\sigma_\epsilon}{\sigma_s^2} & f(L)\sigma_\nu - b(L)d(L)\frac{\sigma_\nu\sigma_\epsilon^2}{\sigma_s^2} \end{pmatrix} \begin{pmatrix} \epsilon_t/\sigma_\epsilon \\ \nu_t/\sigma_\nu \end{pmatrix}. \tag{12}$$

Estimation of representation (12) consists of two parts: first, we estimate and identify the fundamental representation (10); second, we identify (11). More specifically,

1. Estimate a reduced-form VAR for i_t and z_t and identify by imposing $\hat{a}_{12}(0) = 0$ (i.e., the signal does not affect the policy rate on impact). In the bivariate case, this is sufficient to identify u_t and s_t and to obtain an estimate of the impulse response function of equation (10).

2. Estimate $b(L)$ by calculating the roots of $\hat{a}_{12}(L)$, choosing those which are smaller than 1 in modulus in equation (7).

3. Estimate $\sigma_\epsilon/\sigma_\nu$ as the ratio $\frac{\hat{a}_{12}(1)}{\hat{a}_{11}(1)}$. Using $\sigma_\nu^2/\sigma_s^2 + \sigma_\epsilon^2/\sigma_s^2 = 1$, obtain $\widehat{\sigma_\epsilon/\sigma_s}$ and $\widehat{\sigma_\nu/\sigma_s}$ as $\sin(\arctan(\widehat{\sigma_\epsilon/\sigma_\nu}))$ and $\cos(\arctan(\widehat{\sigma_\epsilon/\sigma_\nu})$, respectively.

This provides estimates of all the elements of representations (10) and (11) and, thus, (12).

3.2 Four-variable Specification

We now extend the above framework to a VAR specification that will be also used in the empirical application, which includes two additional variables: a measure of output and prices. In this four-variable VAR, the innovation representation in (10) becomes

$$\begin{pmatrix} y_t \\ p_t \\ i_t \\ z_t \end{pmatrix} = \begin{pmatrix} m_{11}(L) & m_{12}(L) & m_{13}(L) & m_{14}(L) \\ m_{21}(L) & m_{22}(L) & m_{23}(L) & m_{24}(L) \\ q_1(L) & q_2(L) & \frac{c(L)}{b(L)}\sigma_u & \frac{c(L)\sigma_\epsilon^2}{\sigma_s} \\ m_{41}(L) & m_{42}(L) & d(L)\sigma_u & f(L)\sigma_s \end{pmatrix} \begin{pmatrix} w_{1t} \\ w_{2t} \\ u_t/\sigma_u \\ s_t/\sigma_s \end{pmatrix}, \tag{13}$$

where y_t and p_t are time series for output and prices, $q(L) = [q_1(L)\ q_2(L)]$ and w_{1t} and w_{2t} are two structural orthonormal white noise shocks. Within this specification, the condition that s_t does not affect i_t on impact is no longer sufficient to identify the two innovations. Therefore, in order to identify the innovation, u_t, and the signal, s_t, we impose a Cholesky triangularization with output and prices ordered before the policy rate and the signal-revealing variable. That is, $m_{12}(0) = m_{13}(0) = m_{14}(0) = m_{23}(0) = m_{24}(0) = 0$, in addition to the maintained assumption that $c(0) = 0$. The u_t and the s_t will be the third and fourth innovations of this Cholesky representation, respectively. The advantage of this approach is that, by ordering interest rate after prices and output, we make the signal orthogonal to current and past prices and output. This is important to ensure that our identified noise is not contaminated by other factors like demand shocks or other policy shocks. The drawback is that, in the presence of a standard non-anticipated monetary policy shock satisfying the standard zero restrictions of no contemporaneous effect on prices and output, the fed funds rate innovation could mix u_t and the non-anticipated shock. We confront this problem by also identifying the standard policy shock. It turns out that the results obtained by including the non-anticipated shock are almost identical, suggesting that this potential drawback is not empirically relevant.

The structural representation is obtained by post-multiplying the matrix above with the multivariate extension of the matrix that maps innovations to structural shocks, equation (11), that is,

$$\begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & b(L)\frac{\sigma_\nu}{\sigma_s} & -b(L)\frac{\sigma_\epsilon}{\sigma_s} \\ 0 & 0 & \frac{\sigma_\epsilon}{\sigma_s} & \frac{\sigma_\nu}{\sigma_s} \end{pmatrix}. \tag{14}$$

The multivariate model can be estimated by following the same steps as in the bivariate case. Note that the model can be easily extended to include additional variables as long as we impose additional restrictions on the innovation representation. For example, one could include financial time series by ordering them last, assuming that the signal affects financial variables immediately.

4 Empirical Evidence

4.1 Data

We estimate our model at monthly frequency over the sample 1994:01–2016:10.[6] As described earlier, starting the sample in 1994 is motivated by the introduction of policy statements by the FOMC. For output and prices, we use the U.S. Industrial Production (IP) Index and the Consumer Price Index (CPI). Both series are obtained from Haver Analytics. In addition, we have to choose a series that reflects the policy rate and is unaffected by noise—i.e., i_t—and one that reveals the signal, z_t. We use the monthly average of the effective fed funds rate for i_t and choose measures of expectations of the fed funds rate to reveal the signal. As discussed in Section 2.1, Federal Reserve's communications are shown to shift fed fund rate expectations (see, e.g., **?**), thus, making them the natural choice to reveal the signal in monetary policy. In particular, in the baseline specification, we use the Blue Chip Financial Forecast (BCFF) survey to obtain a measure of fed funds rate expectations. In the robustness section, we also use a market-based measure of expectations obtained from fed funds futures.

[6]Our results are robust if we exclude the ZLB period, i.e., use data until December 2008. Impulse responses are similar but the confidence bands are wider due to the smaller sample size.

4.1.1 Survey-based Expectation Measures

First, we employ survey-based expectations of the fed funds rate. The BCFF is the only one that provides forecasts of the Federal Reserve's policy rate per se. Since 1982, the BCFF survey has been conducted monthly, covering approximately 50 analysts ranging from broker-dealers to economic consulting firms. The BCFF is published on the first day of each month and presents forecasts from a survey conducted during two consecutive business days one to two weeks earlier. The precise dates of the survey vary and are not generally noted in the publication. Since April 1983, each month the BCFF has provided the forecasts of the average interest rate over a particular quarter, beginning with the current quarter and up to four or five quarters into the future.[7] For example, in January, the forecast of the current quarter is given by the average expected realization over January, February and March, and the one-quarter-ahead forecast is given by the average expected realization over April, May, and June.

Therefore, the monthly BCFF forecasts are fixed-event forecasts of interest rates over the quarter, implying that their forecast horizon changes with each month in the quarter. We construct fixed-horizon forecasts by weighting the two given fixed-event forecasts following **?** (or see **?** for an application to the survey data of GDP and prices). We focus on the one-quarter- to four-quarters-ahead forecasts and define the six-months-ahead (fixed-horizon) forecast as follows. In the first month of the quarter, the six-months-ahead forecast is simply the forecast of the one-quarter-ahead forecast. In the second month of the quarter, the six-months-ahead forecast is obtained by taking the average of the one-quarter- and two-quarters-ahead forecasts with weights equal to 2/3 and 1/3, respectively. The six-months-ahead forecast for the final month of the quarter is the weighted average of the one-quarter- and two-quarters-ahead forecast with weights equal to 1/3 and 2/3. The nine-months-ahead forecasts are calculated as the weighted average of the two-quarters- and three-quarters-ahead forecasts given by the survey with weights similar to the ones discussed above. The 12-months-ahead forecasts are defined accordingly. Finally, we use the consensus forecast (mean across the 50 analysts).

4.1.2 Market-based Expectation Measures

Second, we use market-based expectations of the fed funds rate. The fed funds futures contract price represents the market opinion of the average daily fed funds effective rate as calculated and reported by the Federal Reserve Bank of New York for a given calendar month. It is designed to capture the market's need for an instrument that reflects Federal

[7] Before 1983, forecasts only exist for the current and then every other quarter.

Reserve monetary policy. Fed funds futures and options have long been regarded as an effective means of tracking market expectations of monetary action by the FOMC. Futures for the fed funds rate started trading in the late '80s (December '88) but only up to a six-months-ahead horizon. Meaningful trading volumes of up to 24 months ahead begin only in 2004 (up to 36 months ahead in 2011). We use six-months-ahead fed funds futures as an alternative measure for expectations of future monetary policy. One disadvantage of working with market-based expectations measures such as futures is that they contain a risk premium (that is increasing with horizon). (See, e.g., **?** and **?** for a more general discussion.) We follow **?**, and use the difference between the future price before and after FOMC announcement dates to purge for risk premia. Because FOMC meetings are not held on a monthly basis, to transform a monthly series we assume that the daily change in the fed funds rate is zero in months with no meeting (see **?**, among others). Finally, the data on fed funds futures are obtained from Bloomberg, and the FOMC announcements dates are obtained from the Federal Reserve's website.[8]

4.2 Bivariate VAR

We start by estimating a VAR containing the policy rate and its expectations, i.e., the noise-free and signal-revealing series, respectively. Specifically, the VAR includes the fed funds rate and the BCFF expectations of the fed funds rate at the six-month horizon. We include nine lags in line with the Akaike Information Criterion (AIC) and identify the innovation, u_t, the signal, news and noise shocks as described in Section 3.1; i.e., the signal does not affect the policy rate on impact. Figure 3 shows the impulse response functions of the fed funds rate and its survey-based expectations for the signal and the news and noise shocks, respectively. Light- and dark-shaded areas represent the confidence bands at the 90% and 68% levels, respectively, and are obtained by **?**'s method.

The signal shock increases fed funds rate expectations on impact but does not affect the policy rate (by assumption). Afterwards the signal shock increases the policy rate significantly. Decomposing the signal between news and noise, fed funds rate expectations increase on impact following both the news and noise shock. However, the noise shock has a bigger impact effect. The effect of noise turns insignificant after about five months. In line with theory, the effect of the noise shock on the policy rate is small and insignificant across all horizons.

[8]See `https://www.federalreserve.gov/monetarypolicy/fomc_historical_year.htm`.

4.3 Four-variable VAR

Our benchmark specification includes the log of IP, the log of CPI, the effective fed funds rate and six-months-ahead BCFF expectations of the fed funds rate.[9] As explained in Section 3, identification is achieved by assuming that IP and prices do not react on impact to the policy rate innovation and the signal. Moreover, the signal does not affect the fed funds rate on impact.

Figure 4 shows the impulse response function of the four variables in the VAR to the signal, news and noise shocks. As before, light- and dark-shaded areas represent confidence bands at the 90% and 68% level, respectively. As expected, the signal shock increases fed funds expectations (by about 10 basis points) and significantly anticipates the future policy rate. Moreover, the signal decreases IP significantly at all horizons with a peak effect of circa -0.4 percentage points after about three years. Prices also decrease significantly following the signal shock.

Let us now consider effects of news and noise shocks. First, note that the estimates of σ_ϵ/σ_s and σ_ν/σ_s are 0.54 and 0.85, respectively, implying that the signal is quite noisy. The noise, as predicted by the model, has no significant effect on the fed funds rate at all horizons. However, the news shock increases the fed funds rate significantly with a delay, reaching its peak response after about a year. The response turns insignificant after around two years. Further, the news shock increases fed funds expectations significantly for about two years, while the noise shock does so for about a quarter.

Turning to macroeconomic variables, the news shock decreases IP in the medium to long run as the response turns negative after about two years (significantly negative after three years).[10] In contrast, the noise shock decreases IP significantly in the short run, reaching its maximum response of -0.4 percentage points after about a year. The noise shock response of IP reverts after about two years. The effects of the noise shock seem to vanish once agents learn that the signal was just noise. At the same time, the actual news starts to show its effect on IP. As for prices, a news shock seems to negatively affect prices in the long run (albeit not significantly), while the noise shock decreases prices significantly across all horizons.

[9] In the case of four-and five-variable specifications, we include 6 lags. Our results are robust to the choice of the lag length, e.g., including 9 lags.

[10] The slightly positive response of IP in the short run (though not significant) could indicate the presence of the Fed information effect reflecting macroeconomic news in FOMC announcements (see **?** and **?**, among others). In that case, news about future monetary policy tightening do not signal the anticipated monetary policy action but rather stronger-than-anticipated economic fundamentals. In an unreported exercise including BCFF forecasts of GDP, we find that a news shock decreases expectations of output across all horizons (significantly), thus, providing little empirical support for the Fed information effect. This is in line with **?** who revisit the analysis in **?** and **?**, and conclude that there is little role for a Fed information effect.

Moreover, Table 4 presents the estimated decomposition of the forecast error variance at different horizons. The signal explains between 11% and 19% of variations in the fed funds rate, providing further evidence that interest rate decisions are partly anticipated. It explains 60% of the variance in fed funds expectations on impact and afterwards between 20% and 24% supporting our choice to use fed funds rate expectations as the signal-revealing variable. Concerning the macroeconomic variables, the signal innovation explains a relatively large fraction of IP (4%–20%) and the signal can explain up to 8% of the forecast error variance of prices in the long run.

Turning to the analysis of news and noise shocks, on impact, monetary policy expectations are largely driven by noise but less so at longer horizons as news takes on a bigger role. In line with our assumption, the fed funds rate is barely explained by noise and its largest driver is the monetary policy news shock, explaining between 77% and 83% of its variation. Fluctuations in IP and CPI seem to be driven more by noise than news surrounding future monetary policy decisions. At the longer horizon, the noise shock accounts for up to 15% and 8% of the variance of IP and prices, respectively. News accounts for up to 12% and 2% of the long-run variation of IP and prices, respectively.

4.4 Historical Decomposition

Our empirical model allows us to gain first insights on how effectively central bank announcements affect agents' expectations. Using a historical decomposition, we can assess the relevance of the noise shock for fed funds rate expectations over our sample. Therefore, we can discover periods when monetary policy announcements were particularly noisy, i.e., when they not fully reveal the future actual path of the policy rate. As described earlier, this could be due to the lack of clear communication or lack of credibility by the central bank.

Figure 5 reports the fed funds rate expectations (blue solid line) along with the component of the series that is due to the noise shock (red line) and the difference between the policy rate expectations and the noise component (blue dashed line). We also plot the federal funds target rate (black dotted line). Several interesting findings emerge. First, the noise component fluctuates over time and at times can account for up to about 40 bps in policy rate expectations. Noise in monetary policy peaked during the easing cycles of the early 2000s and following the global financial crisis in 2007. Also, during the tightening period of the mid-1990s and mid-2000s, the noise shock played an important role in forming fed funds rate expectations. Finally, the noise component remained relatively low over the ZLB period. Note that this is not surprising as 6-months-ahead expectations remained relatively flat over the ZLB period as forward guidance at the ZLB moved longer-term expectations of the policy rate more. Interestingly, for the period surrounding the lift off of the federal funds rate in 2015 the noise component was persistently positive and reached about 20bps as agents expected the Federal Reserve to increase interest rates sooner.

Finally, there are reasons to think that the clarity of signals sent by the Federal Reserve may have changed or perhaps improved over time. For example, after issuing a statement for the first time in 1994, the Federal Reserve has become more and more transparent in its policy deliberations. The FOMC also releases minutes and quarterly projections and holds press conferences. Further, each Fed Chair has their own style of conducting monetary policy and communicating it. Looking at the historical decomposition, we can gain first insights into this issue. While the noise component of fed funds rate expectations shows cyclical variations, it seems to not have become less relevant since 1994, suggesting that there has not been a vast improvement in signal extraction.[11]

5 Additional Analysis

In what follows, we assess the robustness of our results when employing alternative measures of fed funds expectations, i.e., first, survey expectations at the nine-month and 12-month horizon, and second, the daily change in fed funds futures at the six-month horizon. Next, we provide evidence on the nature of monetary policy before 1994. Further, we perform additional analysis, studying the effects of monetary policy news and noise in financial markets. Finally, we assess the role of unanticipated (conventional) monetary policy shocks in our setting.

5.1 Alternative Measure of Expectations

First, we use the BCFF survey-based expectations at the nine-months- and 12-months-ahead horizons. Figure 6 shows the impulse responses for the four-variate VAR including the nine-months-ahead fed funds expectations. Responses are very similar. The signal decreases output and prices significantly across all horizons. (The responses of prices to the signal are not always significant in the short run.) The effects of the signal on the fed funds rate and its expectations at the nine-month horizon are nearly identical with our benchmark specification. Moreover, the responses of IP and prices to news and noise shocks remain similar. The corresponding figure including the 12-months-ahead survey expectations are again very similar and are not presented here, for the sake of brevity.

In addition, let us consider the estimates of σ_ϵ/σ_s and σ_ν/σ_s. Recall that in the case

[11]Note that at the ZLB, the noise component remained relatively low as communication mainly moved fed funds rate expectations beyond the horizon used in this paper.

of six-month survey expectations, these ratios are 0.54 and 0.85, respectively, implying that the signal is quite noisy. Table 2 summarizes these ratios for alternative expectations horizons. The signal becomes noisier as the horizon increases. This is quite intuitive and suggests that the Federal Reserve provides relatively clearer signals for the near future.

Given that the survey-based expectations are published at the monthly frequency, one could argue that other news shocks, different from the monetary policy news, such as news about TFP, could influence fed funds rate expectations. This would imply that our identified monetary policy news shock could potentially mix different shocks. We address this concern by using the market-based measure of interest rate expectations described in Section 4.1.2. In particular, we replace the fourth variable in our four-variate specification with the monthly and cumulated representation of the daily change in six-months-ahead fed funds futures around FOMC announcement dates.[12] This measure of expectations reflects the monetary policy news contained in the announcement and is unlikely to be influenced by other macroeconomic news. Figure 7 reports the responses for signal, and news and noise shocks, respectively. Responses show the same patterns as before, although less significant.

5.2 Monetary Policy before 1994

In the sections above, we argued that there is little support for monetary policy anticipation before 1994. So, one could ask what results are obtained by the news-noise econometric framework using an estimation sample that stops in 1993. The impulse responses for the four-variate VAR estimated over 1983:04-1993:12 are provided in Figure 8. Over this sample period, neither the signal shock, the news shock nor the noise shock have any significant effects. Moreover, the signal shock has no significant effect on the fed funds rate, consistent with the view that before 1994, there was little anticipation of future monetary policy decisions.[13]

5.3 News, Noise, and Financial Markets

We now assess the effects of news and noise for financial markets. To do so, we separately estimate five-variate VARs, each including one of the following financial market variables: the excess bond premium (EBP), the corporate bond spread, the S&P 500 stock price index, and the VIX. In particular, the EBP is obtained from **?** and is a popular indicator of tightness in credit markets. The EBP estimates the extra compensation demanded by

[12]Like **?** and **?**, we cumulate the market-based measure. The rationale for using the cumulated series, which is I(1) by construction, is that the output and price series are generally considered I(1); hence, if the I(0) series were included, the VAR would be statistically unbalanced.

[13]The same results are obtained when estimating the bivariate VAR over 1983:04 - 1993:12.

bond investors for bearing exposure to U.S. non-financial corporate credit risk beyond the compensation for expected losses. For the corporate bond spread, we use the difference between the Moody's seasoned BAA and AAA corporate bond yields.

Figure 9 shows the responses of the financial market variables to signal, news and noise shocks. For the sake of brevity, we do not present the responses of the macroeconomic variables since they are very similar to the responses obtained in our benchmark specification. The signal increases the EBP, the corporate spread and volatility in financial markets as measured by the VIX for about a year, while it decreases stock prices. When we decompose the signal into news and noise, the monetary policy news shock has a significant effect on the EBP and stock prices in the short run. Moreover, noise surrounding future monetary policy decisions affects all financial market indicators significantly on impact and up to about a year. Looking at the variance decompositions, the noise shock seems to be a more important driver of all financial market variables in the short run. Moreover, the noise shock can explain between 3% and 15% of the variation in stock prices while news explains between 1% and 5%. Finally, the noise shock explains between 3% and 9% of the variation in the VIX.

5.4 The Role of Non-anticipated Monetary Policy

A potential drawback of our approach is that the innovation in the fed funds rate estimated with the Cholesky representation could potentially mix the innovation u_t and the non-anticipated policy shock, if present. Here we explicitly identify the non-anticipated shock, in addition to the anticipated one, in order to check whether the results are unchanged and confirm the validity of our procedure.

In order to identify the non-anticipated monetary policy shock, we rely on the high-frequency identification approach based on fed funds futures data. In particular, we add the daily change in current-month fed funds futures around FOMC announcements, i.e., the current surprise, to our benchmark VAR. We order the current surprise (in cumulated terms) after IP and prices. Similar in spirit to **?**, the current surprise is included in the VAR before our measure of fed funds expectations.[14] The third shock in the innovation representation can then be interpreted as the non-anticipated monetary policy or surprise shock (surprise changes in the current fed funds rate target), which is orthogonal to the signal.

[14] **?** extract the first two principal components of the daily changes in fed funds futures across several horizons. By performing a suitable rotation of these unobserved factors, they show that they can be given a structural interpretation as a "current federal funds rate target" factor, corresponding to surprise changes in the current fed funds rate target, and a "future path of policy" factor, corresponding to changes in futures rates out to horizons of one year that are independent of changes in the current funds rate target.

Figure 10 shows the responses to the non-anticipated monetary policy shock. IP and prices decrease following a surprise change in the current fed funds target rate. (However, we can observe a light version of the price puzzle in the very short run.) The responses of IP and CPI to the signal innovation remain unchanged. Similarly, the results remain unchanged for news and noise shocks. Moreover, the current surprise does not react to noise, as remains the case for the fed funds rate. Interestingly, the news shock increases the current surprises and the fed funds rate with a delay (as before). This makes sense as future changes in the fed funds rate are only partly anticipated. Hence, news is also associated with future surprises.

Turning to the variance decompositions, we find that the signal plays a relatively more important role for variations in IP than the non-anticipated shock. The surprise shock explains between 1% and 7% of IP variations, while the signal explains between 4% and 16%. However, the surprise seems to explain a larger fraction of the long-run variation in prices than the signal does. Further, we find that the role of news and noise for variations in IP and prices is relatively unchanged. Noise explains between 6% and 19% of the variance in output and between 3% and 18% of the variance in prices.

Alternatively to using the surprise in current-month futures, we include the informationally robust monetary policy surprises by **?**. This series controls for central bank information effects in monetary surprises.[15] To provide an additional robust check, we now include the surprise in its original form (rather than in cumulated terms) and again we order it after IP and prices in the VAR.[16] Figures 12 and 13 show the responses to surprise and signal, and news and noise shocks, respectively. A very similar picture emerges and responses are robust to the inclusion of this alternative measure of non-anticipated monetary policy.

6 Conclusion

In this paper, we introduce imperfect information to the conduct of monetary policy. Agents receive news concerning future monetary policy decisions but observe only a noisy signal that can be decomposed into the news shock and the noise shock. As time passes, agents observe the actual interest rate decisions and can distinguish the news from noise. In this setting, empirical analysis becomes challenging as standard VAR methods fail. Against this backdrop, we rely on non-standard VAR methods involving rotations of future VAR residuals.

[15] Details on the construction of the series can be found in **?**

[16] For brevity, we do not show the impulse responses corresponding to a model which includes the informationally robust surprises in cumulated terms. Results are very similar.

We provide new insight into how to characterize monetary policy shocks since the mid-1990s by assessing the role of news and noise in monetary policy. We find that interest rate decisions are partly anticipated. Output and prices decrease following a signal shock, revealing potential contractionary monetary policy actions in the future. Interestingly, the signal is quite noisy, implying that output and prices react sizably to noise in monetary policy. Moreover, noise surrounding future monetary policy decisions disturbs financial markets significantly as it increases the EBP, the corporate spread, and financial market volatility and decreases stock prices.

Our results suggest the following for the conduct of monetary policy. First, noise surrounding monetary policy is economically costly and can disrupt financial markets. Second, forward guidance (in the sense of guiding the future path of interest rates) can be valuable if clearly communicated and if a central bank can commit to its future decisions.

Tables and Figures

Table 1: ***Four-Variate VAR: Variance Decomposition***

Variable	Horizon (months)					
	Impact	6	12	24	48	84
			Signal			
IP	0.0	3.7	6.1	8.4	16.7	19.9
CPI	0.0	4.0	4.3	3.1	4.9	8.0
FFR	0.0	10.9	17.8	19.4	18.7	18.2
E(FFR)	58.5	24.1	23.7	22.2	21.2	20.7
			News			
IP	0.0	0.0	0.2	0.3	7.4	12.2
CPI	0.0	0.5	0.5	1.0	0.8	1.7
FFR	0.0	79.8	83.2	82.2	79.6	77.2
E(FFR)	26.4	82.5	83.5	81.2	78.4	76.2
			Noise			
IP	0.0	5.2	10.2	13.5	14.9	14.7
CPI	0.0	4.1	4.9	5.2	6.7	7.9
FFR	0.0	2.3	0.8	0.5	0.5	0.8
E(FFR)	65.8	2.3	0.9	0.7	0.8	1.0

Notes: Variance decomposition in the four-variate VAR. The entries are the percentage of variance explained by the shocks at the specified horizons.

Table 2: ***Noise-to-Signal and News-to-Noise Ratio***

	Expectation Horizon		
	6-month	9-month	12-month
σ_ϵ/σ_s	0.54	0.49	0.32
σ_ν/σ_s	0.85	0.87	0.95
$\sigma_\epsilon/\sigma_\nu$	0.63	0.57	0.34

Table 3: *Five-Variate VARs with Financial Indicators: Variance Decomposition*

Variable	Horizon (months)					
	Impact	6	12	24	48	84
	Signal					
EBP	8.5	14.4	13.0	12.2	10.5	11.3
BAA-AAA	5.6	12.1	11.4	12.0	12.5	12.7
S&P 500	3.6	15.9	15.0	10.8	13.1	13.8
VIX	4.3	9.6	9.3	9.6	10.0	10.1
	News					
EBP	3.6	6.5	5.9	6.1	9.4	11.7
BAA-AAA	1.3	0.4	3.7	8.5	17.4	17.9
S&P 500	1.1	2.9	1.9	1.4	3.8	4.8
VIX	1.2	1.5	2.7	4.4	12.9	13.4
	Noise					
EBP	5.0	8.4	7.7	7.6	7.2	6.8
BAA-AAA	4.4	15.6	17.4	16.3	14.0	13.9
S&P 500	2.5	13.5	15.0	13.4	13.1	12.9
VIX	3.1	9.0	8.2	8.0	6.9	6.8

Notes: Variance decomposition in the five-variate VARs including one of the following financial indicators: the EBP, the BAA-AAA spread, the S&P 500 index, the VIX. The entries are the percentage of variance explained by the shocks at the specified horizons.

Table 4: ***Five-Variate VAR with Conventional Monetary Policy Shock: Variance Decomposition***

Variable	Horizon (months)					
	Impact	6	12	24	48	84
	Surprise					
IP	0.0	0.8	1.2	1.6	3.6	6.5
CPI	0.0	0.9	1.0	1.7	3.6	7.0
Current Surprise	99.7	91.5	82.6	76.0	55.9	44.8
FFR	8.0	10.8	7.5	9.8	12.1	10.9
E(FFR)	1.9	8.2	6.7	9.5	11.1	10.1
	Signal					
IP	0.0	4.0	6.1	7.9	15.2	16.3
CPI	0.0	3.8	3.6	2.0	2.5	4.1
Current Surprise	0.0	4.2	10.7	15.1	10.6	12.7
FFR	0.0	11.1	17.4	17.3	16.5	15.6
E(FFR)	63.8	25.0	23.9	20.4	19.5	18.3
	News					
IP	0.0	0.4	0.2	0.2	5.8	6.9
CPI	0.0	1.3	1.1	3.3	2.7	1.7
Current Surprise	0.0	4.6	12.3	13.7	9.2	7.8
FFR	0.0	57.1	65.6	59.7	56.5	51.5
E(FFR)	57.6	69.5	69.7	60.2	57.5	52.7
	Noise					
IP	0.0	6.4	14.9	19.9	18.7	18.6
CPI	0.0	3.1	6.1	10.5	14.4	17.7
Current Surprise	0.0	0.4	0.8	3.8	13.9	16.8
FFR	0.0	14.4	11.9	10.7	10.1	11.9
E(FFR)	34.0	7.4	8.6	8.8	8.5	10.4

Notes: Variance decomposition in the five-variate VAR identifying the conventional monetary policy shock (surprise shock). The entries are the percentage of variance explained by the shocks at the specified horizons.

Figure 1: ***The Signal-Extraction Problem in Monetary Policy***

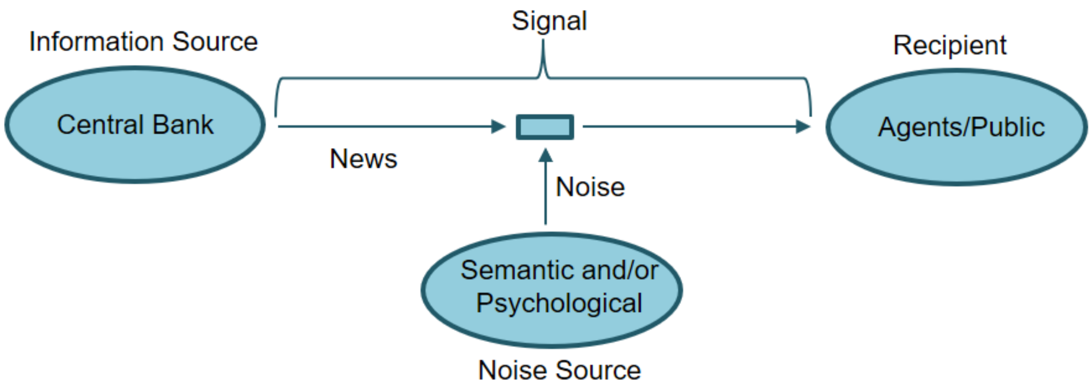
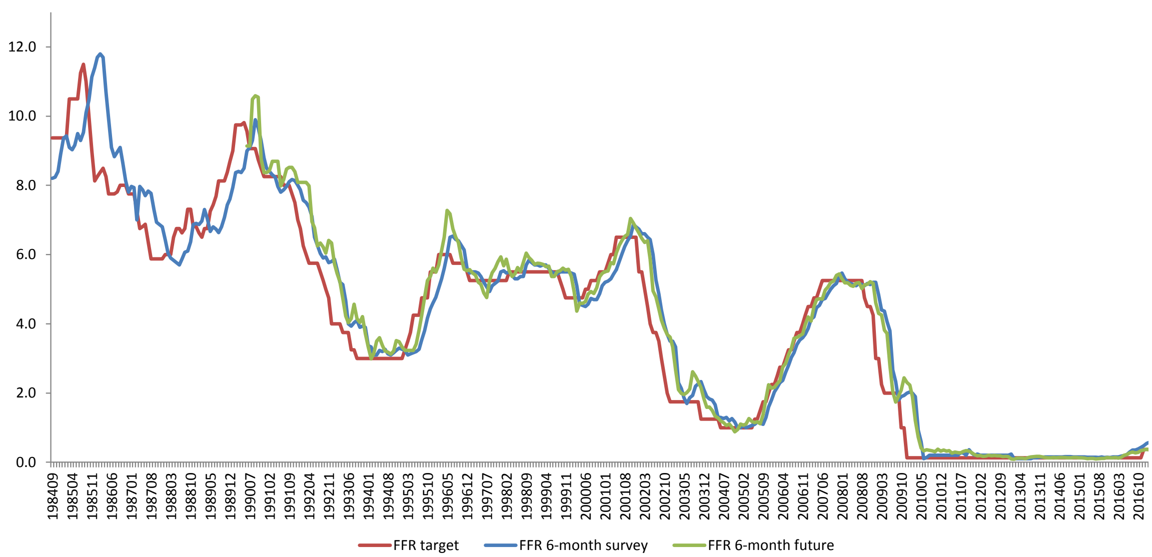
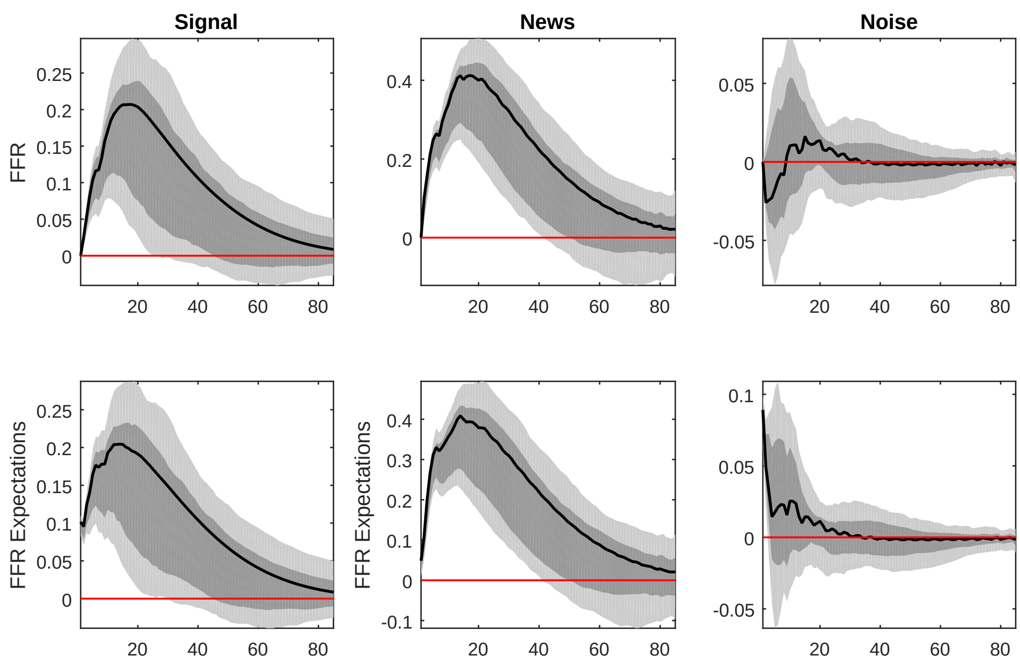


Figure 2: ***Fed Funds Rate and its Expectations***



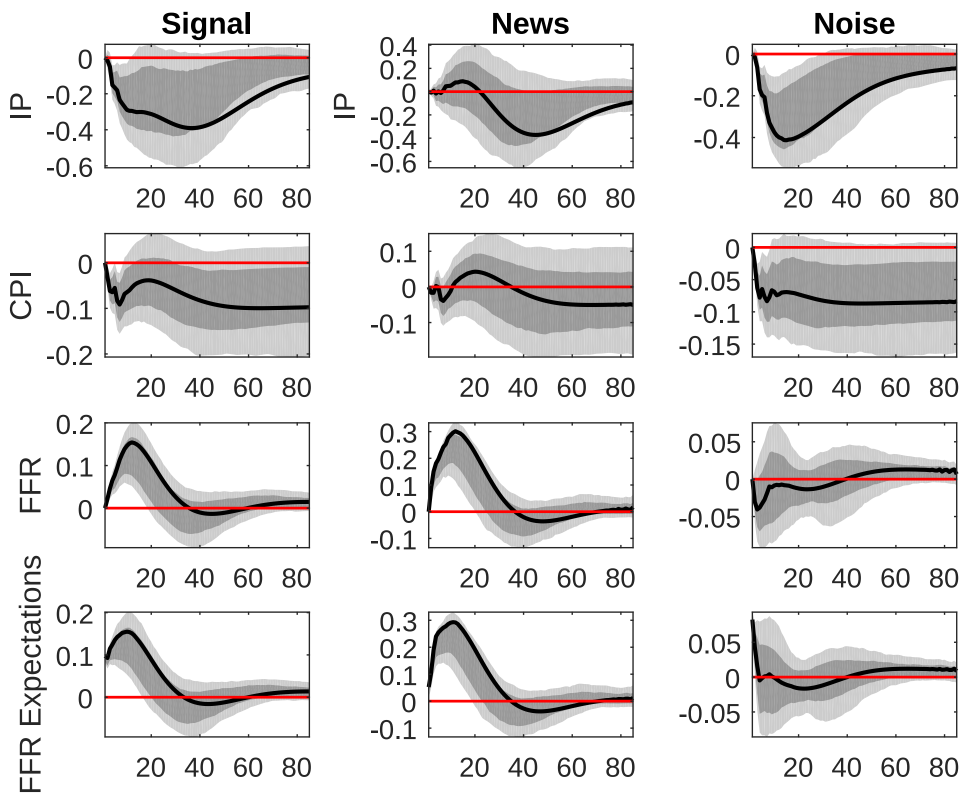
Notes: Fed funds rate at time t*,* i_t*, along with six-months-ahead survey and market expectations at* $t-6$*,* $E_{t-6}(i_t)$*.*

Figure 3: ***Bivariate VAR: Signal, News, and Noise***



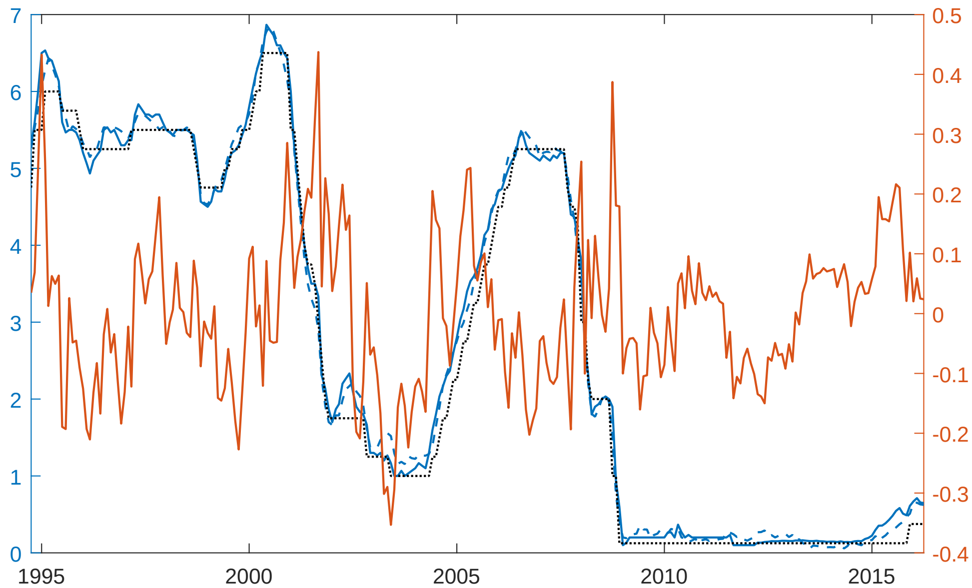
Notes: Bivariate VAR containing the fed funds rate and six-months-ahead survey-based fed funds expectations. Estimation sample: 1994 January – 2016 October.

Figure 4: ***Four-variate VAR: Signal, News, and Noise***



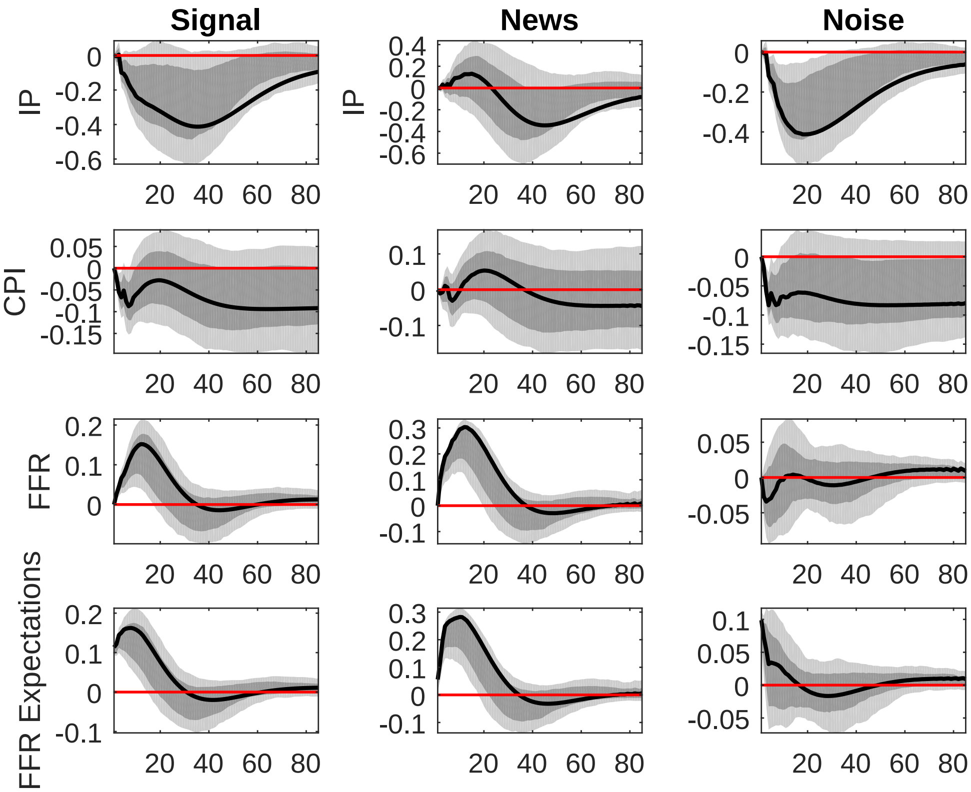
Notes: VAR containing logarithm of IP, the logarithm of CPI, the fed funds rate and six-months-ahead survey-based fed funds expectations. Estimation sample: 1994 January – 2016 October.

Figure 5: ***Historical Decomposition of Fed Funds Rate Expectations***



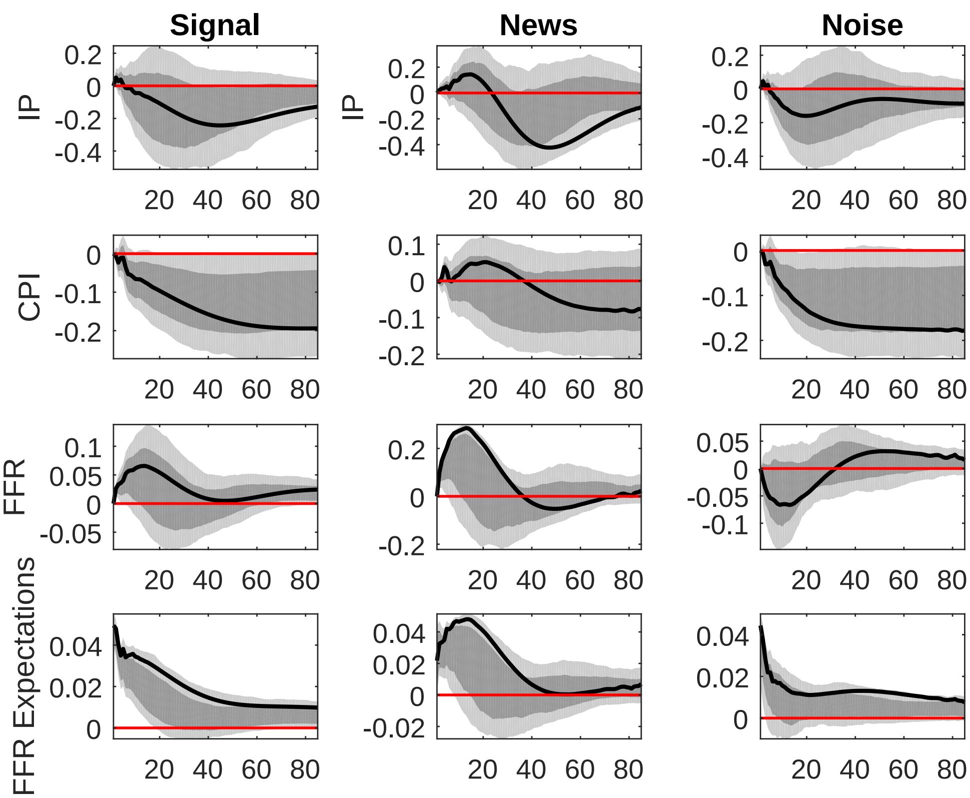
Notes: Historical decomposition in the VAR containing logarithm of IP, the logarithm of CPI, the fed funds rate and six-months-ahead survey-based fed funds expectations. Solid blue line: six-months-ahead survey-based fed funds rate expectations (left axis). Solid red line: noise component of the fed funds rate expectations (right axis). Dashed blue line: difference between the fed funds rate expectations and the noise component (left axis). Dotted black line: federal funds target rate. The decomposition is truncated at time $T-6$ *since end-of-sample estimates are inaccurate.*

Figure 6: ***Four-variate VAR (Incl. Nine-month Expectations): Signal, News, and Noise***



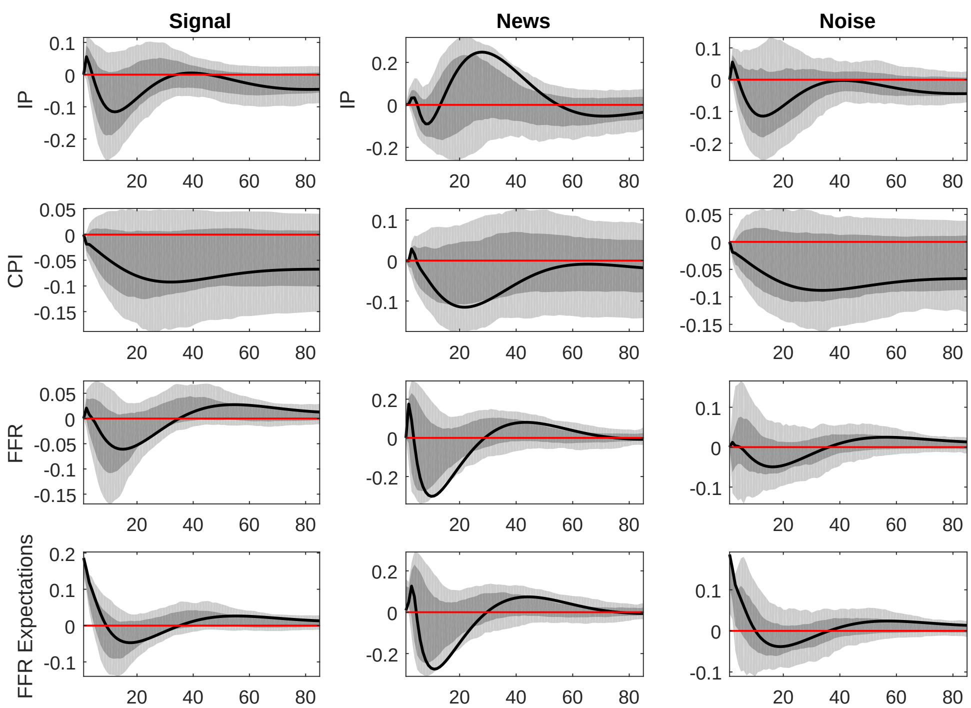
Notes: VAR containing logarithm of IP, the logarithm of CPI, the fed funds rate and nine-months-ahead survey-based fed funds expectations. Estimation sample: 1994 January - 2016 October.

Figure 7: ***Four-variate VAR (Incl. Market-based Expectations): Signal, News, and Noise***



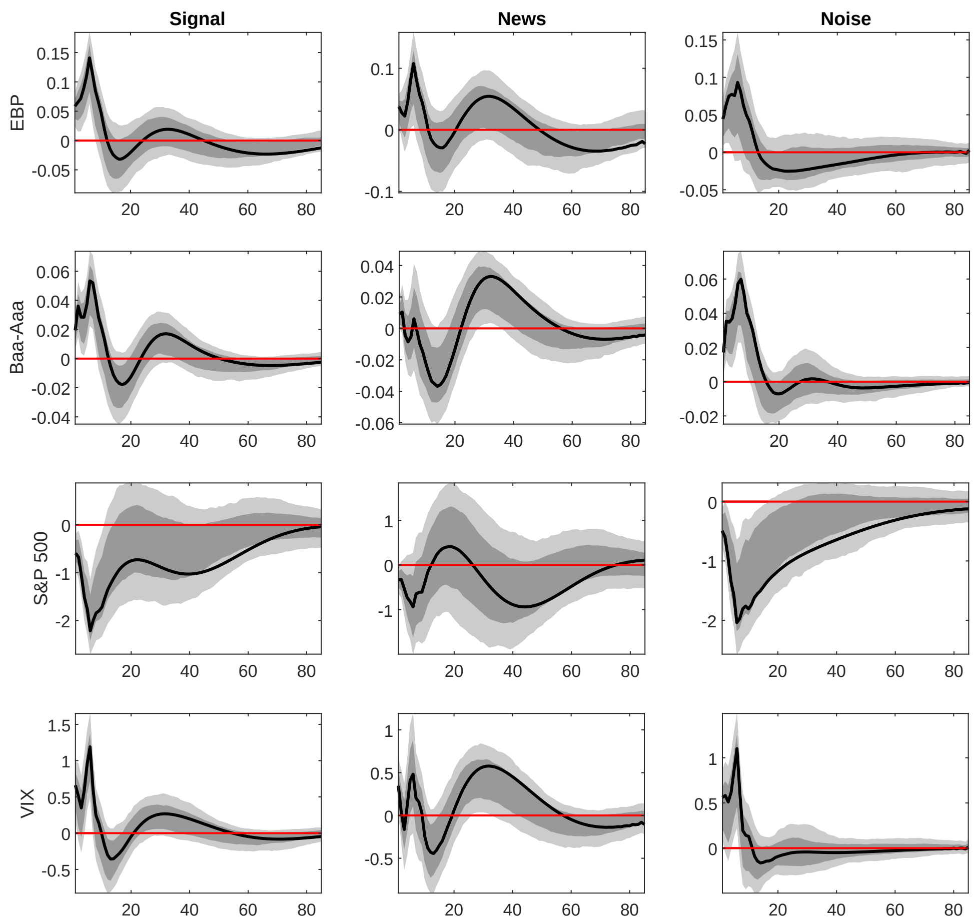
Notes: VAR containing logarithm of IP, the logarithm of CPI, the Fed funds rate and six-months-ahead market-based fed funds expectations. Estimation sample: 1994 January - 2016 October.

Figure 8: ***Four-variate VAR before 1994: Signal, News, and Noise***



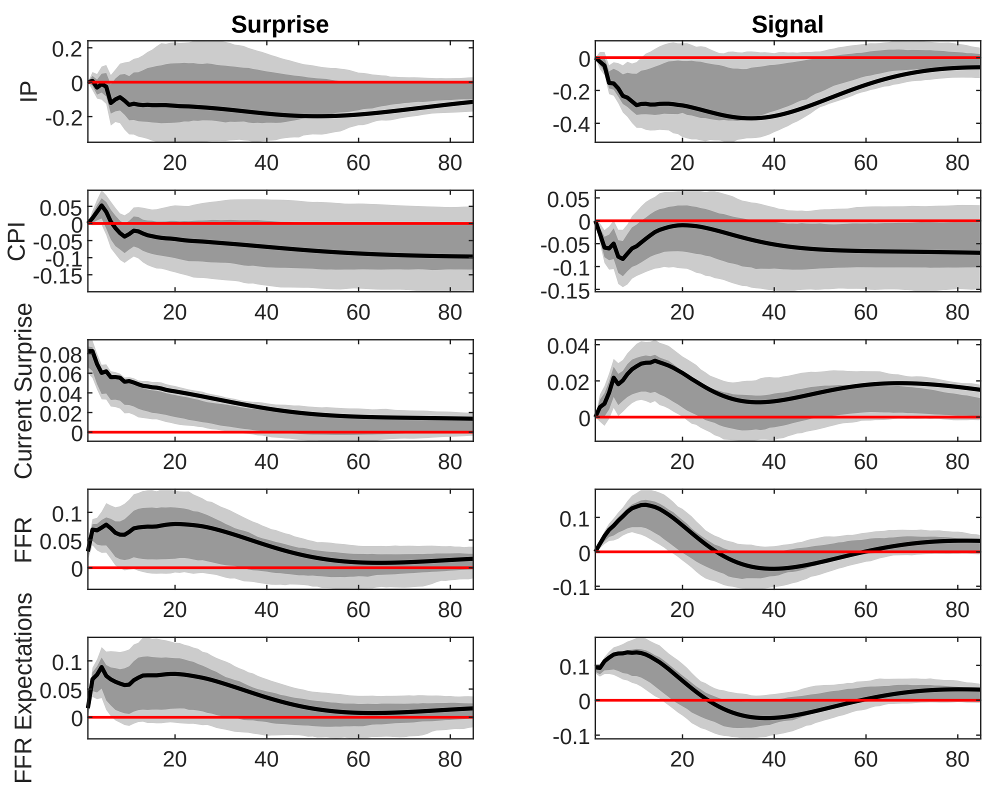
Notes: VAR containing logarithm of IP, the logarithm of CPI, the fed funds rate and six-months-ahead survey-based fed funds expectations. Estimation sample: 1983 April – 1993 December.

Figure 9: ***Five-variate VARs with Financial Indicators: Signal, News, and Noise***



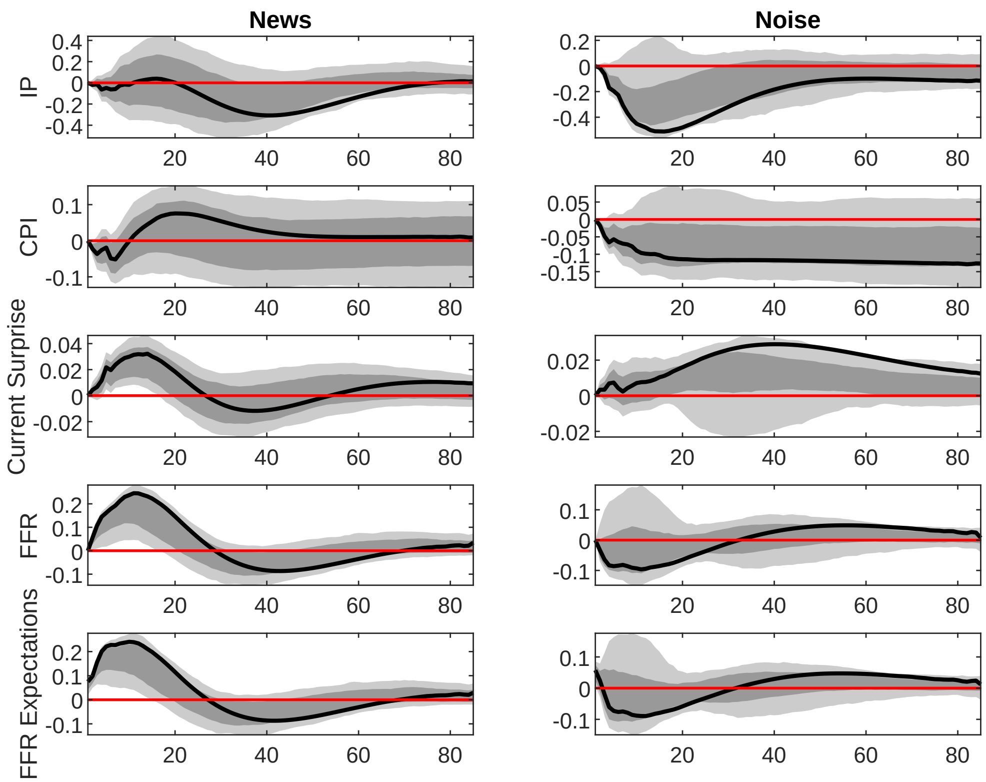
Notes: Five-variate VARs each containing the logarithm of IP, the logarithm of CPI, the fed funds rate, survey-based fed funds expectations (six months ahead), and the EBP or the BAA-AAA spread or the logarithm of the S&P 500 or the VIX, respectively. Estimation sample: 1994 January – 2016 October. (In the case of the EBP, the sample stops in August 2016 due to data availability.)

Figure 10: ***Five-variate VAR with Conventional Monetary Policy Shock I: Surprise and Signal***



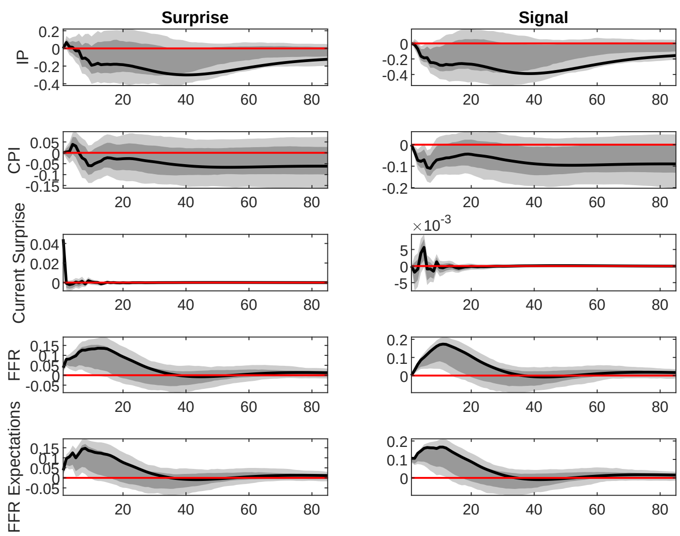
Notes: Five-variate VAR containing logarithm of IP, the logarithm of CPI, the current-month surprises, the fed funds rate and six-months-ahead survey-based fed funds expectations. Estimation sample: 1994 January - 2016 October.

Figure 11: *Five-variate VAR with Conventional Monetary Policy Shock I: News and Noise*



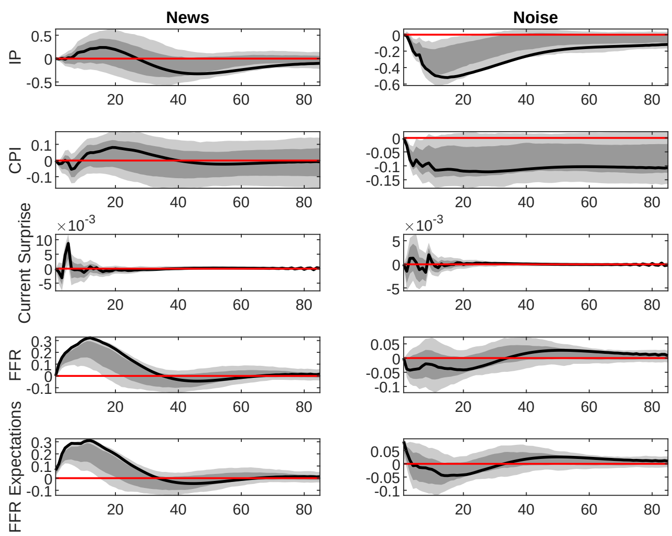
Notes: Five-variate VAR containing logarithm of IP, the logarithm of CPI, the current-month surprises, the fed funds rate and six-months-ahead survey-based fed funds expectations. Estimation sample: 1994 January - 2016 October.

Figure 12: ***Five-variate VAR with Conventional Monetary Policy Shock II: Surprise and Signal***



Notes: Five-variate VAR containing logarithm of IP, the logarithm of CPI, the informationally robust surprises, the fed funds rate and six-months-ahead survey-based fed funds expectations. Estimation sample: 1994 January - 2009 December.

Figure 13: ***Five-variate VAR with Conventional Monetary Policy Shock II: News and Noise***



Notes: Five-variate VAR containing logarithm of IP, the logarithm of CPI, the informationally robust surprises, the fed funds rate and six-months-ahead survey-based fed funds expectations. Estimation sample: 1994 January - 2009 December.