Central Bank Information Shocks*

Marek Jarociński[†] Peter Karadi[‡]

This version: February 2017

Preliminary and incomplete: please do not quote or circulate

Abstract

This paper studies the impact of central bank announcements on asset prices and the macroeconomy. Central bank announcements simultaneously convey information about interest rate policy and the central bank's assessment on the economic outlook. The paper disentangles the surprises caused by policy shocks and information shocks using sign restrictions on high-frequency surprises in a Bayesian VAR on US data. It relies on information inherent in high-frequency comovement of interest rates and stock prices around policy announcements: a surprise policy tightening raises interest rates and reduces stock prices, while the complementary positive information shock raises both. The paper finds that information shocks constitute a non-negligible share of high-frequency surprises. A representative central bank information shock is akin to a temporary demand shock that monetary policy partly offsets. It still significantly increases the price level, and eases financial conditions, but has only a weakly positive impact on output. A monetary policy tightening purged from the impact of information shocks induces a flexible price-level decline with a persistent downturn and tighter financial conditions.

Keywords: Central Bank Private Information, Monetary Policy Shock, High-Frequency Identification, Structural VAR, Event Study

JEL codes: E32, E52, E58

*All opinions expressed are personal and do not necessarily represent the view of the European Central Bank or the European System of Central Banks. We wish to thank Refet Gürkaynak for sharing his data and Michele Lenza, Giorgio Primiceri, Oreste Tristani, Srecko Zimic for their comments and suggestions. Maria Dimou, Cinzia Guerrieri and Andras Lengyel provided outstanding research assistance.

[†]Directorate General Research, European Central Bank. E-mail: marek.jarocinski@ecb.int

[‡]Directorate General Research, European Central Bank. E-mail: peter.karadi@ecb.int

1 Introduction

On January 22, 2008 during the early phase of the 2007-2009 US financial crisis, the US Federal Open Market Committee (FOMC) reduced its federal funds rate target by 75 basis points. This came as an easing surprise, because the market only expected a 50 basis points cut. The S&P 500 stock market index of blue chip companies, however, *dropped* almost 17 basis points within the half-hour window of the announcement. Such event is not unique: in our sample in around 30% of cases we observe such a positive comovement of interest rate and stock market surprises. This might seem puzzling in the face of a broad theoretical consensus that predicts stock price appreciation after a policy easing. It is less surprising, however, if we notice that in the accompanying statement, the FOMC explained that it "took this action in view of a weakening of the economic outlook and increasing downside risks to growth." In our view, this communication had an independent influence on stock valuations. In this paper we disentangle central bank information shocks from standard monetary policy shocks and assess their impact on asset prices and the macroeconomy.

We propose to identify central bank information shocks by analysing the high-frequency co-movement of financial variables that are influenced by the policy actions, like interest rates and stock markets, around a narrow window of the policy announcement. This way, we are using market prices to reveal information that is not directly available for the econometrician. A standard monetary policy tightening leads to lower (fundamental[1]) stock market valuation according to a broad range of theoretical models. The reason is simple: the present value of future payoffs declines because, first, the discount rate increases with higher real interest rates and rising risk premia and, second, the expected payoffs decline with the deteriorating outlook caused by the policy tightening. If, instead, stock markets increase in spite of a surprise monetary policy tightening, we read it as an indication for the presence of an accompanying information shock.

In this paper, we set out to disentangle the policy shocks and the central bank information shocks in a Bayesian structural vector autoregression (VAR). In the VAR, we augment standard monthly variables on interest rates, the price level, economic activity and financial indicators with high-frequency financial-market surprise variables. The methodology is closely related to proxy VARs (Stock and Watson, 2012; Mertens and Ravn, 2013) that use high-frequency surprises as external instruments to identify monetary policy shocks (Gertler and Karadi, 2015). Our contribution is to use sign restrictions on multiple high-frequency surprises to identify multiple contemporaneous shocks. In particular, we use the 3-months-ahead federal funds future surprise to measure changes in expectations about short term interest rates and the S&P 500 index to measure changes in stock valuation within a half-hour window around FOMC announcements. We assume that within this narrow window only two structural shocks drive the financial-market surprises. First, a monetary policy shock. As we explained above,

[1] The contemporaneous impact of the policy tightening of any bubble component of the stock valuation is indeterminate. (see e.g. Galí, 2014)

we require that a surprise monetary policy tightening (that raises our interest rate surprise measure) to reduce stock valuations. Second, a central bank information shock. This is the complementary shock that is assumed to lead to a positive comovement of the interest rate and the stock market surprises. This can be understood as positive news about the economy that leads simultaneously to higher stock valuations and a tightening of systematic monetary policy response.

We track the dynamic response of key macroeconomic variables to our identified shocks. Our aim is twofold. First, we set out to obtain impulse responses to monetary policy shocks that are purged from the effects of the information shock. These shocks are directly comparable to shocks to monetary policy rules in standard models. Second, we set out to analyse the impact of the central bank information shocks on financial markets and the macroeconomy. This could shed some light on whether asymmetric information between the central bank and the public is a realistic assumption. If the answer is positive, a natural follow-up exercise is to assess nature of the information the central bank has advantage about.

We find that central bank information shocks account for around one third of the high-frequency variation in the 3-months-ahead federal funds futures rate. This is nonnegligible. We find that even though our monetary policy shocks are broadly similar to monetary policy shocks identified without controlling for information shocks, there are important differences. Similarly to previous results, we find that a monetary policy tightening leads to a significant contraction in output and a tightening of financial conditions. A key difference from previous results is that our purged monetary policy shock induces a more pronounced price-level decline. We hypothesize that the bias caused by the presence of information frictions might account for the presence of the price puzzle in some relevant subsamples (see e.g. Barakchian and Crowe, 2013).

The central bank information shock leads to a significant impact on key macroeconomic variables. This is notable, because ineffective central bank announcements as a result of symmetric information or random high-frequency variation around monetary policy shocks could have as well led to insignificant macroeconomic impact. Instead, we find that a high-frequency stock market appreciation accompanied by monetary policy tightening around policy announcements leads to persistently higher short-term interest rates, a significantly higher price level and improving financial conditions. The impact on real activity is weakly positive. We argue that these responses are consistent with the central bank revealing information about current and future *demand* conditions and tightening its policy to counteract its impact on the macroeconomy. This countervailing impact could mitigate the impact on economic activity.

Related literature Our paper contributes to an important strand of the literature that assesses the impact of high-frequency financial-market surprises around key monetary policy announcements on asset prices (Kuttner, 2001; Gürkaynak, Sack and Swanson, 2005; Bernanke and Kuttner, 2005) and the macroeconomy (Gertler and Karadi, 2015; Paul, 2015). Similarly to classic approaches (Bernanke and Blinder, 1992; Christiano, Eichenbaum and Evans, 1996), the aim of this literature is to identify exogenous variation around systematic monetary policy, which then can be used to assess the causal impact of the policy. As long as the market efficiently incorporates all publicly available information about the current and expected evolution of relevant variables and their likely impact on policy, true deviations from systematic policy will be reflected in financial market surprises. A sufficiently narrow window around the announcement ensures that shocks unrelated to monetary policy announcements do not bias the measures. However, policy announcements come systematically with central bank communication about the economic outlook, which can bias the predictions of these approaches. Our contribution is to use multiple high-frequency variables to separate monetary policy shocks from concurrent central bank information shocks and track their dynamic impact on financial variables and the macroeconomy.

Our paper also fits into a long line of empirical research assessing the extent of information asymmetry between the central bank and the public. Romer and Romer (2000) argues that the US Federal Reserve has superior ability relative to the private sector to process publicly available information to produce economic forecasts. They show that the FRB staff forecasts on inflation and output have better forecasting performance that popular private forecasts, in the sense that the staff forecasts should get all the weight relative to the private forecasts in an optimal forecasting equation. Furthermore, they argue that the private sector can use policy actions to learn about the confidential FRB staff forecasts. Faust, Swanson and Wright (2004) challenges this view and shows evidence against the claim that surprises were informative about the Fed's private information. New data leads to a different conclusion: Barakchian and Crowe (2013) and Campbell, Fisher, Justiniano and Melosi (2016) show in a updated sample that the private information of the Fed, measured as the difference of the FRB staff forecast and private forecasts, can be used to predict monetary policy surprises around subsequent monetary policy announcements. This suggests that surprises can be informative about the central bank information. Our paper tests the existence of private information revelation indirectly through identifying information shocks as orthogonal shocks that hit the economy concurrently with monetary policy shocks. We find that the subsequent behavior of the economy is consistent with the hypothesis of revelation of some private information that actually materializes, on average.

Our paper complements recent research like Campbell, Fisher, Justiniano and Melosi (2016) and Hansen and McMahon (2016), which aims to quantify the impact of central bank information revelation on expectations and the macroeconomy. Campbell, Evans, Fisher, Justiniano, Calomiris and Woodford (2012) coined the instructive term 'Delphic' forward guidance to distinguish it from 'Odyssean' forward guidance. Delphic shocks reveal central bank information about the future state of the economy that is foreseen to influence future interest rates. Odyssean forward guidance, in contrast, is a commitment about future interest rates independently of future state of the economy. The distinction is analogous to the distinction between our central bank information and monetary policy shocks. Our question is somewhat broader than theirs: while their focus is on communication about *future* policy, our focus is on shocks to both current and future policy. Campbell, Fisher, Justiniano and Melosi (2016) show that private forecasts that are revealed through policy actions, which they measure as the fitted value in a regression on federal funds futures surprises on the Fed's private information, lead to subsequent increases in private sector expectations, albeit with a lag. Hansen and McMahon (2016) use methods in computational linguistics to turn announcements into quantitative measures of central bank communication on the state of the economy and on policy that can be introduced into a VAR framework. Our approach is different. Instead of using proxies created from analysing the language of announcements or from measures of private information comparing FRB staff to private forecasts, we use the information-processing power of the markets and identify central bank information shocks from the high-frequency comovement of interest rate and stock market surprises. We then track the dynamic impact of expectations and realized macroeconomic variables as a response to such shocks in a VAR framework.

Nakamura and Steinsson (2013) estimates a structural model with central bank private information about economic fundamentals (see also Zhang, 2016). The model can account for relevant stylized facts, notably that expected real GDP growth increases after a high frequency monetary policy tightening, in contrast to conventional models with symmetric information. They assume perfect correlation of the policy and the news shocks, and use their model to analyse the separate impact of the news component. In contrast, to separately identify two orthogonal shocks, our methodology presupposes the presence of multiple independent signals reaching the market, both about policy and economic outlook. This requires that the market does not require an accompanying policy action to consider an announcement credible, but considers independent central bank communication credible, at least partially. As we have alluded to this above, evidence on the effectiveness of forward guidance communication suggests that central bank communication can indeed be highly credible (see e.g. Gürkaynak, Sack and Swanson, 2005; Bodenstein, Hebden and Ricardo, 2012; Wu and Xia, 2016). Relative to their structural model, our VAR imposes weaker restrictions on the data, and delivers a broader set of evidence on the dynamic responses to monetary policy and information shocks than the stylized facts used by these authors. Our evidence can be used to assess the empirical performance of their framework, as well as alternative models.

The remainder of the paper proceeds as follows. We describe our methodology in Section 2. In Section 3, we describe the data we use and Section 4 presents our results. Section 5 presents some robustness exercises and Section 6 concludes.

2 The econometric approach

In this section we explain how we estimate a joint econometric model of high-frequency monetary policy surprises and low-frequency macroeconomic variables and how we identify structural shocks in this model. The model enables us to combine two approaches to shock identification familiar from VARs: a variant of the external instruments approach and the sign restrictions approach. Our estimation is Bayesian. An important practical feature of our approach is that it can handle missing data on monetary policy surprises.

2.1 Estimation of a VAR with monetary policy surprises

Let y_t be a vector of N_y macroeconomic variables observed in period t and let m_t be a vector of N_m high frequency monetary policy surprises in period t. To construct m_t we first record monetary policy surprises, i.e. high frequency movements of financial variables around policy announcements and then aggregate them to the same frequency as y_t by adding them up (see Section 3.1 for details). We consider three specifications of a VAR with m_t and y_t.

Specification A is the unrestricted VAR

$$\begin{pmatrix} m_t \\ y_t \end{pmatrix} = \sum_{p=1}^{P} \begin{pmatrix} B_{MM}^p & B_{MY}^p \\ B_{YM}^p & B_{YY}^p \end{pmatrix} \begin{pmatrix} m_{t-p} \\ y_{t-p} \end{pmatrix} + \begin{pmatrix} c_M \\ c_Y \end{pmatrix} + \begin{pmatrix} u_t^m \\ u_t^y \end{pmatrix}. \tag{1}$$

Specification B imposes a restriction that the variables m_t are i.i.d., i.e. satisfy $m_t = u_t^m$. The resulting VAR is

$$\begin{pmatrix} m_t \\ y_t \end{pmatrix} = \sum_{p=1}^{P} \begin{pmatrix} 0 & 0 \\ B_{YM}^p & B_{YY}^p \end{pmatrix} \begin{pmatrix} m_{t-p} \\ y_{t-p} \end{pmatrix} + \begin{pmatrix} 0 \\ c_Y \end{pmatrix} + \begin{pmatrix} u_t^m \\ u_t^y \end{pmatrix}. \tag{2}$$

Specification C imposes additionally the restriction that the variables y_t do not depend on the lags of m_t, resulting in

$$\begin{pmatrix} m_t \\ y_t \end{pmatrix} = \sum_{p=1}^{P} \begin{pmatrix} 0 & 0 \\ 0 & B_{YY}^p \end{pmatrix} \begin{pmatrix} m_{t-p} \\ y_{t-p} \end{pmatrix} + \begin{pmatrix} 0 \\ c_Y \end{pmatrix} + \begin{pmatrix} u_t^m \\ u_t^y \end{pmatrix}. \tag{3}$$

Currently we focus on specification B based on an informal criterion: the impulse responses change very little when moving from A to B. This suggests that the restrictions in B are only weakly binding, and hence it is advisable to impose them and conserve degrees of freedom. In the next version of the paper we plan to test the restrictions in B and C formally using Bayes factors. Now we explain how we estimate specification B.

Let B and Σ denote the parameters of the VAR, where

$$B = (B_{YM}^1, B_{YY}^1, ..., B_{YM}^P, B_{YY}^P, c_Y)', \text{ var} \begin{pmatrix} u_t^m \\ u_t^y \end{pmatrix} = \begin{pmatrix} \Sigma_{MM} & \Sigma_{MY} \\ \Sigma_{YM} & \Sigma_{YY} \end{pmatrix} = \Sigma,$$

We introduce a Minnesota-type prior specified as an independent normal-inverted Wishart prior, $p(B, \Sigma) = p(B)p(\Sigma)$, where

$$p(\Sigma|\underline{S}, \underline{v}) = \mathcal{IW}\left(\underline{S}, \underline{v}\right), \tag{4}$$

$$p(\operatorname{vec} B|\underline{B}, \underline{Q}) = \mathcal{N}(\operatorname{vec} \underline{B}, \underline{Q}), \tag{5}$$

$\mathcal{IW}$ denotes the Inverted Wishart distribution and $\mathcal{N}$ denotes the normal distribution. We set the prior parameters $\underline{B}, \underline{Q}, \underline{S}, \underline{v}$ following Litterman (1979) and the ensuing literature. Namely, in $\underline{B}$ the coefficient of the first own lag of each variable is 1 and the remaining entries are zero. $\underline{Q}$ is a diagonal matrix implying that the standard deviation of lag p of variable j in equation i is $\lambda_1 \sigma_i / \sigma_j p^{-\lambda_3}$. Unless indicated otherwise we use standard values $\lambda_1 = 0.2, \lambda_3 = 1$. σ_i (σ_j) is the standard error in the autoregression of order P of variable i (j). $\underline{S}$ is a diagonal matrix with σ_i^2, $i = 1, ..., N_m + N_y$ on the diagonal. $\underline{v} = N + 2$. All these choices are standard in the Bayesian VAR literature.

We generate draws from the posterior with the Gibbs sampler, at the same time taking care of the missing values in our dataset. In the Gibbs sampler we draw in turn from three conditional posteriors i) $p(\Sigma|Y, M, B)$, ii) $p(B|Y, M, \Sigma)$ and iii) we draw the missing observations in M, where M is a $T \times N_m$ matrix collecting observations on m_t for $t = 1, ..., T$ and Y is a $T \times N_y$ matrix collecting observations on y_t for $t = 1, ..., T$. The conditional posterior of Σ in i) is inverted Wishart, and the conditional posteriors of B and of the missing observations of m in ii) and iii) are normal. See the Appendix for the derivations of these conditional posterior densities.

2.2 Identification: Combining high-frequency identification and sign restrictions

This subsection explains how we combine high-frequency identification and sign restrictions in order to identify the structural shocks of interest. To fix ideas we explain the identification in the baseline model.

In the baseline model we identify two shocks: a *monetary policy shock* and another, complementary shock which we will call *central bank information shock*. We use two main assumptions to isolate these shocks.

1. Monetary policy surprises m_t are affected only by monetary policy and central bank information shocks, and not by other shocks. This is because variables m_t are measured in a narrow time window around monetary policy communications. Hence, the probability that other shocks systematically occur during the same time window is low.

2. A contractionary monetary policy shock is associated with an interest rate increase and a drop in stock prices. A positive central bank information shock is the complementary shock, i.e. the shock associated with an increase in both interest rates and stock prices.

Table 1 reports the restrictions on the contemporaneous responses of all variables (in rows) to all shocks (in columns) in the baseline model. In this model m consists of two variables, an interest rate and a stock market index, while y is a vector of macroeconomic variables.

Table 1: Identifying restrictions in the baseline VAR model

	variable	shock Monetary Policy	 Central Bank Information	 other
m (high frequency)	interest rate	$+$	$+$	0
	stock index	$-$	$+$	0
y (low frequency)	...	$\bullet$	$\bullet$	$\bullet$

We compute the posterior draws of impulse responses imposing sign and zero restrictions following Rubio-Ramirez, Waggoner and Zha (2010) and Arias, Rubio-Ramirez and Waggoner (2014). In our case the zero restrictions are particularly easy to impose. For each draw of model parameters from the posterior we find a rotation of the first two Choleski shocks that satisfies our sign restrictions. It is easy to see that this rotation satisfies the zero restrictions as well. More in detail, or each draw of Σ from the posterior we compute its lower-triangular Choleski decomposition, C. Then we postmultiply C by a matrix $Q = \begin{pmatrix} Q^* & 0 \\ 0 & I \end{pmatrix}$, where Q^* is a 2×2 orthogonal matrix obtained from the QR decomposition of a 2×2 matrix with elements drawn from the standard normal distribution. We repeat this until finding the Q such that CQ satisfies the sign restrictions.

3 Data

3.1 High-frequency variables

We measure asset-price changes around 241 FOMC announcements between 1990 and 2016.[2] Our dataset is an updated version of Gürkaynak, Sack and Swanson (2005). As they do, we measure changes within an half-hour window around FOMC policy statements initiated 10 minutes before and ending 20 minutes after the statement is released. We turn high-frequency surprises into monthly variables by summing them up over each calendar month.

Our baseline econometric model uses changes in the 3-months-ahead federal funds futures and the (logarithm of the) S&P 500 stock market index as high-frequency surprise measures. Federal funds futures are traded in the Chicago Board of Trade; the 3-months-ahead contract exchanges a constant interest for the average federal funds rate over the course of the third

[2] Before 1994, the FOMC did not explicitly announce its policy decisions. Instead, the markets learned about them from the open-market operations regularly conducted around 11:15 am the day following the FOMC meeting. On these days, our surprises are measured around this time. Since 1994, the FOMC issues a regular press release about its policy decisions accompanied by its assessment of the state of the financial markets and the economy. On these days, we measure surprises around the time of the press release.

calendar month from the contract.[3] We use the 3-months-ahead contract, because its change conveniently reflects the shift in the expected federal funds rate following the next policy meeting[4], so they incorporate information also about near-term forward guidance. Furthermore, they are insensitive to events when the market is taken off guard by the timing of the surprise between the current and the next meeting. These 'timing' surprises can be expected to have minor impact on macroeconomic outcomes, but can drive measures that concentrate on surprises related to particular policy meetings. The S&P 500 is a stock market index of blue chip companies; Wilshire 5000 is a market-capitalization weighted broad stock market index. The value of these indices is recorded at regular intervals, usually multiple times every second.

We analyse the impact of our shocks on a number of other high-frequency asset prices. The surprise change in the actual policy rate is best reflected in the current-month federal funds futures. We rescale the price change to reflect a surprise in the units of the federal funds rate change by multiplying it with a constant measured as (days during the calendar month)/(days remaining in the calendar month after the announced fed funds change), as in Kuttner (2001). This is necessary, because the contract refers to the average federal funds rate over the current calendar month, while the policy change only influences federal funds rates in the remainder of the month. Additionally, we report changes in the benchmark 2-year, 5-year and 10-year nominal and 5-year and 10-year inflation protected Treasury yields. The benchmarks refer to the last issue (on-the-run) of these Treasury bonds. We measure inflation compensation as a difference between the nominal and the real Treasury yields (breakeven inflation rates). We also report surprise changes in the dollar/euro exchange rate (decrease means dollar appreciation).

3.2 Low-frequency variables

Our baseline VAR includes 5 monthly variables. We use the average 1-year constant-maturity Treasury yield as our monetary policy indicator (Gertler and Karadi, 2015). The advantage of using a longer rate than the targeted federal funds rate is that it incorporates measures of forward guidance and therefore remains a valid measure of monetary policy stance also during the period when the federal funds rate is constrained by the zero lower bound.

We include the GDP and the GDP deflator in log levels as measures of activity and prices. We interpolate them to monthly frequency following the framework of Stock and Watson (2010). The methodology uses a Kalman-filter to distribute the quarterly GDP and GDP deflator series across months using a series of monthly datasets that are closely related to economic activity and prices. We show that our results are robust to using industrial production and the consumer price index.

We include the average S&P 500 stock market index (in log levels) and the excess bond premium (Gilchrist and Zakrajsek, 2012) as financial variables in our VAR. The response of the stock market to our identified shocks helps us to assess the persistence in the change in the

[3] Our measures are based on a tick-by-tick dataset of actual futures trades.

[4] During most of our sample, around 6 weeks elapse between regular policy meetings

stock valuations that necessarily occur at high frequency as a result of our sign restrictions. The evolution of the excess bond premium provides important information about the impact on general financial conditions. Furthermore, the variable incorporates high-quality information about the current and expected development of the economy as aggregated by the financial markets, so its inclusion improves the performance of our small-scale VAR (Caldara and Herbst, 2016).

We assess the nature of the shocks that we identify by analysing the response of other variables added one-by-one to our baseline VAR. The S&P 500 dividends are included in log levels and measure the dividend payouts of S&P stocks every month. The VIX is a standard proxy for economic uncertainty. It reflects the implied volatility in S&P 500 option prices. It is only available since 1990, so we start the estimation sample for this extended VAR on this date. Our data on expectations of professional forecasters are also only available from 1990. We use the real GDP growth and CPI expectations collected by Consensus Economics. We transform the current-year and next-year average expectations into constant-horizon 1-year expectations.[5]

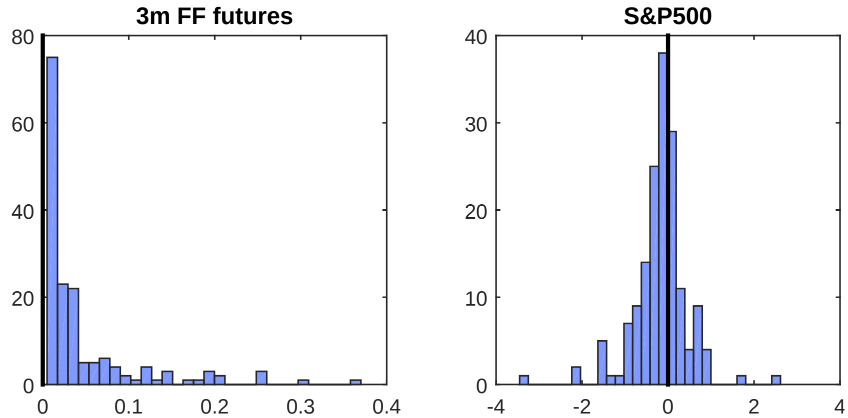
4 Results

To motivate our analysis, Figure 1 reports the histogram of the surprises in the 3-month fed funds futures and in the S&P500 index, normalized so that the fed funds futures surprise is positive. More in detail, whenever the fed funds surprise is negative we multiply both surprises by -1. We also omit the observations for which the fed funds surprise was zero. The key lesson we take from this figure is that positive surprises in fed funds futures can be accompanied by either positive or negative surprises in the S&P500 index. According to most models a monetary policy tightening (loosening) should depress (stimulate) the stock market. This indeed happens in 66% of the cases. However, in the remaining 34% of the cases the interest rate and the stock market move in the same direction.

There are two possible ways to account for the above observation. One way is to think that the stock market surprises are particularly noisy (the stock market is indeed very volatile). In this case, the surprises plotted above reflect monetary shocks plus some random noise. Another way is that the positive comovement of the interest rate and the stock market is triggered by some economic shock different from the monetary policy shock, which also gets transmitted to the economy simultaneously with the central bank policy announcements. Below we report the evidence in favor of the latter explanation.

[5] Our expectation measure (EXP_{12m}) is a weighted average of the current-year EXP_{CY} and next-year EXP_{NY} expectations reported by Consensus Economics: $\mathrm{EXP}_{12m} = \frac{1-(i-1)}{12}\mathrm{EXP}_{CY} + \frac{i-1}{12}\mathrm{EXP}_{NY}$, where the weights are determined by share of the current and the next calendar years in the following 12 months period (i is the current calendar month).

Figure 1: Histogram of the surprises in the 3-month fed funds futures and in the S&P500 index, normalized so that the 3-month fed funds futures is always positive.



4.1 Impulse responses in the baseline specification

The m vector in our baseline specification consists of two variables: i) the surprise in the 3-month fed funds futures and ii) the surprise in the S&P500 index. The y vector consists of five variables: i) one-year government bond yield, ii) the S&P500 index, iii) real GDP, iv) GDP deflator and v) the excess bond premium (EBP). The VAR includes 12 lags and it follows specification B, i.e. all the lags of m have coefficients restricted to zero. The frequency is monthly and the sample is from July 1979 to August 2016.

Figure 2 reports the impulse responses of all the variables to the two shocks we identify. Each of the two columns shows responses to a different shock. Note first, that in this specification variables m are modeled as i.i.d., so their impulse responses only last one period. Since the resulting plots are difficult to read, in all the subsequent figures we omit the impulse responses of the m variables and instead report their contemporaneous responses in a table. Table 2 reports these responses in the baseline specification. By construction the responses satisfy the sign restrictions. Looking at the medians, a standard monetary policy shock is associated with positive 5 basis points surprise in the 3-month fed funds futures and a negative 41 basis points surprise in the S&P500 stock index. A standard central bank information shock is associated with a positive 3 basis points surprise in the 3-months fed funds futures and a positive 28 basis points surprise in the S&P500 stock index.

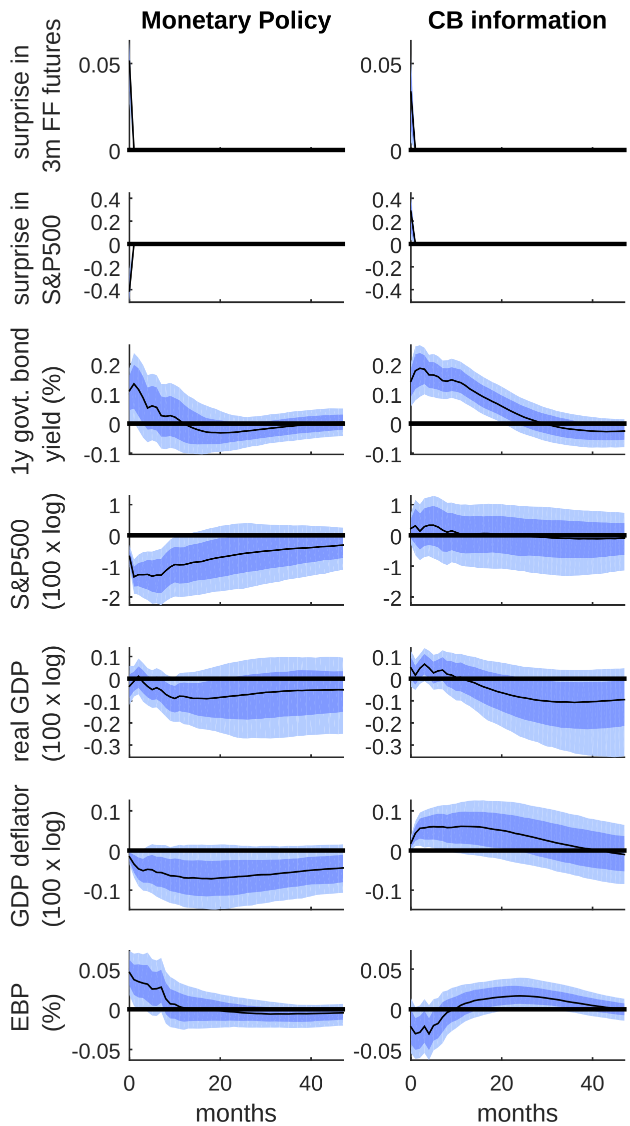
Coming back to Figure 2 we can see how the monthly variables y respond to the shocks pinned down by the above combinations of high-frequency surprises. Three observations stand out.

First, we can see that the impulse responses in the two columns are very different. This means that a different comovement of financial variables in the half-hour window around monetary policy announcement foretells a very different dynamics of macroeconomic and financial variables in the months following the shock. Recall that we impose no restrictions on the

Table 2: Contemporaneous impulse responses of m to one standard deviation monetary policy and central bank information shocks, baseline VAR. Percentiles of the posterior density.

surprise in:	Monetary Policy		CB information	
	50pct	(5pct, 95pct)	50pct	(5pct, 95pct)
3m FF futures (percent)	0.05	(0.026, 0.060)	0.03	(0.003, 0.052)
S&P500 (percent)	-0.41	(-0.510, -0.222)	0.28	(0.030, 0.451)

Figure 2: Impulse responses to one standard deviation monetary policy and central bank information shocks, baseline VAR. Median (line), percentiles 16-84 (darker band), percentiles 5-95 (lighter band).



responses of the low frequency variables y, the only identifying restrictions are imposed on the responses of m.

Second, the responses reported in the right-hand side column, labeled central bank information shock, are new in the literature. The one-year government bond yield increases persistently. The monthly S&P500 index does not fall, its impulse response is not significantly different from zero. Real GDP stays roughly the same or, if anything, increases slightly in the first months. GDP deflator increases persistently during the first months by about 5 basis points. The excess bond premium falls by about 2 basis points. These responses are consistent with responses to a news shock about improving *demand* conditions that are partly offset by tightening interest rate policy.

Third, the responses to a monetary policy shock are quite close to the findings in the literature, i.e. they entail a contraction in real activity and prices, a stock market bust and an increase in the excess bond premium. In the next section we report a detailed comparison with a more standard identification of monetary policy shocks. The main difference we find is that the response of prices is more vigorous under our identification. In the cases when a standard identification generates a price puzzle (i.e. an increase in prices after a contractionary monetary policy shock), our identification is free of the price puzzle. We conclude that the monetary policy shocks we identify are a refinement of the monetary policy shocks known from literature, we eliminate the contamination by the central bank information shocks.

Table 3: Variance decomposition: the share of the total variance explained by each shock at horizons of one and two years. Baseline model.

		Monetary Policy		C.B. Information	
	variable	1 year	2 years	1 year	2 years
m	3-month fed funds future	0.65		0.35	
	S&P500	0.66		0.34	
y	1-year govt. bond yield	0.10	0.09	0.27	0.24
	S&P500	0.09	0.08	0.02	0.02
	Real GDP	0.04	0.05	0.02	0.03
	GDP deflator	0.06	0.08	0.06	0.06
	Excess Bond Premium	0.06	0.06	0.04	0.04

Note: Posterior means. For the i.i.d. variables in m the forecast variance does not depend on the horizon, so for these variables we only report a single number.

Table 3 reports the contributions of the two shocks to the forecast variances of all the variables at horizons of one and two years. For the i.i.d. variables in m the forecast variance obviously does not depend on the horizon, so for these variables we only report a single number. We can see that monetary policy shocks account for about two thirds of the variance of the surprises, and central bank information shocks account for the remaining one third. Turning to variables y, we see that monetary policy shocks account for 10% of the variance of 1-year bond yields and 9-8% of the S&P500 index and 6% of the excess bond premium. They also account for 4-5% of real GDP and 6-8% of the GDP deflator, which are relatively high shares compared with the literature. Central Bank information shocks are also relevant. Most strikingly, they contribute about a quarter of the variance of the 1-year bond yields. They also account for 2-3% of the variance of real GDP and 6% of the variance of GDP deflator, so their contributions to the macroeconomic fluctuations are also nontrivial.

4.2 Responses of other high frequency surprises

We reestimate the model including other high frequency surprises in vector m. The surprises in the 3-month fed funds future and in S&P500 are ordered first and we follow the same identification as before.[6] In this version of the model we continue to obtain similar impulse responses of the macroeconomic variables, so we omit them for brevity. Instead we focus on the contemporaneous responses of the additional high frequency surprises, reported in Table 4. We can see that the Wilshire index behaves similarly as the S&P500: falls after the monetary policy shock and increases after the central bank information shock. Interest rates at all maturities move up after both shocks, but after the monetary policy shock they move more. The response of the longer term rates to the central bank information shock is not significantly different from zero. Finally the dollar appreciates against the euro and the yen, but only after the monetary policy shock the appreciation is significant.

4.3 Responses of other low frequency variables

Responses of additional low frequency variables, especially survey-based expectations, reinforces our hypothesis that the central bank information shock carries information about transitory demand pressures. Figure 3 reports the responses of low frequency variables that we add, one by one, to the baseline model. We can see that the two shocks have opposite effects on GDP growth and inflation expectations measured by surveys: a monetary policy tightening depresses both expectations and a positive central bank information shock boost them. The positive comovement of growth and inflation expectations suggests that the information carried by the latter shock is information about the demand. Dividends decrease and VIX jumps up after a monetary policy shock. The opposite happens after the central bank information shock: VIX falls and dividends increase (though not significantly). These impulse responses reinforce the conclusion that the two shocks we identify have very different effects on the economy.

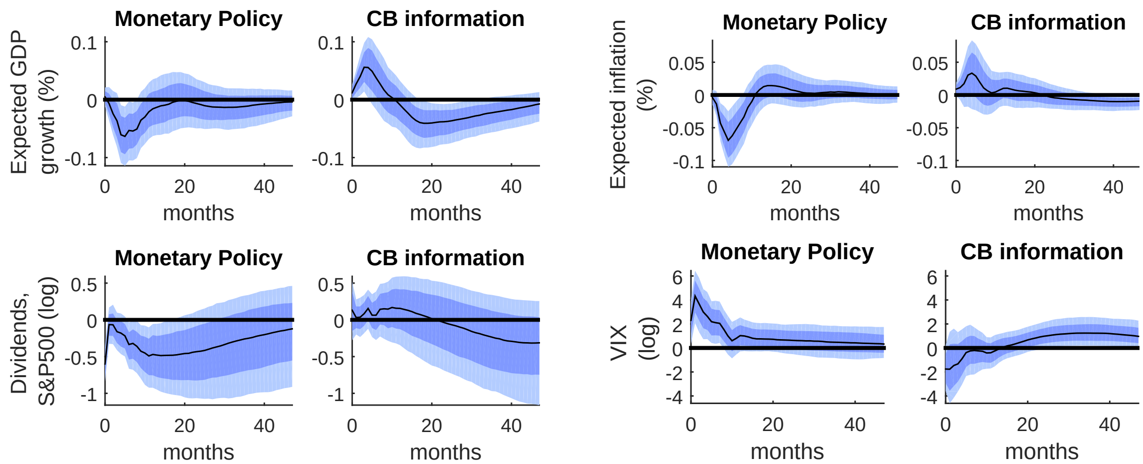
[6] The implicit assumption is that any variance in the other surprises that is not explained by the monetary policy and central bank information shocks is due to idiosyncratic noise.

Table 4: Contemporaneous impulse responses of m to one standard deviation monetary policy and central bank information shocks, in percent. Model with an extended vector m. Percentiles of the posterior density.

surprise in:	Monetary Policy		CB information	
	50pct	(5pct, 95pct)	50pct	(5pct, 95pct)
SP500	-0.42(*)	(-0.516, -0.227)	0.28(*)	(0.027, 0.450)
WILSHIRE	-0.44*	(-0.536, -0.265)	0.23	(-0.030, 0.431)
Current month fed funds future	0.06*	(0.032, 0.073)	0.04*	(0.001, 0.061)
3-month fed funds future	0.05(*)	(0.028, 0.065)	0.03(*)	(0.004, 0.056)
2-year bond yield	0.04*	(0.026, 0.046)	0.02	(-0.007, 0.033)
5-year bond yield	0.03*	(0.020, 0.033)	0.00	(-0.011, 0.019)
10-year bond yield	0.02*	(0.010, 0.021)	-0.00	(-0.013, 0.008)
EURO per USD	-0.26*	(-0.329, -0.179)	-0.08	(-0.217, 0.066)
YEN per USD	-0.15*	(-0.205, -0.101)	-0.03	(-0.117, 0.065)

Note: * highlights the cases where 95 or more percent of the posterior density is on the same side of zero. For the 3-month fed funds future the S&P500 this happens by construction (because of the sign restrictions), so we put the asterisk in brackets, (*).

Figure 3: Impulse responses of other low frequency variables to monetary policy and central bank information shocks. Median (line), percentiles 16-84 (darker band), percentiles 5-95 (lighter band).



5 Robustness

5.1 Comparing with the simple proxy variable identification of monetary policy shocks

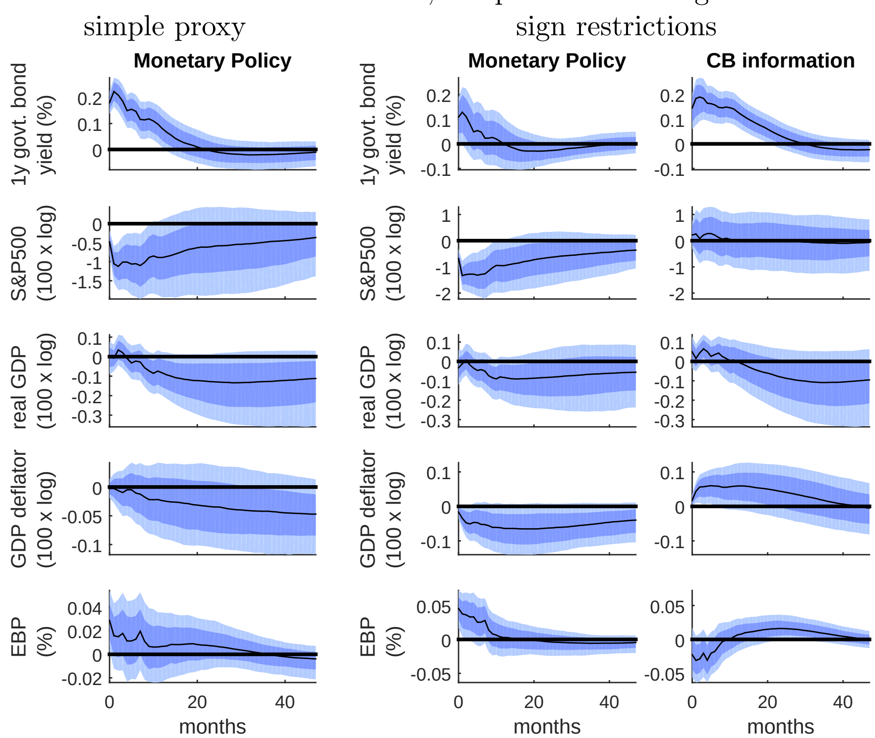
Table 5: Identifying restrictions in the simple proxy variable identification of monetary policy shocks

	variable	shock Monetary Policy	other
m (high frequency)	interest rate	$+$	0
y (low frequency)	$\dots$	$\bullet$	$\bullet$

The monetary policy shocks that we identify in the baseline model are a refinement of the shocks identified in the previous literature. Papers such as Gertler and Karadi (2015), Barakchian and Crowe (2013) and others identify monetary policy shocks using variants of the following 'simple proxy variable identification'. The identifying restrictions are that $cov(m, \epsilon^{MP}) > 0$ and that $cov(m, \epsilon^i) = 0$ for all ϵ^i other than the monetary policy shock ϵ^{MP}. Table 5 reports these restrictions. The specific procedures differ across papers. For example, Gertler and Karadi (2015) use the *external instruments* approach, i.e. they do not introduce m into the VAR and instead use it in auxiliary regressions outside the VAR. However, the key identifying

Figure 4: Impulse responses to monetary policy and central bank information shocks, sign restrictions and simple proxy variable identification, across subsamples. Median (line), percentiles 16-84 (darker band), percentiles 5-95 (lighter band).

A. Real GDP and deflator, sample Jul.1979-Augu.2016



B. IP and CPI, sample Jul.1979-Aug.2016

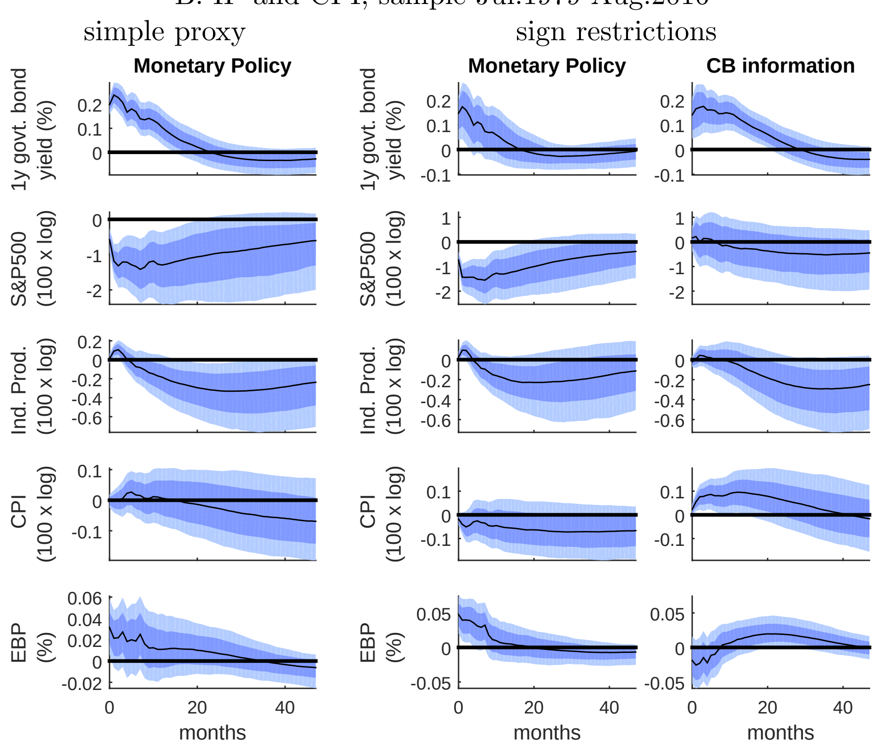
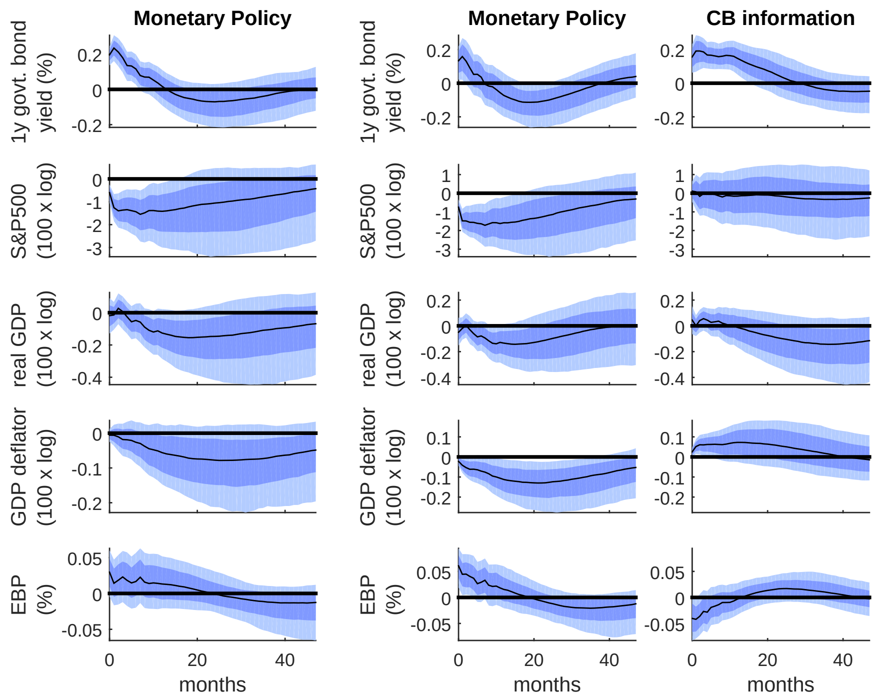


Figure 5: Impulse responses to monetary policy and central bank information shocks, sign restrictions and simple proxy variable identification, across subsamples. Median (line), percentiles 16-84 (darker band), percentiles 5-95 (lighter band).

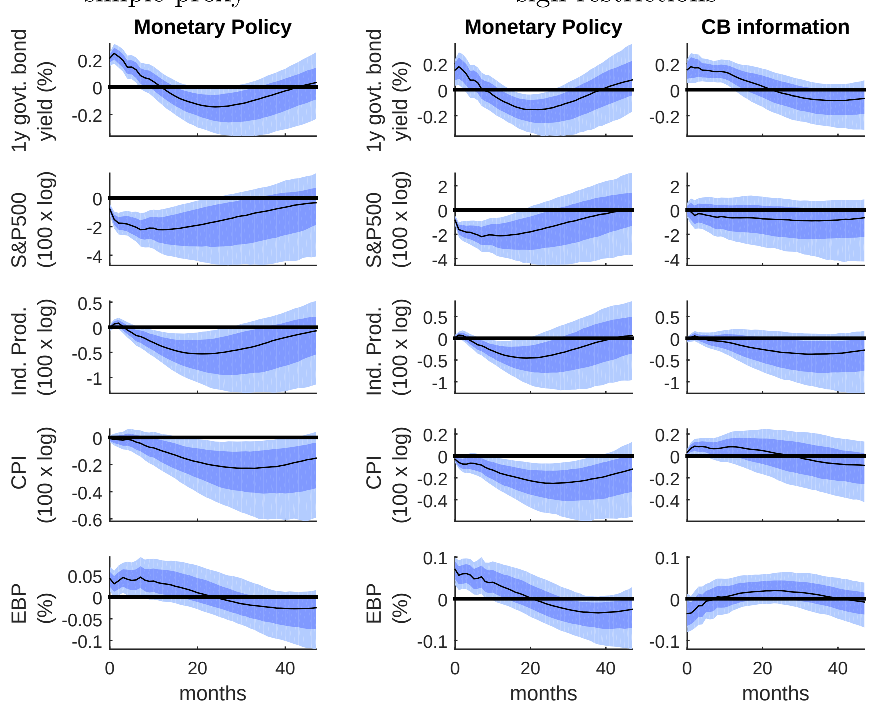
C. Real GDP and deflator, sample Jul.1979-Dec.2008

simple proxy sign restrictions



D. IP and CPI, sample Jul.1979-Dec.2008

simple proxy sign restrictions



restrictions are the two restrictions above. We find that these impulse responses obtained with the simple proxy variable identification are similar to those reported in Gertler and Karadi (2015).

Figure 4 illustrates that our baseline model is a refinement of the simple proxy variable identification. The responses of all variables are qualitatively similar. The main difference is that in the sign restrictions approach the negative response of prices is more vigorous and in the case where the simple proxy variable identification yields a price puzzle, shown in panel B, the sign restriction eliminates it.

5.2 A model with factors extracted from surprises

In an extension of the baseline model we extract factors from the surprises in order to model a long vector m more efficiently. Since the surprises are not collinear, we assume that in addition to the monetary policy and central bank information shocks they are affected also by idiosyncratic noise. To get rid of this idiosyncratic noise we extract two common factors (principal components) from a set of surprises. We assume that in these principal components the idiosyncratic noise cancels and thus they are only driven by the central bank-related shocks. Therefore, we place these two principal components first and rotate them until satisfying the sign restrictions on the interest rates and the stock market surprises. Table 6 reports the identifying restrictions.

Table 6: Identifying restrictions in the VAR model with factors of m.

	variable	shock Monetary Policy	 Central Bank Information	 other
	first p.c.	•	•	0
	second p.c.	•	•	0
m (high frequency)	interest rate	+	+	•
	stock index	−	+	•
	...	•	•	•
y (low frequency)	...	•	•	•

Table 7 reports the responses of the surprises collected in m. At least three lessons flow from this table. First, the short-term interest rates (current-month and 3-months fed funds futures) move more strongly after a monetary policy shock than after the central bank information shock. The longer-term interest rates (2, 5 and 10 year bond yields) move similarly. Second, the dollar appreciates more after the central bank information shock. Third, break-even inflation rates fall after the monetary policy shock, while they either do not change or increase after the central bank information shock.

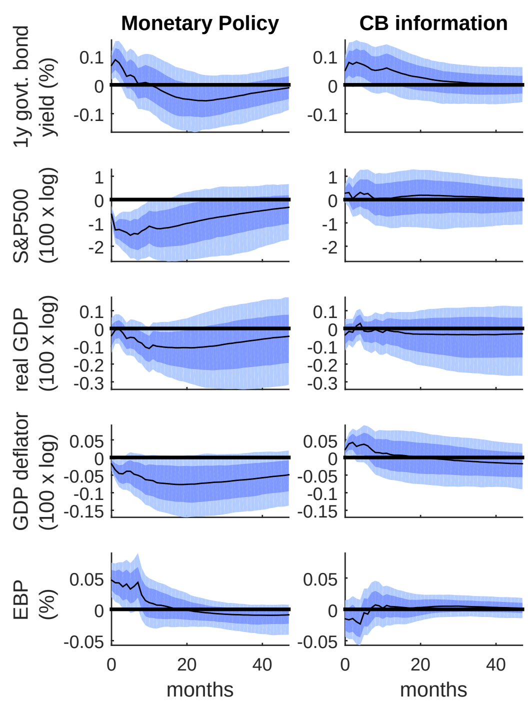
Table 7: Contemporaneous impulse responses of m to one standard deviation monetary policy and central bank information shocks. Model with factors of m. Percentiles of the posterior density.

	Monetary Policy		CB Information	
	50pct	(5pct, 95pct)	50pct	(5pct, 95pct)
S&P500	-0.46	-0.520, -0.382	0.12	0.007, 0.287
Current month fed funds future	0.06	0.051, 0.072	0.01	-0.010, 0.034
3-month fed funds future	0.05	0.043, 0.061	0.02	0.002, 0.038
2-year bond yield	0.04	0.029, 0.055	0.04	0.021, 0.051
5-year bond yield	0.03	0.016, 0.040	0.03	0.022, 0.043
10-year bond yield	0.02	0.008, 0.024	0.02	0.015, 0.029
Euros per USD	-0.20	-0.340, -0.073	-0.38	-0.460, -0.269
Break-even inflation 5-years	-0.01	-0.010, -0.003	0.00	-0.002, 0.006
Break-even inflation 10-years	-0.01	-0.014, 0.003	0.01	0.000, 0.015

Table 8: Variance decomposition: share of total variance explained by each shock at horizons of one and two years. Model with factors of m.

	variable	Monetary Policy		C.B. Information	
m	S&P500	0.79		0.11	
	NASDAQ	0.04		0.14	
	Current month fed funds future	0.37		0.03	
	3-month fed funds future	0.49		0.10	
	2-year bond yield	0.51		0.37	
	5-year bond yield	0.37		0.46	
	10-year bond yield	0.22		0.33	
	Euros per USD	0.21		0.38	
	Break-even inflation 5-years	0.05		0.01	
	Break-even inflation 10-years	0.08		0.02	
		1 year	2 years	1 year	2 years
y	1-year govt. bond yield	0.03	0.03	0.03	0.03
	S&P500	0.09	0.08	0.02	0.02
	Real GDP	0.04	0.04	0.02	0.02
	GDP deflator	0.06	0.08	0.03	0.03
	Excess Bond Premium	0.06	0.06	0.03	0.03

Figure 6: Impulse responses of low frequency variables to monetary policy and central bank information shocks. Model with factors of m. Median (line), percentiles 16-84 (darker band), percentiles 5-95 (lighter band).



6 Conclusion

We argued that systematic central bank communication released jointly with policy announcements can bias high-frequency identification of monetary policy shocks, but creates an opportunity to empirically assess the impact of central bank communication on the macroeconomy. We have separated standard monetary policy shocks from central bank information shocks in a structural VAR and tracked the dynamic response of key macroeconomic variables. We have found that the presence of information shocks can marginally bias the results of simple high-frequency monetary policy identification, especially that of the price-level response. We have also found that a representative central bank information shock is similar to news about an upcoming demand shock that the central bank partly offsets.

Our results on the quantitative response to monetary policy shocks can be used to improve the calibration of models used for monetary policy analysis. Our results on the impact of central bank communication about the real economy gives support to models that assume that the central bank has some advantage in processing information about the economy over the private sector, especially about demand conditions. Our evidence can contribute to formulating realistic models that could be used to draw normative conclusions about central bank communication. We leave this for future research.

References

Arias, Jonas E., Juan F Rubio-Ramirez, and Daniel Waggoner (2014) "Inference Based on SVARs Identified with Sign and Zero Restrictions: Theory and Applications," *FRB International Finance Discussion Papers, No. 1100.*

Barakchian, S Mahdi and Christopher Crowe (2013) "Monetary Policy Matters: Evidence from New Shocks Data," *Journal of Monetary Economics*, Vol. 60, pp. 950–966.

Bernanke, Ben S and A. S. Blinder (1992) "The Federal Funds Rate and the Channels of Monetary Transmission," *American Economic Review*, Vol. 82, pp. 901–921.

Bernanke, Ben S and Kenneth N Kuttner (2005) "What Explains the Stock Market's Reaction to Federal Reserve Policy?" *The Journal of Finance*, Vol. 60, pp. 1221–1257.

Bodenstein, Martin, James Hebden, and Nunes Ricardo (2012) "Imperfect Credibility and the Zero Lower Bound," *Journal of Monetary Economics*, Vol. 59, pp. 135–149.

Caldara, Dario and Edward Herbst (2016) "Monetary Policy, Real Activity, and Credit Spreads: Evidence from Bayesian Proxy SVARs," *FRB Finance and Economics Discussion Series.*

Campbell, Jeffrey R, Charles L Evans, Jonas DM Fisher, Alejandro Justiniano, Charles W Calomiris, and Michael Woodford (2012) "Macroeconomic Effects of Federal Reserve Forward Guidance," *Brookings Papers on Economic Activity*, pp. 1–80.

Campbell, Jeffrey R, Jonas DM Fisher, Alejandro Justiniano, and Leonardo Melosi (2016) "Forward Guidance and Macroeconomic Outcomes Since the Financial Crisis," in *NBER Macroeconomics Annual 2016, Volume 31*: University of Chicago Press.

Christiano, Lawrence J, Martin Eichenbaum, and Charles Evans (1996) "The Effects of Monetary Policy Shocks: Evidence from the Flow of Funds," *The Review of Economics and Statistics*, pp. 16–34.

Faust, Jon, Eric T Swanson, and Jonathan H Wright (2004) "Do Federal Reserve Policy Surprises Reveal Superior Information about the Economy," *Contributions to Macroeconomics*, Vol. 4, pp. 1–29.

Galí, Jordi (2014) "Monetary Policy and Rational Asset Price Bubbles," *The American Economic Review*, Vol. 104, pp. 721–752.

Gertler, Mark and Peter Karadi (2015) "Monetary Policy Surprises, Credit Costs, and Economic Activity," *American Economic Journal: Macroeconomics*, Vol. 7, pp. 44–76.

Gilchrist, Simon and Egon Zakrajsek (2012) "Credit Spreads and Business Cycle Fluctuations," *The American Economic Review*, Vol. 102, pp. 1692–1720.

Gürkaynak, Refet S, Brian Sack, and Eric Swanson (2005) "The Sensitivity of Long-Term Interest Rates to Economic News: Evidence and Implications for Macroeconomic Models," *American Economic Review*, pp. 425–436.

Hansen, Stephen and Michael McMahon (2016) "Shocking Language: Understanding the Macroeconomic Effects of Central Bank Communication," *Journal of International Economics*, Vol. 99, pp. S114–S133.

Kuttner, Kenneth N (2001) "Monetary Policy Surprises and Interest Rates: Evidence from the Fed Funds Futures Market," *Journal of Monetary Economics*, Vol. 47, pp. 523–544.

Litterman, Robert B. (1979) "Techniques of Forecasting Using Vector Autoregressions," Federal Reserve Bank of Minneapolis Working Paper number 115.

Mertens, Karel and Morten O Ravn (2013) "The Dynamic Effects of Personal and Corporate Income Tax Changes in the United States," *The American Economic Review*, Vol. 103, pp. 1212–1247.

Nakamura, Emi and Jón Steinsson (2013) "High Frequency Identification of Monetary Non-Neutrality: The Information Effect," *National Bureau of Economic Research.*

Paul, Pascal (2015) "The Time Varying Transmission of Monetary Policy Surprises," mnpublished manuscript.

Romer, David H. and Christina D. Romer (2000) "Federal Reserve Information and the Behavior of Interest Rates," *American Economic Review*, Vol. 90, pp. 429–457.

Rubio-Ramirez, Juan F., Daniel F. Waggoner, and Tao Zha (2010) "Structural Vector Autoregressions: Theory of Identification and Algorithms for Inference," *Review of Economic Studies*, Vol. 77, pp. 665–696.

Stock, James H and Mark W Watson (2010) "Monthly GDP and GNI - Research Memorandum," manuscript.

——— (2012) "Disentangling the Channels of the 2007–09 Recession," *Brookings Papers on Economic Activity*, Vol. 2012, pp. 81–135.

Wu, Jing Cynthia and Fan Dora Xia (2016) "Measuring the Macroeconomic Impact of Monetary Policy at the Zero Lower Bound," *Journal of Money, Credit and Banking*, Vol. 48, pp. 253–291.

Zhang, Donghai (2016) "The Information Channel of Monetary Policy," unpublished manuscript.