Central Bank Information Shocks*

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Abstract

Central bank announcements simultaneously convey information about monetary policy and the central bank's assessment of the economic outlook. This paper disentangles these two components and studies their effect on the economy with a structural vector autoregression. It relies on the 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 central bank information shock raises both. These two shocks have intuitive and very different effects on the economy. Ignoring the central bank information shocks biases the inference on monetary policy non-neutrality. We make this point formally and offer an interpretation of the central bank information shock using a New Keynesian macroeconomic model with financial frictions.

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

JEL codes: E32, E52, E58

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1 Introduction

The extent of monetary policy non-neutrality is a classic question in macroeconomics (Christiano, Eichenbaum and Evans, 2005). To measure the causal effect of policy, one needs to control for the presence of unobserved independent variation in economic fundamentals that the policy endogenously responds to. Central bank announcements can help overcome this identification issue. They generate unexpected variation in policy that can be used to assess the impact of monetary policy on real activity (Gertler and Karadi, 2015; Nakamura and Steinsson, 2013). These announcements, however, reveal information not just about policy, but also about the central bank's assessment of the economic outlook. In this paper, we ask whether the surprises in these assessments, 'central bank information shocks,' have a sizable macroeconomic impact. If they do, this provides evidence on the relevance of central bank communication, and shows that disregarding these shocks can lead to biased measurements of monetary non-neutrality.

Consider a revealing example. On January 22, 2008 during the early phase of the 2007-2009 US financial crisis, the US Federal Open Market Committee (FOMC) surprised the market with a larger-than-expected, 75 basis point federal funds rate cut. The S&P 500 stock market index, however, instead of appreciating as standard theory would predict, showed a sizable decline within 30 minutes of the announcement. Such an event is not unique: around one third of FOMC announcements since 1990 are accompanied by such a positive co-movement of interest rate and stock market changes. The observation is less surprising, 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 pessimistic communication depreciated stock valuations independently of the policy easing. In this paper, we disentangle variation caused by policy changes from that caused by central bank information and assess their impact on asset prices and the macroeconomy.

We propose to separate monetary policy shocks from contemporaneous information shocks by analysing the high-frequency co-movement of interest rates and stock prices around a narrow window of the policy announcement. This co-movement is informative, because standard theory has unambiguous prediction on its direction after a policy change. According to a broad range of models, a pure monetary policy tightening leads to lower (fundamental[1]) stock market valuation. 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. So we identify a monetary policy shock through a negative co-movement between interest rate and stock price changes. If, instead, stock markets and interest rates co-move positively, we read it as an indication for the presence of an accompanying information shock. This way, we use

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

market prices to learn the content of the signal inherent in central bank announcements, which would not be otherwise readily available to the econometrician.

We assess the dynamic impact of the policy shocks and the central bank information shocks using a Bayesian structural vector autoregression (VAR). In our baseline VAR on US data, we augment standard monthly variables - interest rates, the price level, economic activity and financial indicators - with variables reflecting high-frequency financial-market surprises. The methodology is closely related to proxy VARs (Stock and Watson, 2012; Mertens and Ravn, 2013) that use high-frequency interest rate 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 and 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, a monetary policy and a central bank information shock influence systematically the financial-market surprises. We disentangle the two shock based on their high-frequency co-movement, as explained above, and track their dynamic response on key macroeconomic variables. 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 the presence of any asymmetric information between the central bank and the public. A natural follow-up exercise is to assess the nature of the information the central bank has advantage about.

We find that the direction of the stock market response within half an hour of the policy announcement is highly informative about the response of the economy in the months to come. An unanticipated interest increase accompanied by a stock price decline (a negative co-movement shock) leads to a significant contraction in output and a tightening of financial conditions. This looks like the effects of a monetary policy shock in standard models. A key difference from a standard high-frequency identification of monetary policy shocks that fails to control for the information content of the announcements 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).

By contrast, an unanticipated interest increase accompanied by a stock price increase (a positive co-movement shock) leads to a significantly higher price level and improving financial conditions. The impact on real activity is weakly positive. We call this a central bank information shock. It is notable that this shock, although it is also associated with an increase in the interest rates, affects many other variables in the opposite direction to the monetary policy shock. This rules out the ineffectiveness of central bank communication. If the central bank had no information advantage relative to the public and stock market surprises around policy announcements were just random noise, this shock would not differ systematically from the monetary policy shock. We argue that the observed responses are consistent with the central bank revealing private information about current and future *demand* conditions and tightening its policy to counteract its impact on the macroeconomy.

We apply the same identification to the euro area and the findings are similar, so our points are not only US-specific. We construct a dataset of euro area high-frequency surprises associated with the ECB policy announcements, and run a similar VAR. In the euro area our identification is crucial, because here the standard high-frequency identification leads to a puzzle: financial conditions improve after a monetary policy tightening, contradicting standard theory. With our identification the puzzle disappears. Monetary tightening leads to a contraction and declining price level with slightly, though not significantly, worsening financial conditions. Central bank information shocks lead to strongly improving activity, a somewhat higher price level, better financial conditions, and an offsetting monetary policy tightening, similarly to the US. We also find that the importance of central bank information shocks relative to pure monetary policy shocks is higher in the euro area than in the US. This is in line with the more transparent communication policy of the European Central Bank relative to the Federal Reserve Board throughout our sample period.

We offer a structural interpretation of our baseline results through the lens of a New Keynesian macroeconomic model. The model is a version of Gertler and Karadi (2011), in which monetary policy impacts economic activity through both nominal rigidities and financial frictions. Monetary policy influences output, because output is partly demand determined as a standard consequence of sticky prices. Financial frictions, in turn, amplify the impact of the policy shock through a financial accelerator mechanism. We introduce a simple central bank 'communication policy' into the model. In particular, we assume that the central bank has information advantage about a future shock, and it reveals this private information to the public in a statement. The communication is exact and credible. We estimate key parameters of the model through matching the impulse responses of our VAR to those of the model.

We find that purging the impact of central bank information shock from a monetary policy shock influences the conclusions one would draw on the relative importance of nominal versus financial frictions. If one naively disregarded the impact of central bank information shocks, the excessively sticky price-level response would imply high nominal stickiness. This, in turn, would generate output responses that would alone match those observed in the data. So no further financial amplification would become necessary. As a result, financial frictions would be estimated to be small, and the model would not be able to match the observed response of corporate bond spreads.

If, instead, monetary policy shocks are purged from the impact of central bank information shocks, the more flexible price-level response implies moderate nominal rigidities. Financial frictions, in contrast, are estimated to be sizable. This helps the model to match both the large output response and the observed increase in corporate bond spreads. We conclude that financial frictions play a prominent role in the transmission of monetary policy shocks.

We also use the model to learn about the nature of the central bank information shocks. In particular, we ask which single shock would imply impacts consistent with those observed in our VAR. We find that a financial asset-valuation shock is broadly consistent with the observed responses. It matches both the increase in price-level and output and the decline in stock prices and corporate spreads, unlike popular alternatives.

Related literature Our paper contributes to a long line of research that assesses the impact of high-frequency financial-market surprises around key monetary policy announcements on asset prices (Kuttner, 2001; Gürkaynak, Sack and Swanson, 2005b; Gürkaynak, Sack and Swanson, 2005a; Bernanke and Kuttner, 2005) and the macroeconomy (Gertler and Karadi, 2015; Nakamura and Steinsson, 2013; Paul, 2017). Similarly to classic approaches (Bernanke and Blinder, 1992; Christiano, Eichenbaum and Evans, 1996), this literature assesses the causal impact of policy through identifying exogenous variation around systematic monetary policy. True deviations from systematic policy are reflected in financial market surprises as long as the market efficiently incorporates publicly available information to form its expectations. However, policy announcements come systematically with central bank communication about the economic outlook. As long as this communication moves private sector expectations about the macroeconomy and interest rates, their presence can bias the predictions of conventional 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 about the economy between the central bank and the public. Romer and Romer (2000) presents evidence that the US Federal Reserve has superior ability relative to the private sector to process publicly available information and produce economic forecasts. In particular, they show that the FRB staff forecasts on inflation and output have better forecasting performance that popular private forecasts. Furthermore, they find that the private sector can use policy actions to learn about the confidential FRB staff forecasts. More recently, Barakchian and Crowe (2013) and Campbell, Fisher, Justiniano and Melosi (2016) confirmed this latter finding and showed that Fed's private information[2] partly accounts for observed monetary policy surprises, suggesting that surprises can indeed be used to back out some of the Fed's private information. With this, they challenged the findings of Faust, Swanson and Wright (2004) based on a shorter sample. Our paper tests the existence of private information revelation indirectly. We identify information shocks that hit the economy in parallel with monetary policy shocks. We find that the subsequent behavior of the economy is consistent with the central bank revealing private information that indeed materializes, on average.

[2]Measured as the difference of the FRB staff forecast and private forecasts

Our paper complements recent research that aims to quantify the impact of central bank information revelation on expectations and the macroeconomy. Focusing on the effects of interest rate forward guidance, Campbell, Evans, Fisher and Justiniano (2012) instructively distinguished 'Delphic' from 'Odyssean' forward guidance. Delphic shocks, analogously to our central bank information shocks, reveal central bank information about the future state of the economy. In contrast, Odyssean forward guidance is a commitment about future interest rates independently of the future state of the economy, analogously to our monetary policy shocks. Campbell et al. (2016) show that private forecasts that are revealed through policy actions lead to subsequent increases in private sector expectations, albeit with a lag. Del Negro, Giannoni and Patterson (2015) also present event study evidence of Delphic and Odyssean components of US forward guidance announcements. 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 (see also Miranda-Agrippino, 2016; Lakdawala and Schaffer, 2016b), we use the information-processing power of the markets and identify central bank information shocks from the high-frequency co-movement of interest rate and stock market surprises. We analyse conventional interest rate shocks, and most of our identification comes from the period before the US interest rates reached their zero lower bound. We track the dynamic impact of expectations and realized macroeconomic variables as a response to such shocks in a VAR framework. Our paper is most closely related to the approach used in Andrade and Ferroni (2016), which we learned about recently. Similarly to us, they use sign restrictions and high frequency data to separately identify Delphic and Odyssean shocks. Differently from us, however, they concentrate on forward guidance shocks in the euro area and they use the co-movement of breakeven inflation rates and interest rates to distinguish between the shocks. Notably, we show that information revealed by breakeven rates are already included in our identification, in the sense that adding restrictions on breakeven rates do not change our baseline results.

Nakamura and Steinsson (2013) and Melosi (2017) estimate structural models with central bank private information about economic fundamentals (see also Zhang, 2016). The models have improved fit and they are better able to match relevant stylized facts than conventional models with symmetric information. They both assume that information is only conveyed through interest rate setting and disregard independent communication policy. Since 1994, the US Federal Reserve regularly accompanies its policy announcements with a press statement on its views about the economic outlook. Contrary to the previous papers, we consider this as a separate policy tool with which the central bank can guide expectations potentially independently from its interest rate setting. This requires that the market considers 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, 2005b; Bodenstein, Hebden and Nunes, 2012; Wu and Xia, 2016). Relative to structural models, our VAR imposes weaker restrictions on the data, and delivers a broad set of evidence on the dynamic responses to monetary policy and information shocks. Our evidence can be used to assess the empirical performance of these frameworks, as well as alternative models.

The remainder of the paper proceeds as follows. In Section 2 we describe the data on monetary policy surprises. Section 3 presents our econometric approach. Section 4 reports the baseline results for the US, followed by evidence on the euro area in Section 5. Section 6 presents a structural interpretation of our results. Section 7 concludes.

2 Interest rate and stock price surprises

In this section we describe our data on monetary policy surprises and present the stylized fact that motivates our subsequent analysis: that many positive interest rate surprises are accompanied by stock price increases and many negative interest rate surprises are accompanied by stock price declines.

Throughout the paper, we refer to financial asset price changes around monetary policy announcements as 'surprises.' Prices reflect expectations, so they only change to the extent the announcement surprises the markets. Following much of the related literature we measure the surprises in an half-hour window starting 10 minutes before and ending 20 minutes after the announcement (Gürkaynak, Sack and Swanson, 2005b).

2.1 The US dataset

We measure asset-price changes around 239 FOMC announcements from 1990 to 2016. Our dataset is an updated version of Gürkaynak, Sack and Swanson (2005b). 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 and 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.

Our baseline measure of the policy surprise is the change in the 3-months-ahead federal funds future. These contracts exchange a constant interest for the average federal funds rate over the course of the third calendar month from the contract. They future conveniently reflects the shift in the expected federal funds rate following the *next policy meeting*.[3] This horizon has two advantages. First, changes in these futures combine surprises about actual rate-setting and near-term forward guidance, so they constitute a broad measure of the overall

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

monetary policy stance. Second, they are insensitive to 'timing' surprises (short-term advancement or postponement of a widely expected policy decision, occasionally announced during an unscheduled policy meeting). Such 'timing' surprises can be expected to have minor impact on macroeconomic outcomes, but can have a large impact on futures contracts shorter than three months. Federal funds futures are traded in the Chicago Board of Trade. Our surprises are based on a tick-by-tick dataset of actual futures trades.

Our baseline measure of the stock price surprise is the change in the S&P500, an index based on 500 large companies. As we mentioned above, we measure the change in the index 10 minutes before and 20 minutes after the announcement. The narrow, intraday window makes sure that the "pre-FOMC announcement drift" documented by Lucca and Moench (2015) has no discernible impact on our measurement. Even though, puzzlingly, the S&P500 index tends to increase substantially in the 24 hours prior to scheduled FOMC announcements (by 49 basis points on average between 1994 and 2011), the average 30-minutes return in our sample is only 1.7 basis points with a standard deviation of 60 points. So there is no intra-day drift. This is in line with the observation of Lucca and Moench (2015), who show that the average return *after* the announcement until market close is approximately zero. Furthermore, they also show that the "drift" is uncorrelated with the surprises in the fed funds futures or with the response of the S&P500 to the announcements.

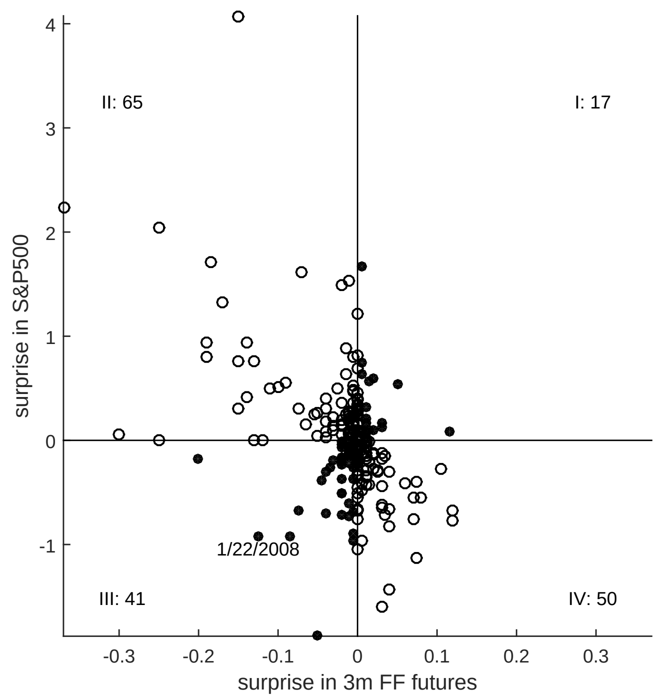
2.2 'Wrong-signed' responses of stock prices to interest rate surprises

We now document a notable stylized fact about the surprises. Namely, many positive interest rate surprises are accompanied by positive stock market surprises, and many negative interest rate surprises are accompanied by negative stock market surprises. This can be puzzling at first glance, because textbook economics implies that an interest rate surprise should move stock prices in the opposite direction (see e.g. Bernanke and Kuttner, 2005).

Figure 1 shows the scatter plot of surprises in the 3-month federal fund futures and in the S&P500 stock index. Empty circles reflect events with a negative co-movement between interest rates and stock prices (as predicted by the basic asset pricing theory, quadrants II and IV), while filled circles highlight events with a counterintuitive positive co-movement (quadrants I and III). We report the number of data points in each quadrant (66 data points are uncounted, because they lie exactly on one of the borders). The figure shows that the outcome observed on January 22, 2008 discussed earlier is not unique, there are more examples of 'wrong-signed' stock market responses to announcements. Overall, 34% of the internal data points are in quadrants I and III with wrong-signed stock market responses. They are not limited to any particular period, but occur throughout our sample (see Section 4.4).[4]

[4] The proportion and sizes of 'wrong-signed' stock market responses remain similar for alternative measures of the surprises. In the appendix we replace the 3-months fed funds futures with the first principal component of surprises in current and 3-months-ahead fed funds futures and 2-,3-,and 4- quarters ahead 3-months eurodollar futures. We also replace the S&P500 surprise with the first principal component of three stock indices.

Figure 1: Scatter plot of interest rate and stock price surprises. The 3-month federal funds futures and the S&P500 index.



Note: Black filled circles highlight the data points where both surprises have the same sign. The number in each quadrant is the number of data points in the quadrant (not counting the data points for which one of the surprises is zero).

There are two possible ways to account for the 'wrong-signed' stock market responses to announcements. One way is to attribute them to random noise in the stock market (the stock market is indeed very volatile). Another way is to attribute them to some non-policy disturbance that occur systematically at the time of the central bank policy announcements. Below we present evidence in favor of the latter explanation. We start by designing an econometric framework to decompose surprises into distinct shocks and tracking their effects on the economy.

3 The econometric approach

In this section we explain how we estimate a joint econometric model of high-frequency 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 structural VARs: high-frequency identification and sign restrictions. An important practical feature of our approach is that it can handle missing data on high-frequency surprises.

Our estimation is Bayesian. This is first, because standard Bayesian inference accounts for estimation uncertainty in a nonstandard setup like ours, which uses partial identification due to sign restrictions, and accommodates missing data. Second, we follow the large Bayesian VAR literature that uses the priors of Litterman (1979) to prevent overfitting of a model with many free parameters.

3.1 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 aggregate the intra-day surprises to the same frequency as y_t by adding them up. Our baseline model is a VAR with m_t and y_t and a restriction that m_t does not depend on the lags of either m_t or y_t and has zero mean,

$$\begin{pmatrix} m_t \\ y_t \end{pmatrix} = \sum_{p=1}^{P} \begin{pmatrix} 0 & 0 \\ B_{YM}^p & B_{YY}^p \end{pmatrix} \begin{pmatrix} m_{t-p} \\ y_{t-p} \end{pmatrix} + \begin{pmatrix} 0 \\ c_Y \end{pmatrix} + \begin{pmatrix} u_t^m \\ u_t^y \end{pmatrix}, \quad \begin{pmatrix} u_t^m \\ u_t^y \end{pmatrix} \sim \mathcal{N}(0, \Sigma), \tag{1}$$

where $\mathcal{N}$ denotes the normal distribution. As long as financial market surprises are unpredictable, the above zero restrictions are plausible. In the Appendix, we show that our results remain basically unchanged when we relax these restrictions.

We choose priors that are standard in the Bayesian VAR literature. Let B collect the coefficients of the VAR, $B = (B_{YM}^1, B_{YY}^1, ..., B_{YM}^P, B_{YY}^P, c_Y)'$. We introduce a Minnesota-type prior specified as an independent normal-inverted Wishart prior, $p(B, \Sigma) = p(B)p(\Sigma)$, where

$$p(\Sigma | \underline{S}, \underline{v}) = \mathcal{IW}\left(\underline{S}, \underline{v}\right), \tag{2}$$

$$p(\text{vec}\, B | \underline{B}, \underline{Q}) = \mathcal{N}(\text{vec}\, \underline{B}, \underline{Q}), \tag{3}$$

$\mathcal{IW}$ denotes the Inverted Wishart 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. $\underline{v} = N + 2$.

We generate draws from the posterior with the Gibbs sampler, at the same time taking care of the missing values in m_t. 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 (standard) derivations of these conditional posterior densities.

3.2 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 in our baseline VAR model.

We identify two structural shocks transmitted through the central bank announcements. For the time being, we call them a *negative correlation shock* and a *positive correlation shock*. We use two assumptions on high-frequency financial variables to isolate these shocks. Unless indicated otherwise, we impose no restrictions on any monthly macroeconomic variables.

1. Monetary policy surprises m_t are affected only by the two announcement shocks (the negative correlation shock and the positive correlation shock), and not by other shocks.

2. A negative correlation shock is associated with an interest rate increase and a drop in stock prices. A positive correlation shock is the complementary shock, i.e. the orthogonal shock that is associated with an increase in both interest rates and stock prices.

The first assumption is justified, because variables m_t are measured in a narrow time window around monetary policy announcements. Hence, it is unlikely that shocks unrelated to the central bank announcement systematically occur at the same time.

We use the second assumption to separate the two central bank announcement shocks. Their orthogonality is a standard requirement of structural shocks. Standard asset pricing theory suggests that a monetary policy tightening implies a decline in stock prices. First, the monetary tightening generates a contraction that reduces the expected value of future dividends. Second, the higher interest rates raise the discount rate with which these dividends are discounted. As a results, the stock price, which is the present discounted value of future dividends, need to decline. Therefore, the negative correlation shock is consistent with news being revealed by monetary policy, so, to a first approximation, we will think about it as a *monetary policy shock*. By contrast, a positive correlation must reflect something in the central bank's announcement that is not policy related. We will call the positive correlation shock a *central bank information shock*. We will show that the empirical results support our interpretation. We will also consider some refinements of this simple identification later. Table 1 provides an overview on the restrictions above on the contemporaneous responses of all variables (in rows) to all shocks (in columns) in the baseline model. The restrictions partition each high frequency surprise into a monetary policy shock component and a central bank information shock component.

To compute the posterior draws of the shocks and the associated impulse responses we proceed as follows. We note that the first assumption (with the associated zero restrictions) implies a block-Choleski structure on the shocks, with the first two shocks forming the first block. Next, we impose the sign restrictions in the first two shocks following Rubio-Ramirez, Waggoner and Zha (2010). For each draw of model parameters from the posterior we find a

Table 1: Identifying restrictions in the baseline VAR model

variable	shock Monetary Policy/ negative correlation	C.B. Information/ positive correlation	other
m_t, high-frequency surprises			
interest rate	+	+	0
stock index	−	+	0
y_t, monthly ...	•	•	•

rotation of the first two Choleski shocks that satisfies the sign restrictions. The prior on the rotations is uniform in the subspace where the sign restrictions are satisfied. More in detail, for 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 a Q such that CQ satisfies the sign restrictions. Then CQ is a draw of the contemporaneous impulse responses from the posterior, and the other quantities of interest can be computed in the standard way. The above procedure, with the QR decomposition of a randomly drawn matrix, implies a uniform prior on the space of rotations Q^* (Rubio-Ramirez, Waggoner and Zha, 2010). The point to note here is that our restrictions only provide set identification, i.e. conditionally on each draw of B and Σ there are multiple values of shocks and impulse responses that are consistent with the restrictions. When computing uncertainty bounds we take all these values into account weighting them according to the uniform prior on rotations. Having a uniform prior on the rotations is less restrictive than imposing the sign restrictions using a penalty function approach as e.g. in Uhlig (2005). Moreover, we also report the robustness to other priors on rotations following Giacomini and Kitagawa (2015).

4 Baseline VAR for the US

4.1 Variables in the baseline VAR

Our baseline VAR includes seven variables: two high-frequency surprise variables (in m_t) and five low-frequency macroeconomic variables (in y_t). m_t consists of the high-frequency surprises in the 3-months-ahead federal funds futures and in the S&P 500 stock market index. y_t includes a monthly interest rate, a stock price index, indicators of real activity, the price level, and financial conditions.

More in detail, we use the monthly average of the 1-year constant-maturity Treasury yield as our low frequency monetary policy indicator. The advantage of using a rate longer than the targeted federal funds rate is that it incorporates the impact 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 (Gertler and Karadi, 2015). As our stock price index, we use the monthly average of the S&P 500 in log levels. Our baseline measures of real activity and the price level is the real GDP and the GDP deflator in log levels. We interpolate real GDP and GDP deflator to monthly frequency following Stock and Watson (2010). This 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. In the appendix, we show that our results are robust to using industrial production and the consumer price index. Finally, as an indicator of financial conditions we include the excess bond premium (EBP Gilchrist and Zakrajsek, 2012). The variable is an average corporate bond spread that is purged from the impact of default compensation. As the authors show, the variable aggregates high-quality forward-looking information about the economy. Therefore, it improves the reliability and the forecasting performance of our small-scale VAR (Caldara and Herbst, 2016).

The VAR has 12 lags and the sample is monthly, from July 1979 to August 2016. The two variables in m_t are unavailable before February 1990. Moreover, the S&P500 surprise is missing in September 2001, when the FOMC press statement took place before the opening of the US market.

We report the results based on 2000 draws from the Gibbs sampler, obtained after discarding the first 2000 draws and keeping every fourth of the subsequent 8000. We obtain the same results also when the chain is 10 times longer. For every draw of B and Σ we find a random rotation matrix Q that delivers the sign restrictions. It is easy to show that for the restrictions in Table 1 such a matrix exists for every nonsingular Σ.

4.2 Impulse responses

Figure 2 presents the sets of impulse responses to a monetary policy and the central bank information shocks, respectively, in panel A, the first and the second columns. The figures make two points obvious. First, our sign restriction on the high-frequency co-movement of interest rates and stock prices separates two very different economic shocks. If, contrary to our hypotheses, the stock market response in the half-hour window around the policy announcement were uninformative about the effect of the announcement on the economy, the impulse responses of macroeconomic variables to interest rate surprises would have been the same in the two columns. This is clearly not the case if one looks at, for example, the striking differences between the responses of prices and the excess bond premium. This is all the more notable given that we impose no restrictions on the responses of these low frequency variables y_t. Second, monetary policy announcements generate not only monetary policy shocks. The second column clearly shows that the positive co-movement of interest rates and stock prices around monetary policy announcements, which is inconsistent with policy shocks, has low frequency consequences. For example, a high-frequency increase in stock prices and interest rate foretells a persistent increase in the future price level. We next discuss the impulse responses in detail.

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

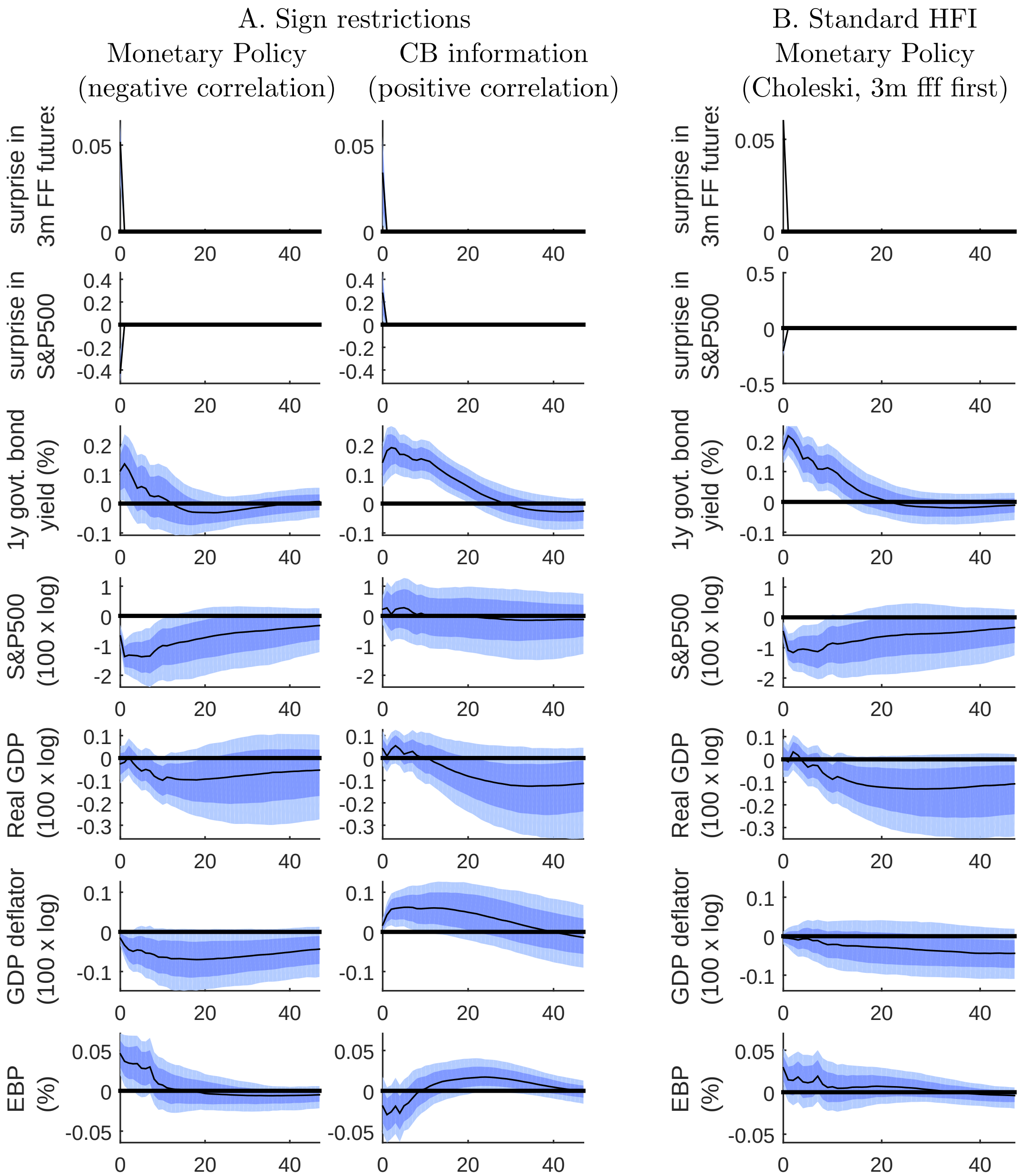


Table 2: Impact responses of high-frequency surprises to shocks. Baseline VAR.

	A. Sign restrictions				B. Standard HFI	
	Monetary policy		C.B. information		Monetary Policy	
	mean	$(5^{pct},95^{pct})$	mean	$(5^{pct},95^{pct}$t)	mean	$(5^{pct},95^{pct})$
3-m f.f. futures	5	(3, 6)	3	(0, 5)	6	(6, 7)
S&P500	-44	(-54, -23)	28	(4, 47)	-21	(-27, -15)

Note: Posterior means and posterior percentiles 5 and 95. In basis points.

The first column shows the responses to a monetary policy shock. Due to the coefficient restrictions in our VAR (1), the high-frequency variables in m_t are iid. They only respond to shocks on impact, and their impulse response function is zero in all other periods. Table 2 reports these impact responses. By construction, the impact responses satisfy the sign restrictions. A monetary policy shock is associated with a 3 to 6 basis points increase of the 3-month fed funds futures and a 23 to 54 basis points drop in the S&P500 index in the 30 minutes window. The response of low-frequency variables are qualitatively in line with previous results in the literature. The 1-year government bond yield increases by around 10 basis points and reverts to zero in about a year. Financial conditions tighten, the stock prices drop by about 1 percent, and the excess bond premium increases by about 5 basis points. Real GDP and the price level both decline persistently by about 10 basis points and 8 basis points respectively. The main quantitative novelty in these responses is the fairly low persistence of the interest rate response and the vigorous price-level decline. We come back to this result in Section 6 and analyze its relevance within a structural model.

The second column shows the responses to the central bank information shock. They are new in the literature. They are associated with an up to 5 basis points increase in the 3-month fed funds futures and a 4 to 47 basis points increase in the S&P500 index in the 30 minutes window. The 1-year government bond yield increases by more than 20 basis points and reverts back to zero in about two years, much slower than after a monetary policy shock. The impact on the financial conditions is mixed: the shock clearly reduces the excess bond premium by about 3 basis points, but has only a mild positive impact on the stock prices at this low frequency. The impact on output and price-level is very different than after a monetary policy shock: here the price-level increases by about 5 basis points, rather than declining as after a monetary policy shock. The increase is very persistent and reverts to 0 in around 3 years. Output increases slightly, rather than declines, though this effect reverses after about a year. In our view, these responses are consistent with the scenario in which the central bank communicates good news about the economy and tightens monetary policy, consistently with its reaction function, to partly offset the effect of the news and and prevent overheating of the economy. The persistent increase in the 1-year government bond yield is in line with such a systematic reaction of the central bank. The policy is unable to completely offset the effects of the news, but it is successful in neutralizing it within a short time span.

Figure 2 illustrates also how the presence of central bank information shocks biases the standard high-frequency identification (HFI) of monetary policy shocks. The standard identification takes all the surprises in the fed funds futures as proxies for monetary policy shocks (and ignores the accompanying stock price movements). This is what we reproduce on panel B of Figure 2. Specifically, this panel shows the impulse responses to the high-frequency federal funds futures surprise, ordered first, in the VAR identified with the Choleski decomposition. By the properties of the Choleski decomposition, the identifying restrictions in this case are

$$cov(m_t^{ff}, \epsilon_t^{MP}) > 0 \text{ and } cov(m_t^{ff}, \epsilon_t^i) = 0 \text{ for all } \epsilon_t^i \text{ other than } \epsilon_t^{MP}, \tag{4}$$

where m_t^{ff} denotes the fed funds futures surprise and ϵ_t^{MP} the monetary policy shock. Identifying restrictions (4) are used among others in Gertler and Karadi (2015) and Barakchian and Crowe (2013).[5]

The figure shows that the standard high-frequency identification mixes the monetary policy shocks with central bank information shocks. The responses in Panel B are qualitatively similar to the 'pure' responses in the first column of panel A, which are purged from the impact of central bank information shock. Both sets of responses show worsening financial conditions and a decline in prices and economic activity. But there are notable quantitative differences. First, the interest rate responses in panel B are larger and more persistent. This is because the standard shock is contaminated with the presence of the central bank information shocks, which have higher and more persistent interest rate effect. As the peak impact on the price-level and output are similar to the pure monetary policy case, this bias could lead one to underestimate the extent of monetary non-neutrality. Second, the response of the price level is muted, because the presence of the central bank information shocks with positive price-level impact masks the vigourous price-level decline observed after a pure monetary policy shock. Third, the impact on the excess bond premium is also biased downwards. Hence the standard identification offers a picture with very rigid prices and a smaller role for financial frictions. However, once we purge the monetary policy shock from its contamination with the central bank information shock, we obtain impulse responses of an economy with less rigid prices but more role for financial frictions. We make these points formally in Section 6.

Both shocks have nontrivial contributions to the overall macroeconomic volatility. Table 3 reports the contributions of the two shocks to the forecast variances of all the variables at the horizon of two years. 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.

[5] The specific implementations of these restrictions differ across papers. For example, Gertler and Karadi (2015) use the *external instruments* approach, i.e. they do not introduce m_t^{ff} into the VAR and instead use it in auxiliary regressions outside the VAR. Caldara and Herbst (2016) and Paul (2017) discuss the relation between the Choleski factorization and the external instruments approach. We verified that in our application the findings are very similar when using both approaches.

Table 3: Variance decomposition: the share of the 2-year forecast variance explained by each shock. Baseline VAR.

	A. Sign restrictions				B. Choleski	
	Monetary policy		C.B. information		Monetary Policy	
	mean	(5^{pct},95^{pct})	mean	(5^{pct},95^{pct})	mean	(5^{pct},95^{pct})
m_t, high-frequency surprises						
3-m f.f. futures	0.66	(0.20, 1.00)	0.34	(0.00, 0.80)	1.00	(1.00, 1.00)
S&P500	0.66	(0.21, 1.00)	0.34	(0.00, 0.79)	0.16	(0.09, 0.24)
y_t, monthly						
1-year yld.	0.09	(0.02, 0.22)	0.25	(0.10, 0.41)	0.19	(0.07, 0.34)
S&P500	0.08	(0.02, 0.19)	0.02	(0.00, 0.07)	0.06	(0.01, 0.15)
Real GDP	0.04	(0.00, 0.13)	0.03	(0.00, 0.08)	0.05	(0.00, 0.13)
GDP deflator	0.08	(0.00, 0.20)	0.06	(0.00, 0.17)	0.03	(0.00, 0.10)
EBP	0.06	(0.01, 0.13)	0.04	(0.01, 0.10)	0.03	(0.01, 0.08)

Note: Posterior means and posterior percentiles 5 and 95.

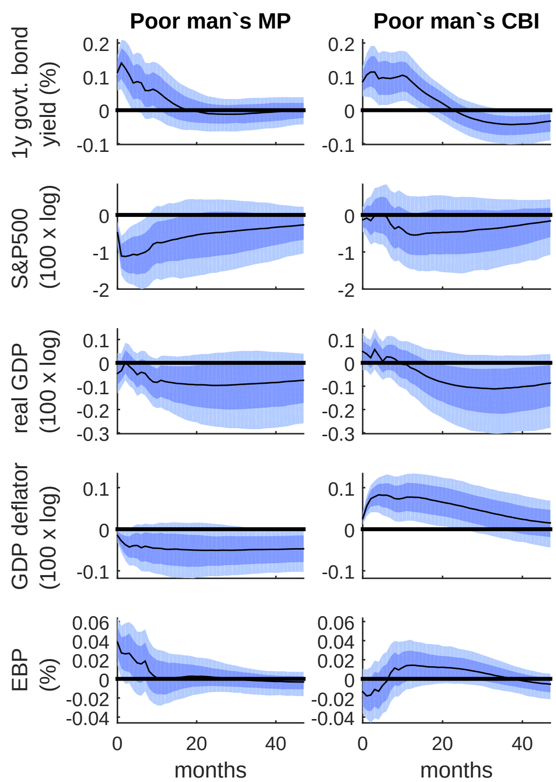
Turning to low-frequency variables y, we see that monetary policy shocks account for 10% of the variance of 1-year bond yields and 9-8% of the S&P500 index and 6% of the excess bond premium. They also account for 4-5% of real GDP and 6-8% of the GDP deflator, which are relatively high shares compared 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.

4.3 'Poor man's' sign restrictions and other robustness checks

We now show that a simpler exercise can lead to similar impulse responses than those obtained by our sign restrictions. In particular, we use fed funds surprises accompanied by a negative co-movement of interest rate and stock market surprises (those from quadrants II and IV of Figure 1) as proxies for monetary policy shocks, and the fed funds futures surprises accompanied by a positive co-movements (those from quadrants I and III) as proxies for central bank information shocks. The implicit assumption in this exercise is that each policy announcement can be classified either as a pure monetary policy shock or as a pure central bank information shock. By contrast, in the sign restrictions approach each announcement is a combination of the two shocks with different, generally non-zero shares. The identifying assumptions behind this exercise are stronger than those of our baseline sign restrictions, but it is also easier to implement. For lack of a better name, we dub this exercise as 'poor man's sign restriction.' Figure 3 reports the impulse responses to these proxies (we place the proxies first and use the

Choleski decomposition to identify the VAR). The impulse responses are strikingly similar to those obtained with sign restrictions.

Figure 3: Impulse responses to one standard deviation shocks, baseline VAR with 'poor man's' sign restrictions. Median (line), percentiles 16-84 (darker band), percentiles 5-95 (lighter band).



The correlation between the posterior mean of the monetary policy shock identified with sign restrictions and the shock from the poor man's procedure is 85%. For the central bank information shock this correlation is 55%. So the sign restrictions and the 'poor man's' sign restrictions do not yield the same shocks, but they do yield shocks with very similar impulse responses.

The impulse responses are also robust when we stop the sample in December 2008 (when the fed funds rate hit the zero lower bound); when we drop the pre-1994 surprises, which were not accompanied by announcements; when we replace the interpolated real GDP and GDP deflator with the Industrial Production Index and Consumer Price Index; and when we replace the surprises in the 3-months fed funds rate and S&P500 with factors extracted from several interest rate and stock market surprises. We show that detailed results in the Appendix.

4.4 The shocks over time

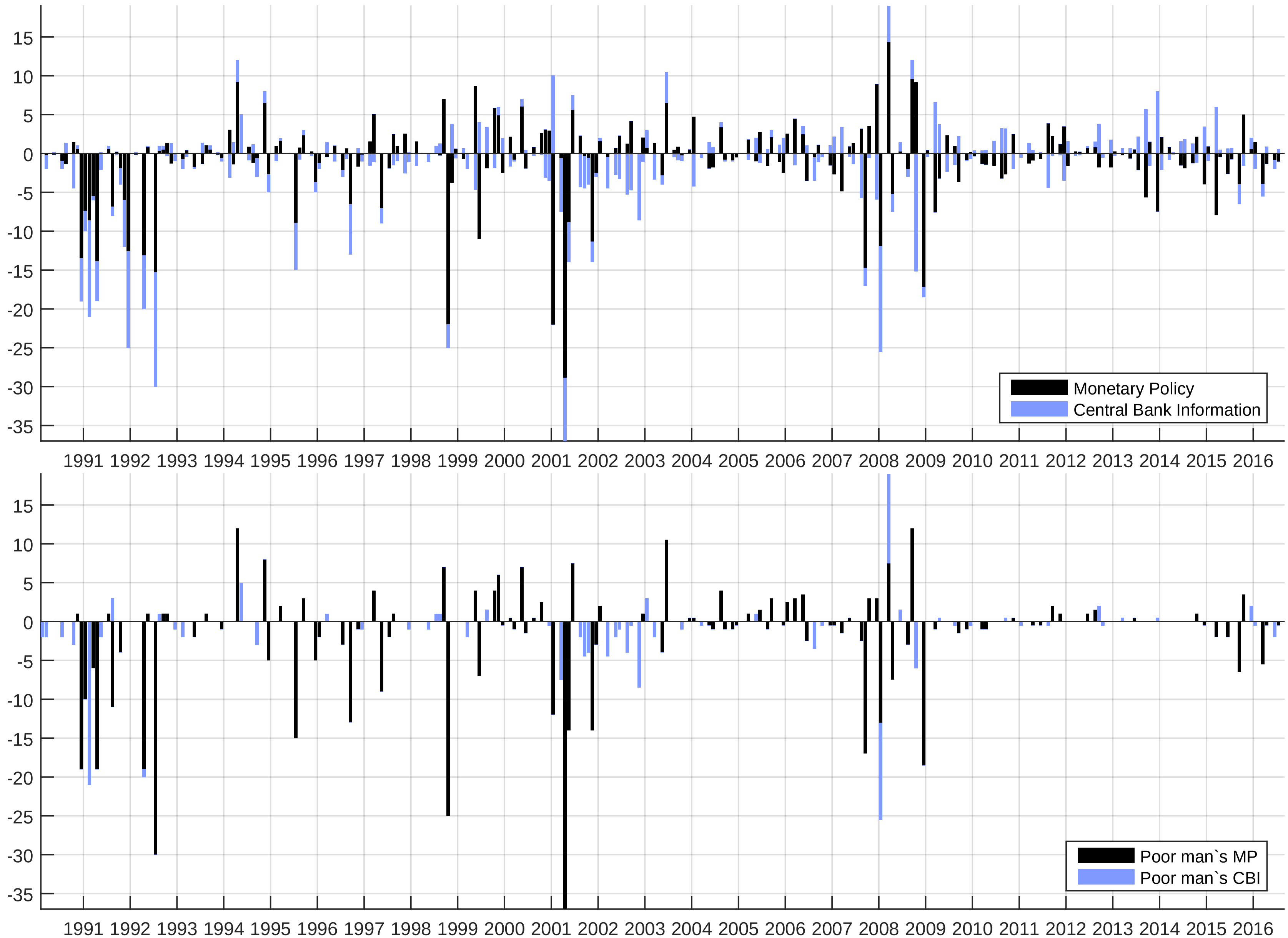
At which occasions were the central bank information shock particularly large? To answer this question Figure 4 plots the monetary policy and central bank information shocks over time. The upper panel reports the shocks obtained with the sign restrictions and the lower panel the 'poor man's' sign restriction shocks. The shocks are scaled in terms of 3-month fed fund futures surprises, in basis points, and summarized by their posterior means.

Figure 4 shows that the largest central bank information shock was the one discussed in the Introduction, which happened on January 22, 2008. Other central bank information shocks are not particularly clustered, but occur all over our sample. One episode worth highlighting is a sequence of negative information shocks from the end of 2000 until the end of 2002, in the wake of the burst of the dot-com bubble. Over this period, the FOMC cut the fed funds rate from over 6% to close to 1%, to offset the worsening demand conditions brought about by the negative stock-market wealth shock and geopolitical risks related to the 2001 September terrorist attack and the run up to the March 2003 Iraq war. The initial major cuts up until the end of 2001 were in line with the predictions of standard historical interest rate rules (Taylor, 2007) and the persistence of easy policy later can be well explained by the moderate pace and 'jobless' nature of the recovery (Bernanke, 2010). The FOMC statements during this period drove expectations through forward-looking communication about the balance of risks surrounding future interest rate changes and the FOMC consistently linked the easy stance of policy to weak demand conditions and high economic uncertainty with down-side risks.[6] The positive co-movement of interest rates and stock market changes over the majority of these announcements suggest that the worse-than-expected outlook of the FOMC led agents to update downwards their views about the economic prospects.

Another interesting observation is that the central bank information and monetary policy shocks are roughly proportional to each other in the pre-1994 period. The pre-1994 period is different from the rest of the sample because until February 1994 the FOMC did not issue a press release (the surprises are measured around the first open market operation after a decision). All that the market participants were observing was the fed funds rate, and based on that they made inference about the monetary policy shock and about the central bank information shock. Theoretical models of central bank information predict that in this case the agents perceive the two shocks as proportional (see Melosi, 2017; Nakamura and Steinsson, 2013). Our estimated shocks in this period are consistent with this prediction.

[6] For example, in August 2001, the FOMC explained that it reduced the target rate by 25 basis points in light of the facts that "Household demand has been sustained, but business profits and capital spending continue to weaken and growth abroad is slowing, weighing on the U.S. economy," and announced that "risks are weighted mainly toward conditions that may generate economic weakness in the foreseeable future." In March 2002, the FOMC announced that it kept its target rate constant despite of the "significant pace" of expansion. It explained that "the degree of the strengthening in final demand over coming quarters, an essential element in sustained economic expansion, is still uncertain." In both of these instances, our methodology assigns overwhelming majority of the interest rate surprise to central bank information shocks.

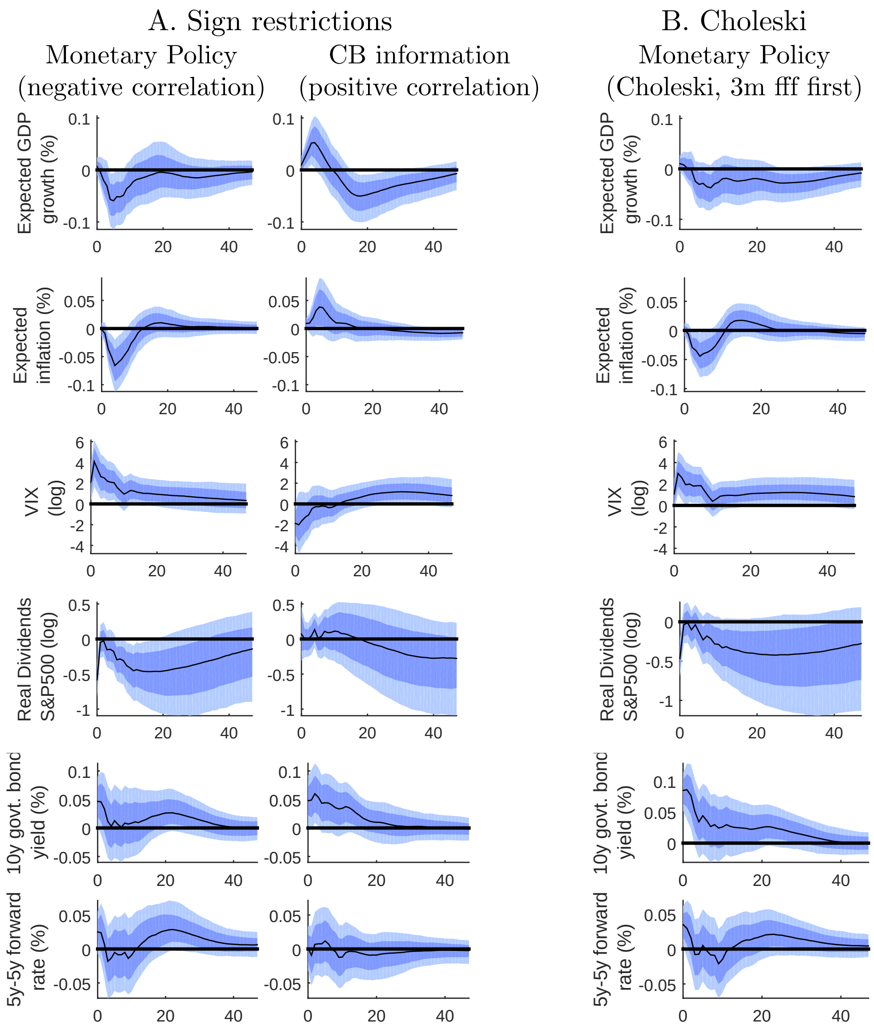
Figure 4: Contributions of shocks to the surprises in the 3-month fed fund futures, aggregated to the monthly frequency. Basis points



4.5 Responses of other variables

Figure 5 reports the responses of low frequency variables that we add, one by one, to the baseline model. We can see that the two shocks that we identify by sign restrictions have opposite effects on a number of important variables. When discussing these results we focus on the responses to central bank information shocks and what we learn about the nature of these shocks.

Figure 5: 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).



The central bank information shock generates an increase in both growth and inflation expectations (see the first two rows of Figure 5). The expectations respond gradually, with most of the effect materializing after a few months, as is often found empirically.[7] The real GDP growth and CPI expectations in these plots come from Consensus Economics. We transform the current-year and next-year average expectations into constant-horizon 1-year expectations.[8] Due to data availability we start the sample in 1990, but this does not change much in the other impulse responses (see Appendix B). The fact that growth and inflation expectations move in the same direction confirm the notion that central bank information shocks convey information about demand pressures.

The subsequent plots show that the central bank information shock reduces the VIX (the implied volatility in S&P 500 option prices). The VIX is a standard proxy for economic uncertainty, only available since 1990. Real dividends (dividend payouts of S&P stocks every month) increase, albeit insignificantly in the first two years, in contrast to their drop after the monetary policy shock. This behavior, in addition to the similarly contrasting reactions of the interest rate spreads, drive the present value of future dividends in contrasting directions, in line with our identification assumptions about high-frequency stock market surprises.

The last two rows show that the central bank information shock does not raise the term premium. In contrast, it temporarily increases after a monetary policy shock (Gertler and Karadi, 2015). We conclude this from the observation that even though the 10-year bond yield increases after both shocks, the five-year forward rate five-years ahead only increases after the monetary policy shock. Since the effect of the monetary policy shock on the 1-year bond yield is only temporary, the increase in the forward rate must reflect a rise in the term premium. By contrast, the forward rate does not respond to the central bank information shock.

4.6 Central bank information about supply

This section refines the identification to address the following potentially relevant critique. When the central bank announces adverse news about the outlook while hiking the interest rate, our baseline sign restriction scheme misclassifies such events as monetary policy shocks. For example, consider news about an adverse supply shock. The stock market declines as a result of lower expected firm profitability, but as the shock is inflationary, the central bank can still choose to increase rates. For another example, consider a negative revision of the potential output. Growth prospects look worse, so the stock market tanks, but inflationary pressures are stronger than believed before, so the central bank increases rates anyway. For both these kinds of information shocks the correlation between the interest rate surprise and the stock price surprise is negative, so our baseline VAR classifies them as monetary policy

[7] Notably, controlling for the central bank information channel eliminates the counterintuitive positive effect of a monetary policy shock on expected GDP growth on impact, as emphasized by Nakamura and Steinsson (2013).

[8] 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).

shocks. To redress this problem, we refine the identification scheme by adding an additional high-frequency variable to vector m_t and an additional set of restrictions, as in Table 4.

The variable we add is the change in the 2-years ahead break-even inflation rate on the day of the FOMC announcement. We construct the variable by taking the difference between the 2-year constant-maturity yields of nominal and real (inflation-protected) Treasuries (Gürkaynak, Sack and Wright, 2007, 2010).

Table 4: Identifying restrictions in the VAR with central bank information about supply

Variable	Shock: Monetary Policy	C.B. Info. Demand	C.B. Info. Supply	other
m_t, high-frequency surprises				
interest rate surprise (30m window)	+	+	+	0
stock index surprise (30m window)	−	+	−	0
break-even infl. surprise (daily)	−	+	+	0
y_t, monthly ...	•	•	•	•

Table 5: Impact responses of high-frequency surprises to shocks. Separating central bank information about demand from central bank information about supply.

	Monetary policy		C.B. Info. Demand		C.B. Info. Supply	
	mean	(5^{pct},95^{pct})	mean	(5^{pct}, 95^{pct})	mean	(5^{pct},95^{pct})
3-m f.f. futures	5	(2, 6)	2	(0, 5)	2	(0, 5)
S&P500	-21	(-42, -3)	27	(5, 45)	-34	(-48, -8)
2-year break-even inflation	-4	(-5, -1)	2	(0, 4)	2	(0, 4)

Note: Posterior means and posterior percentiles 5 and 95. In basis points.

After a monetary policy shock inflation is expected to falls and after a favorable news about demand inflation is expected to rise, so we require inflation compensation to do the same, as Table 4 shows.[9] We disentangle the new *central bank information about supply* shock from the monetary policy shock, by requiring that the 2-year breakeven inflation rate increases after the

[9]These assumptions are not completely innocuous. Inflation compensation is driven both by expected inflation and by inflation premium. We have shown that the shocks lead to changes in financial conditions, and this can influence the required inflation premium independently from expected inflation. If we assume that inflation premium moves in the same direction as the excess bond premium does, than our assumptions are conservative: expected inflation necessarily declines if inflation compensation does after a monetary policy shock, and expected inflation necessarily increases if inflation compensation does after a news about demand shock.

news shock.[10] Table 5 reports the impact responses that reflect these assumptions. We can see modest changes of break-even inflation on the day of the FOMC annuncements.

Figure 6: Impulse responses to one standard deviation shocks. Median (line), percentiles 16-84 (darker band), percentiles 5-95 (lighter band). VAR with central bank information about supply.

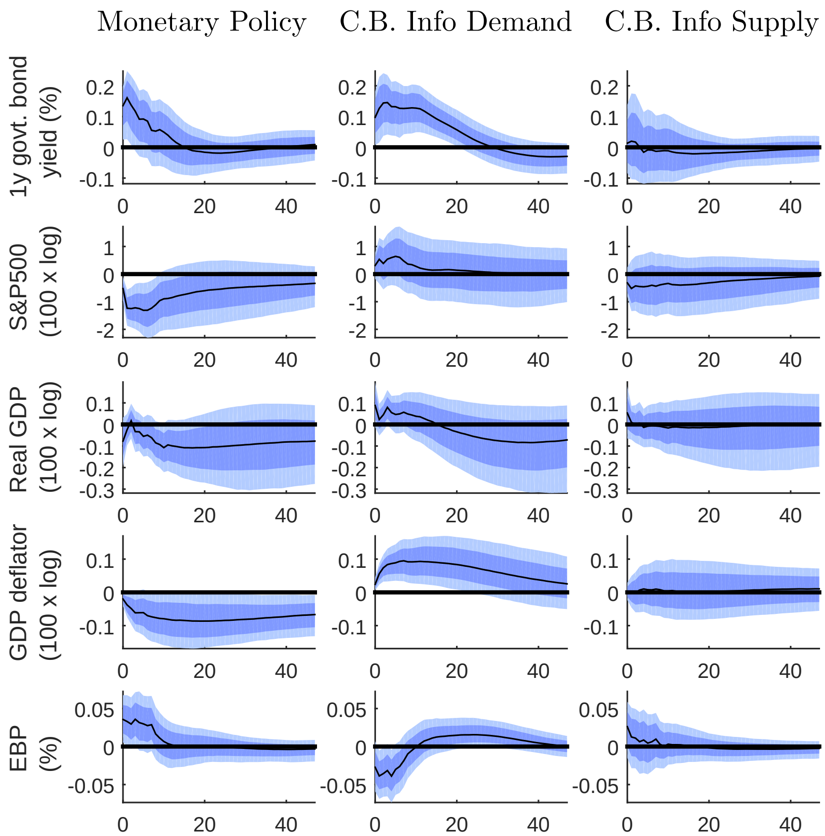


Figure 6 reports the responses of low frequency variables to the three shocks we now identify. Two lessons stand out. First, the responses to monetary policy and central bank demand information shocks are robust to adding a new high-frequency observable and a third shock. The main difference is that inflation responses become somewhat more pronounced and that this time the low frequency stock market response to central bank information about demand is positive (though not very significant). Second, we do not see measurable low-frequency response of activity, the price-level or the interest rate to the central bank information shocks about supply. If anything, financial conditions worsen somewhat after the shock as both stock markets decline and the excess bond premium rises. Instead of an information shock about supply, the shock seems to be more consistent with a fleeting disturbance in financial

[10] Andrade and Ferroni (2016) use the co-movement of interest rates and the break-even inflation rate only (without considering their co-movement with the S&P500) to distinguish Delphic from Odyssean forward guidance in the euro area.

conditions without discernible impact on the economy and without triggering any monetary policy response. Overall, we conclude that our previous conclusions remain robust also under this more refined identification.

5 Euro area evidence

In this section, we analyze the robustness of our baseline US results by applying our methodology to euro area data. This application deserves particular attention, because, as we show below, standard high-frequency identification of monetary policy shocks here leads to results that are inconsistent with theoretical predictions. Our methodology resolves this issue.

5.1 The euro area dataset

We have constructed a novel euro area high-frequency financial-market surprise dataset along similar lines as the Gürkaynak, Sack and Swanson (2005b) data for the US. This dataset contains 284 ECB policy announcements from 1999 to 2016. Analogously to the US, we use 30-minute windows around press statements and 90-minute windows around hour-long press conferences and some relevant speeches, both starting 10 minutes before and ending 20 minutes after the event.[11] Whenever there is a press conference after a press statement our surprise measure is the sum of the responses in the two windows.

The narrow window minimizes the chances that unrelated regular news announcements bias our measure, which may be more of an issue in Europe than in the US. For example, our window around regular press statements by the ECB at 13:45 CET excludes monetary policy announcements of the Bank of England (BoE) released at 12:00 CET the same day in a sizable part of our sample.[12]

In the euro area dataset, we record surprises in the Eonia interest rate swaps with maturities 1 month up to 2 years, and the Euro Stoxx 50, a market capitalization-weighted stock-market index including 50 blue-chip companies from 11 Eurozone countries.

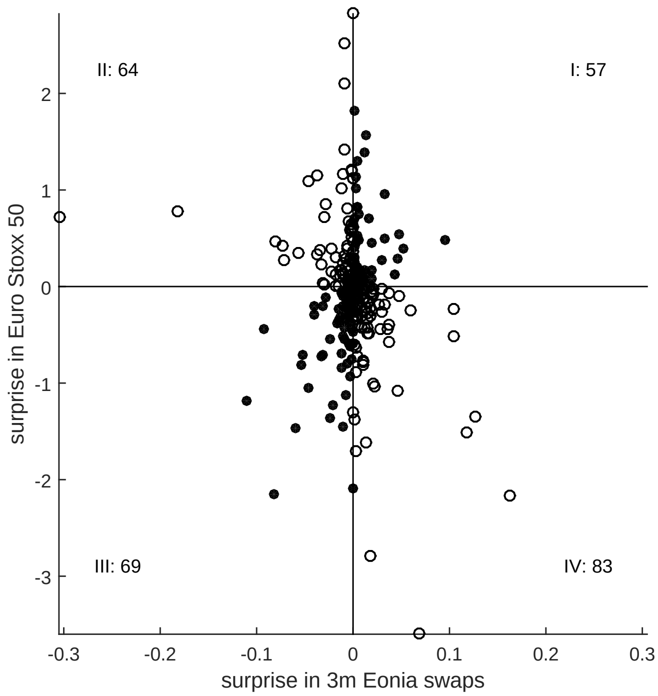
The 'wrong-signed' responses of stock prices are even more of an issue in the euro area than in the US. In the following analysis, we focus on the 3-months Eonia swap and on the Euro Stoxx 50. Figure 7 shows the scatter plot of the surprises. This time 46% of the data points are in quadrants I and III with 'wrong-signed' reactions of stock prices to interest rate surprises, even more than in the US.[13] This is in line with the more transparent communication policy

[11]The dataset contains 275 announcements and 9 speeches of the ECB president: the 'whatever it takes' speech in London on July 26, 2012, as well as 8 speeches announcing various aspects of the ECB's nonstandard monetary policies. We omit the 8 speeches on nonstandard monetary policies unless explicitly mentioned otherwise.

[12]US initial jobless claims announcements systematically coincide with the start of the press conferences. We check, whether this announcement contaminates our surprise measure by regressing the surprise component in these announcements (relative to Bloomberg consensus). The effects explain only around 1 percent of the variability of the surprise. We conclude that we can ignore the impact of the US data release.

[13]Recall that in the US 34% of the datapoints with non-zero surprises were in quadrants I and III. This proportion is 32% in the US sample starting in 1999, like in the euro area.

Figure 7: Scatter plot of the surprises in the 3-month Eonia swaps and in the EuroStoxx50 index



Note: Filled circles highlight the data points where both surprises have the same sign. The number in each quadrant is the number of data points in the quadrant.

of the European Central Bank (ECB). For example, the ECB organizes press conferences since 1999, while the first press conference was introduced only in 2011 in the US. Furthermore, the ECB announces staff forecasts promptly after they are produced, while these are made public in the US with a 5-year delay.

5.2 Euro area impulse responses

Our main lesson extends to euro area data: The immediate stock market response to a monetary policy announcement is informative about the announcement's longer-run economic consequences. In addition, we obtain a number of new findings. We have estimated a VAR for the euro area constructed similarly to our US baseline. In this VAR we use the German 1-year government bond yield to capture the safest one-year interest rate. Furthermore, we use the BBB bond spread to capture financial conditions, as no excess bond premium measure is available for the euro area. The other variables are analogous: we use the blue-chip STOXX50 index and an interpolated real GDP and GDP deflator series. Figure 8 presents the impulse responses for three identifications: a standard high-frequency identification, sign restrictions and poor man's sign restrictions.

The impulse responses after a monetary policy shock obtained with the standard high-frequency identification (Panel A) lead to responses that are inconsistent with predictions of standard theory. In particular, first, stock prices increase, and second, corporate bond spreads fall in response to this shock. Hence, in the euro area the standard high-frequency identification fails and it is obvious that one needs to decompose the monetary policy surprises further, as we do in this paper.

The baseline sign restrictions deliver a more plausible monetary policy shock, except for one issue: the response of the 1-year bond yield is insignificant. Therefore, we add one more sign restriction to the identification: we postulate that the impact response of the 1-year bond yield must be positive. The resulting impulse responses are in Panel B of Figure 8. Two differences from the US stand out. First, the stock market response to the central bank information shock is large and positive, while it was insignificant in the US. Second, the response of output to the central bank information shock is stronger, and the response of prices is weaker than in the US. Many of the responses are not significant, but overall, like in the US, they leave no doubt that the two shocks are very different. A positive monetary policy shock is a conventional policy tightening. A positive central bank information shock looks like positive news about the economy to which the central bank responds to mitigate its impact on prices.

The poor man's sign restriction identification is implemented analogously as in the US and again delivers similar impulse responses as the sign restrictions. The main difference is that this time the impact increase in the 1-year government bond yield is significant and of similar magnitude for both shocks.

5.3 Euro area shocks over time

Figure 9 presents the shocks from the euro area VAR. In the sign restriction identification the monetary policy response to the terrorist attacks in September 2001 involves the largest negative central bank information shocks. There is also a sizeable negative central bank information shock in October 1999, when the ECB announced an increase in the size of its longer term refinancing operations "to contribute to a smooth transition to the year 2000" in light of the then widespread concerns about the "Millenium bug." Another such shock took place in August 2011, when the markets had expected a rate increase and the decision to keep the rates unchanged was received as an easing surprise. The accompanying statement emphasized that uncertainty, especially on financial markets, are "particularly high." The last two events are picked up both by the sign restrictions and their 'poor man's' version.

Figure 8: Impulse responses to one standard deviation shocks, euro area VAR. Median (line), percentiles 16-84 (darker band), percentiles 5-95 (lighter band). Months on the horizontal axis. *The sign restriction identification includes also a restriction that the impact response of the 1-year bond yield is positive.

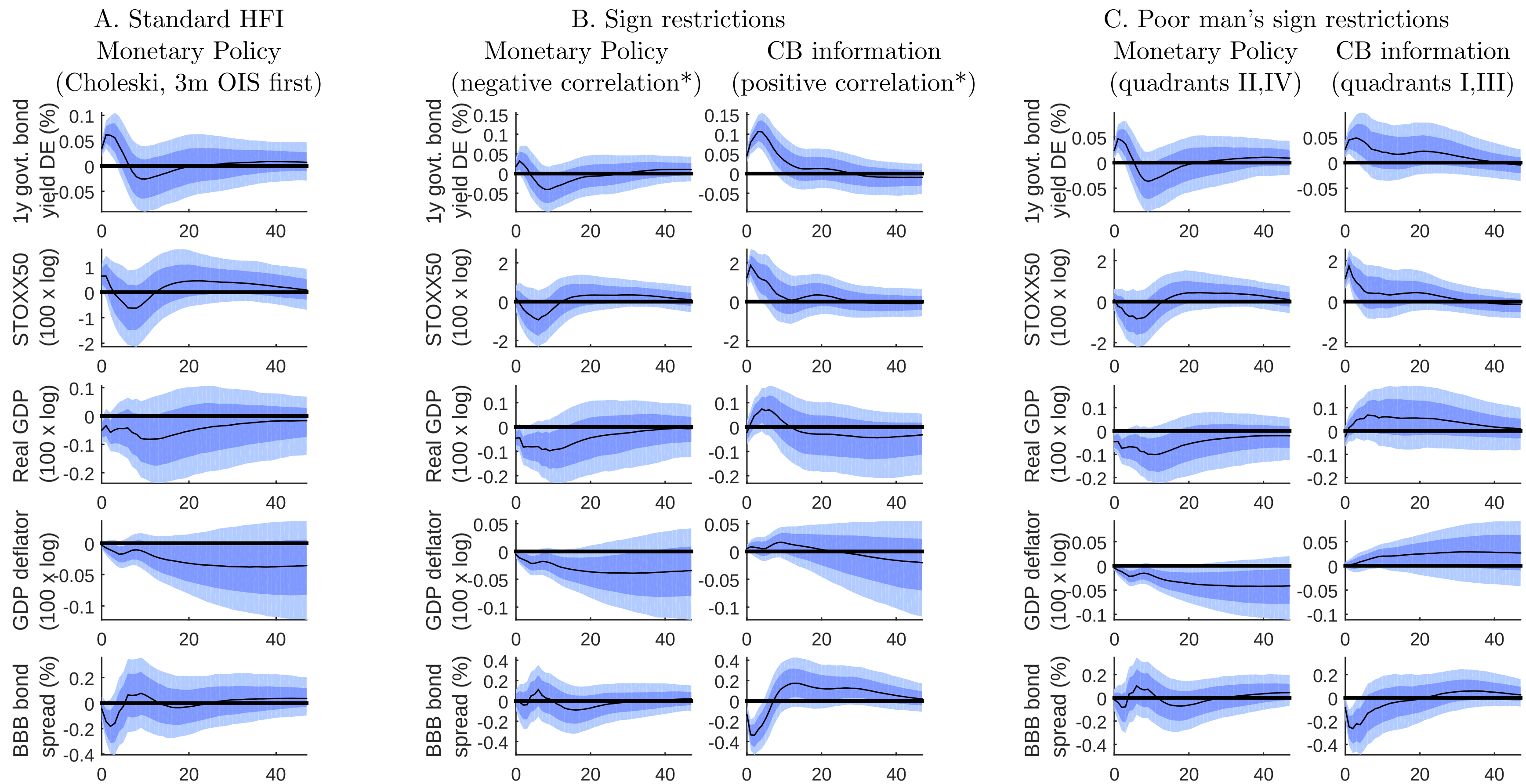
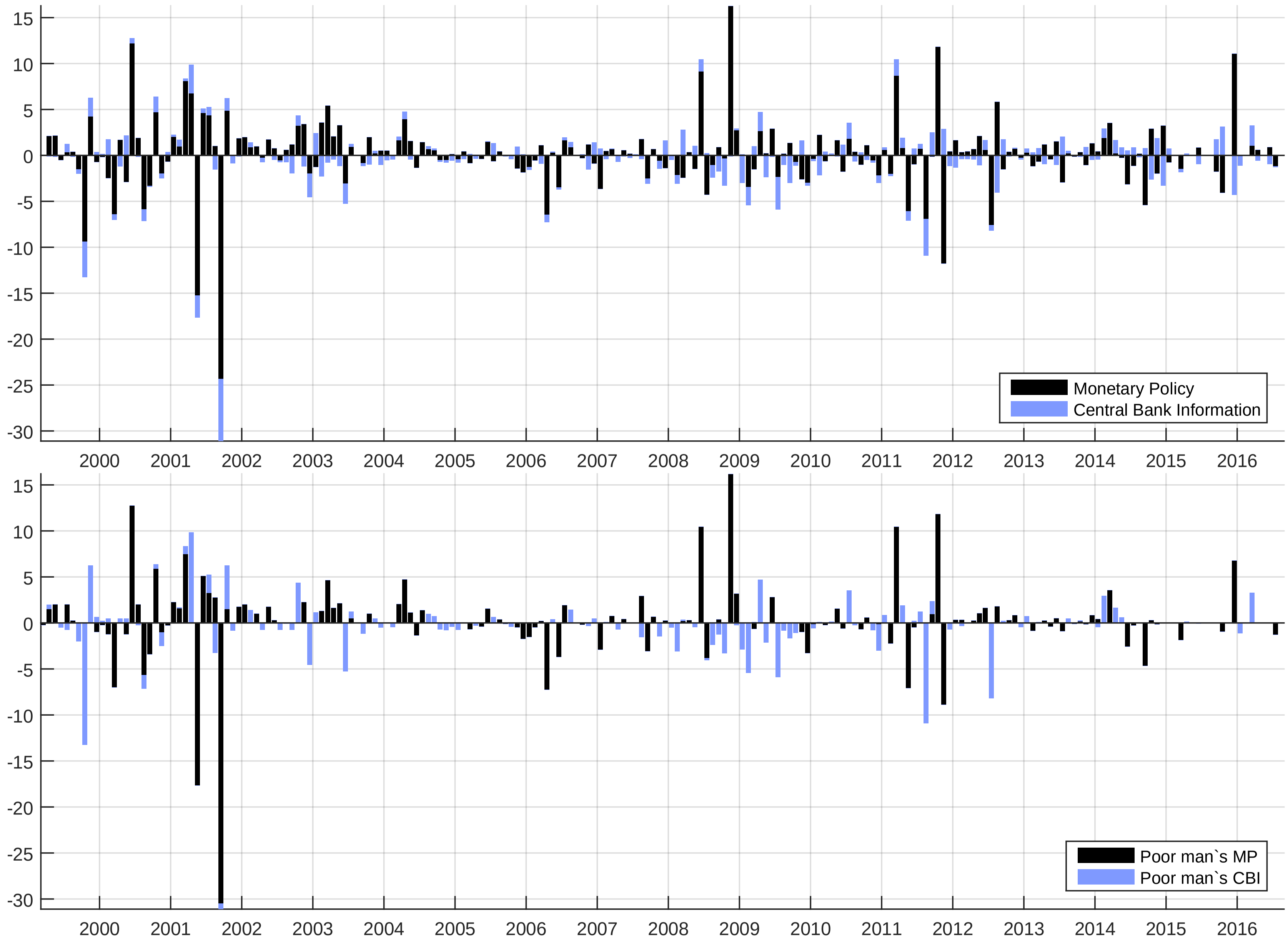


Figure 9: Contribution of shocks to the surprise in the 3-month Eonia swap. Basis points



6 A structural interpretation

In this section, we assess the relevance of our empirical results through the lens of a New Keynesian macroeconomic model. The model closely follows Gertler and Karadi (2011), which is a workhorse New Keynesian framework with balance sheet constrained financial intermediaries. The framework is well suited to analyse the quantitative impact of monetary policy shocks, which are modelled as temporary deviations from a systematic interest rate rule. To obtain an analogue of central bank information shocks, we introduce central bank communication policy to the model. In particular, we assume that the central bank has private information about a future disturbance and reveals this information in advance to the public. Even though news shocks are revealed contemporaneously to monetary policy shocks, they are independent from each other, in line with our empirical framework.

In the model, monetary policy influences real allocations because of two key frictions: nominal rigidities and financial frictions. We ask two questions. First, how does the relative importance of the two key frictions change, if the model matches responses to an estimated monetary policy shock that is purged from the effects of central bank information shocks (our baseline monetary policy shock) versus when it matches unpurged impulse responses (monetary policy shock identified with the standard high-frequency identification). Second, which single structural shock in the model can best approximate the macroeconomic impact of a central bank information shock.

We structure the description of the model below along the lines of the transmission of monetary and central bank information shocks. To conserve space, we describe key equilibrium conditions of the model and relegate their derivations to the appendix. The framework has 7 agents. There are representative households, financial intermediaries, intermediate-good and capital-good producers, retailers, a fiscal authority and a central bank. The representative households consume a basket of differentiated goods, work and save. Financial intermediaries collect deposits and lend to intermediate good firms. Intermediate good firms use capital and labor to produce intermediate goods. They borrow from financial intermediaries and from the household to finance capital acquisitions. Capital-good producers use final goods to generate new capital. Retailers purchase intermediate goods, differentiate them and sell them to the households. Fiscal policy finances its exogenous expenditures with lump sum taxes. The central bank sets interest rates and conducts a communication policy.

6.1 Central Bank

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

$$i_t = \kappa_\pi \pi_t + \kappa_x x_t + \varepsilon_t, \tag{5}$$

where π_t stands for the inflation rate, x_t is a measure of economic slack. We proxy the economic slack with the log deviation of marginal cost of the intermediate good from its steady state. This proxy is proportional to conventional output gap measures. $\kappa_\pi > 1$ and $\kappa_x > 0$ are parameters. The policy temporarily deviates from its systematic component because of monetary policy shocks (ε_t). The shock follows a first-order autoregressive process $\varepsilon_t = \rho_i \varepsilon_t + u_{it}$.

Central bank also conducts a communication policy. Since 1994, the US FOMC has accompanied its policy announcements with an explanation of its views about the economic outlook. This communication gave an explicit channel for the central bank to influence private expectations, potentially independently from its rate setting decisions. We assume that the central bank can move markets with communication not because it has any advantage in collecting data, but because it employs a large number of analysts and researchers giving it an edge in processing economic information. We model the central bank's information advantage simply by assuming that it learns in period t about a future shock (u_{t+2}) well before it materializes. The information shock (u_{t+2}) is independent of the monetary policy shock (ε_t).[14] We assume that the central bank shares its knowledge about the future shock with the public. This communication policy (ψ_t) is exact and credible.[15] The communication policy is our way of introducing central bank information shocks to the model.

$$\psi_t = u_{t+2} \tag{6}$$

This policy assumes truth-telling, which we consider to be a reasonable first approximation to a systematic communication policy. It is not worse than alternative linear rules. Maintaining any constant bias in communication (a constant multiplying the future shock) by understating the size of the disturbance, for example, would be learnt over time. Noisy communication (an additive i.i.d. error term) would also be undesirable, because this would only reduce the effectiveness of policy. Importantly, communication policy here is an additional tool to interest rate policy: Central bank influences agents' perceptions not only through changing its policy instruments, but also through publishing statements. The statements can credibly convey information and move expectations, because the central bank has incentives to maintain the reputation of its communication policy. When reading the statement, the public updates their expectations about the future shock. The shock then indeed materializes in period $t + 2$. The advantage of central bank communication is to inform the public about an upcoming disturbance that they would only realize later.

At this stage, we do not determine the nature of the shock that the central bank has information advantage about. One of our goals in this section is to identify which single shock

[14]This does not mean that interest rates do not respond systematically and contemporaneously to central bank information shocks, as we explain below.

[15]If the announcements were not exact, the public would need to infer the underlying economic and monetary policy disturbances from its observations on the interest rate and communication signals. The public would then optimally allocate some weight to both disturbances based on the relative variance of the shocks. In this realistic framework, no pure monetary policy or central bank information shocks would ever materialize, only some combination of the two. Our empirical method, however, would still identify the two extreme building blocks of the observed shocks. We leave the analysis of this environment for future research.

would best describe macroeconomic responses to a central bank information shock that we identified in the data.

6.2 Nominal rigidities

The real interest rate (r_t) is determined by the Fisher equation

$$i_t = r_t + E_t \pi_{t+1}. \tag{7}$$

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

$$\pi_t - \gamma_P \pi_{t-1} = \beta(E_t \{\pi_{t+1}\} - \gamma_P \pi_t) + \frac{(1-\gamma)(1-\beta\gamma)}{\gamma} x_t, \tag{8}$$

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

6.3 Real effects of monetary policy

Real interest rate influences aggregate demand through its impact on consumption, on investment and, indirectly, on government expenditures. Consumption in the model is governed by the representative households' Euler equation:

$$E_t \{\Lambda_{t,t+1} R_{t+1}\} = 1, \tag{9}$$

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

$$\Lambda_{t,t+1} = \beta_t \frac{\varrho_{t+1}}{\varrho_t}, \tag{10}$$

where β_t is a potentially time-varying discount factor, and ϱ_t is the marginal utility of the consumption. The marginal utility of consumption is given by

$$\varrho_t = (C_t - hC_{t-1})^{-1} - \beta_t h E_t (C_{t+1} - hC_t)^{-1}, \tag{11}$$

where $h \in [0, 1]$ is a parameter governing the strength of consumption habits.

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

Investment is determined by capital good producers. They transform consumption goods into capital goods subject to an investment adjustment cost function (f) and sell them to intermediate good firms for a price Q_t.

$$Q_t = 1 + f\left(\frac{I_t}{I_{t-1}}\right) + \frac{I_t}{I_{t-1}} f'\left(\frac{I_t}{I_{t-1}}\right) - E_t \Lambda_{t,t+1} \left(\frac{I_{t+1}}{I_t}\right)^2 f'\left(\frac{I_{t+1}}{I_t}\right) \tag{12}$$

An increase in real rates reduces the value of capital Q_t. This value equals the present discounted value of future capital returns. It declines, because first, higher real rates cause a downturn and reduce the marginal product value of capital. Second, higher interest rates increase the discount rate, which these future dividends are discounted with. Low price of capital reduces the incentives to invest, and generates a realistic hump-shaped decline in investment, thanks to the functional form of adjustment costs. Aggregate capital (K_{t+1}) evolves according to the following law of motion: $K_{t+1} = \Xi_{t+1}\left[I_t + (1-\delta)K_t\right]$, where $\Xi_t = \exp(\xi_t)$ is a shock to capital quality. It follows a first order autoregressive process $\xi_t = \rho_\xi \xi_{t-1} + u_{\xi t}$. The shock is a reduced form way to introduce variation in the ex post return and the price of capital, and thus it can be interpreted as an asset-valuation shock.

Government expenditure is assumed to be a fraction of aggregate output $G_t = \exp(g_t)Y_t$, where $g_t = \bar{g} + \rho_t g_{t-1} + u_{gt}$ is an autoregressive process. A downturn in output, therefore, reduces government expenditures. Aggregate demand net of investment adjustment costs equals the sum of consumption, investment and government expenditures.

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

$$Y_{mt} = A_t K_t^\alpha L_t^{1-\alpha}, \tag{13}$$

where Y_{mt} is the intermediate good production, $A_t = \exp(a_t)$ is a measure of aggregate technology, which follows an autoregressive process $a_t = \rho_a a_{t-1} + u_{at}$, L_t is labor and α is the capital income share. We denote the price of the intermediate good P_{mt}. Marginal product value of capital is $Z_t = P_{mt}\alpha\frac{Y_t}{K_t}$. Equilibrium in the labor market requires $P_{mt}(1-\alpha)\frac{Y_{mt}}{L_t} = \chi\varrho_t^{-1}L_t^\varphi$, where χ is the relative utility weight of leisure and φ is the inverse Frisch elasticity of labor supply.

6.4 Financial Frictions

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

$$Q_t S_t = Q_t K_{t+1}, \tag{14}$$

where Q_t is the real value of capital. The corporate bonds pay the marginal product value of capital (Z_t) every period and decay geometrically with a parameter $1 - \delta$, where δ is capital depreciation rate. Therefore, their value (Q_t) equals to the value of the capital.[16] The (gross) corporate bond return is

$$R_{kt} = \Xi_t \frac{Z_t + (1 - \delta) Q_t}{Q_{t-1}}. \tag{15}$$

The demand for corporate bonds comes both from financial intermediaries (or bank(er)s) and from households.

$$S_t = S_{bt} + S_{ht}. \tag{16}$$

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

Financial intermediaries face an agency friction. In particular, we assume that they can abscond with a fixed fraction of the assets under their management. If they did this, they would lose the franchise value of their banking licence. To avoid such outcome, households limit the amount of deposits they place in financial intermediaries and effectively set an endogenous leverage (ϕ_t) constraint. The leverage constraint ensures that the bank has enough 'skin in the game' such that it has no incentive to abscond with the assets. The constraint limits the amount of corporate lending that the financial intermediaries can supply (S_{bt}):

$$Q_t S_{bt} = \phi_t N_t, \tag{17}$$

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

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

$$N_t = \sigma \left[(R_{kt} - R_t) \phi_{t-1} + R_t \right] N_{t-1} + \omega. \tag{18}$$

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

The first term on the right hand side captures the net worth from the retained earnings of surviving bankers, while the second term comes from the start-up funds of the new bankers. Retained earnings are scaled by the survival probability of bankers (σ), because exiting bankers repay their net worth as dividends. The retained earnings of surviving bankers come from two terms. Banks earn the gross real return R_t on their net worth and an excess return $R_{kt} - R_t$ on their corporate bond holdings. The latter amounts to the product of their net worth and their leverage ϕ_{t-1}.

How do financial frictions amplify the impact of a monetary policy shock on real activity? As mentioned above, a temporary increase in the nominal rate translates into a higher real rate r_t because of nominal rigidities. Higher real rates reduce consumption through a standard intertemporal substitution mechanism. Furthermore, higher real rates raise the funding costs of banks, and make them raise the required return on corporate bonds ($E_t R_{kt+1}$). Higher discount rate on existing capital reduces its value Q_t, which lowers incentives for investment. This channel is active even without any financial frictions (lax bank balance sheet constraints). Binding leverage constraints of financial intermediaries amplify the impact of the shock through standard financial accelerator mechanisms. Lower value of corporate debt reduces the value of the banking sector assets, and leads to a deterioration in their balance sheet condition. In particular, the asset price drop leads to an amplified decline in their net worth, with a multiplicative factor that is equal to their leverage. The deteriorating balance sheet condition of the banking sector further increases the cost of credit and worsens credit conditions with a further negative impact on investment. The deteriorating outlook further reduces asset prices adding another negative feedback loop.

We assume that households also lend directly to the corporate sector, subject to a portfolio adjustment cost as in Gertler and Karadi (2013). In particular, we assume that the household needs to pay $\kappa(S_{ht} - \bar{S}_h)^2$ if it purchases corporate bonds in excess of $\bar{S}_h$, where $\kappa \geq 0$ is a portfolio adjustment cost parameter. The household demand for corporate bonds is determined by

$$S_{ht} = \bar{S}_h + \frac{1}{\kappa} E_t \Lambda_{t,t+1} \left(R_{kt+1} - R_{t+1} \right), \tag{19}$$

where $\Lambda_{t,t+1}$ is the household's stochastic discount factor. The demand function posits that household respond to increases in corporate bond spreads by increasing their corporate bond holdings. The parameter κ determines the sensitivity of their response. Importantly, as $\kappa \to 0$ the households are ready to increase their holdings without limits for any positive premium. In doing so, they issue credit to the intermediate good firms without constraints and fully replace the constrained banking sector. As κ approaches zero, the predictions of the model approaches those of a model without financial frictions. Therefore, we use this parameter to measure of the extent of financial frictions in our model.

6.5 Pricing additional assets

Our baseline VAR includes a 1-year government bond yield and the excess bond premium. The latter is a yield spread between corporate and government bonds with an average duration of around 7 years. In order to obtain analogous long-term yields in our model, we introduce multiple long-term bonds as perpetuities with geometrically decaying coupons. We calibrate the rate of decay of their coupons (ς_x) to match their duration. The assets are priced through no-arbitrage conditions, but are not held in positive quantities in equilibrium. Government bonds are priced by households, who are assumed to trade them without portfolio adjustment costs. Corporate bonds, by contrast, are traded by the banks, which require excess return.

We denote by q_{xt} the nominal price of a government bond with duration x. It pays ς_x^i unit in each quarter $i = 0, 1, 2, \ldots$. Its steady state (yearly) duration is $1/[4(1 - \varsigma_x/R)]$, where R is the steady state gross real rate (and steady state inflation is 0). Its (gross) nominal yield to maturity is $Y_{xt} = 1/q_{xt} + \varsigma_x$. The no arbitrage condition requires that

$$R_{t+1}\Pi_{t+1} = \frac{1 + \varsigma_x q_{xt+1}}{q_{xt}}. \tag{20}$$

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

$$R_{kt+1}\Pi_{t+1} = \frac{1 + \varsigma_{kx} Q_{xt+1}}{Q_{xt}}. \tag{21}$$

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

6.6 Calibration

We solve the model through first-order perturbation around a non-stochastic steady state. We estimate key parameters of the model through a standard impulse response matching exercise (Christiano, Eichenbaum and Evans, 2005). In particular, we estimate three parameters: (i) the Calvo parameter γ, (ii) the inflation indexation parameter γ_P and (iii) the household portfolio adjustment cost parameter κ together with the size and persistence of the monetary policy shock (σ_i, ρ_i) to match the impulse responses to a monetary policy shock in the model and in the VAR. The first two parameters determine the level of nominal frictions, and the third parameter influences the level of financial frictions in the model. Other model parameters are standard and borrowed from Gertler and Karadi (2011) (the appendix includes a table with a list of parameters). We then assess which shock can best approximate the impulse responses to a central bank information shock. We compare news about 2 quarters ahead disturbance in technology (u_{at+2}), in discount rate ($u_{\beta t+2}$), in government expenditures (u_{gt+2}), or in capital quality ($u_{\xi t+2}$). We estimate the persistence and the size of the disturbances that best approximates our central bank information shock identified in the VAR.

Our baseline impulse responses include 5 variables: the 1-year government bond yield, the GDP and the GDP deflator, the S&P500 stock market index and the excess bond premium. In the model, we match these with the deviations of the following 5 variables from their steady state values: yield to maturity of a 1-year government bond ($\hat{y}_{1t}$), the output $\hat{y}_t$, the price level $\hat{p}_t = \sum_{s=1}^{t} \hat{\pi}_s$, the net worth of financial intermediaries[17] ($\hat{n}_t$) and the excess bond premium ($e\hat{b}p_t$).

We transform monthly VAR impulse responses into quarterly impulse responses by taking simple averages over each quarter. This gives us 16 moments for each observables. We simulate impulse responses from the model and stack the 5 times 16 differences of the VAR and model moments into a vector V. We estimate our model parameters to minimize $V'\Omega V$ scalar, where Ω is a weighting matrix. Following Christiano, Eichenbaum and Evans (2005), Ω is a diagonal matrix. We use the squared inverse of the 90% interpercentile range as weights.

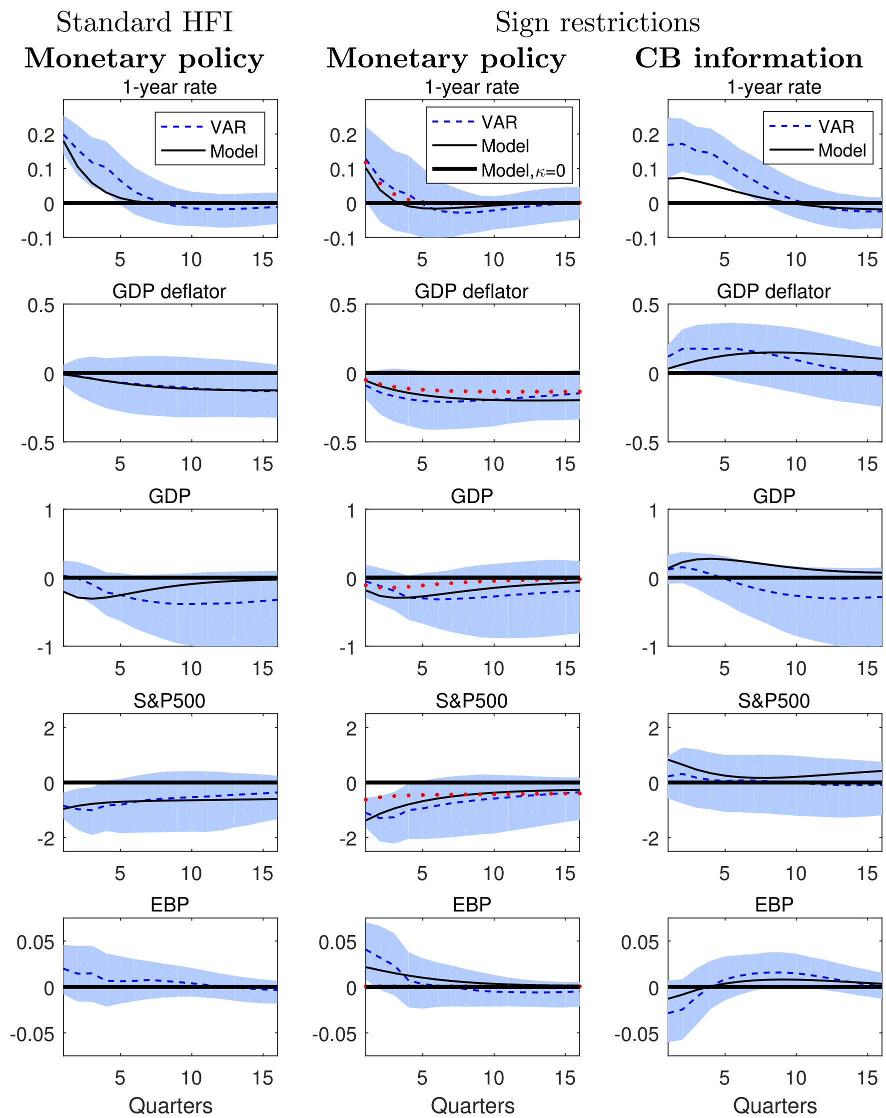
Table 6: Estimated parameters

Parameters	Label	Standard HFI	Sign restrictions
Calvo parameter	γ	0.9	0.72
Inflation indexation	γ_P	0.8	0.0
Portfolio adjustment cost	κ	0.001	0.13
Stdev of monpol shock	σ_i	0.0014	0.0014
Persistence of monpol shock	ρ_i	0.67	0.55
Stdev of info shock	σ_ξ		0.0004
Persistence of info shock	ρ_ξ		0.88

Table 6 lists the estimated parameter values. Figure 10 shows the model implied impulse responses and compares them to the impulse responses from the VAR. We first conduct the exercise using the impulse responses to the monetary policy shock from the standard high-frequency identification, which disregards central bank information shocks. The first column of Table 6 and Figure 10 show the results. The price level response is very sticky in this case, and the model requires high price-stickiness and indexation parameters to capture the impact. These parameters would imply that prices are reset on average every 2.5 years, inconsistently with micro-data evidence. With such a high nominal stickiness, the interest rate shock causes an output decline that severely overestimates the responses predicted by the VAR, especially in the early years. This happens, even though the size and the persistence of the monetary policy shock underestimates the observed yield responses. Relatedly, the financial frictions

[17] Arguably, the equity value of financial intermediaries (N_t) in the model better reflects the equity value of companies measured by the S&P500 than the value of capital (Q_t). The two variables move in tandem in the model, but the former gets amplified by the calibrated leverage, similarly to how S&P500 valuations are amplified by the average leverage of the financial and non-financial firms it incorporates. Our results are robust to using Q_t as a measure of stock market valuations.

Figure 10: Matched impulse responses to monetary policy and central bank information shocks, sign restrictions and standard high-frequency identification, Model (black line), VAR median (blue dashed line), percentiles 5-95 (band).



are estimated to be tiny: the model predicts essentially zero corporate bond spread response, inconsistently with the VAR evidence. If it had estimated higher financial amplification, the model would have fare even worse in matching the observed output response.

Next, we conduct the same exercise using our baseline identification. This monetary policy shock is purged from the impact of the central bank information shock. The second column of Table 6 and Figure 10 show the results. The persistence of the monetary policy shock is now estimated to be significantly lower. With a parameter of $\rho_i = 0.55$ it is able to come close to the observed yield response. The price stickiness is now estimated to be much more moderate. The Calvo parameter is 0.72 and the model does not need any backward indexation to match the observed price level response. This parameter implies that prices are reset somewhat more frequently than once a year, which is not inconsistent with microdata evidence. Such a moderate price stickiness, however, is insufficient to explain the output response, so the model estimates a sizable financial friction parameter; two order of magnitudes larger than in the standard high-frequency identification. This way, it also gets closer to match the observed reaction of the excess bond premium.

The red dotted lines on the figure show the impulse responses if we switch off financial frictions by setting the portfolio adjustment cost to zero ($\kappa = 0$). Notably, the output response becomes substantially more muted, suggesting that financial amplification plays a key role in capturing the extent of real effects of monetary shocks. We conclude that our baseline identification would give substantial weight to financial frictions, and moderate role to nominal frictions in explaining the real effects of monetary policy shocks.

In our last exercise, we ask which single news shock in the model would be broadly consistent with the central bank information shock we identified in the data (see the last column of Figure 10. We find that news about a 2-quarters-ahead capital quality shock is qualitatively as well as quantitatively consistent with our observations. The shock is a positive asset-valuation shock. Higher asset prices raise investment and improve the balance sheets of financial intermediaries. They, in turn, ease credit conditions, which leads to a decline in corporate bond spreads, in line with our observations. This further improves demand conditions which leads to additional increases in output and prices. Monetary policy tightens to partially offset the impact of this financial demand shock. The model somewhat underestimates the yield responses, suggesting that monetary policy in practice responds more forcefully to the information shocks than as predicted by the model. Modifying the Taylor rule to allow additional response to corporate bond spreads would help the model come closer to the observed yield responses (not shown).

Other popular news shocks would have trouble matching the impulse responses not just quantitatively, but also qualitatively. Technology shocks (u_{at+2}) would have trouble capturing the fact that prices and output move in the same direction after the central bank information shock. Other popular demand shocks, like a shock to government expenditure (u_{gt+2}) and household preferences ($u_{\beta t+2}$) would not work in this particular model either. The shocks increase some aggregate demand components so they raise output and prices as in the data, but they actually ‘crowd out’ investment in equilibrium. As a result, the value of capital and net worth declines and corporate spreads increase, inconsistently with the observed patterns.

7 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. We take the first step and show that our baseline monetary policy shock gives a prominent role to financial frictions in monetary transmission. 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 (financial) 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.

Appendix

Appendix A More on the interest rate and stock price surprises in the US

This section shows that the proportion and sizes of 'wrong-signed' responses of stock prices to monetary policy surprises remain similar when we use alternative measures of surprises.

As an alternative measure of the interest rate surprises we compute the "policy indicator" constructed as in Nakamura and Steinsson (2013) (who build on Gürkaynak, Sack and Swanson, 2005b). Namely, this is the first principal component of the surprises in fed funds futures and eurodollar futures with one year or less to expiration. Five indicators enter into it: the current-month federal funds future, the 3-months federal funds future, and the eurodollar futures at the horizons of two, three and four quarters. The advantage of the policy news index is that it captures even more of the forward guidance. The disadvantage is that it relies on the eurodollar futures which are not as liquid as the federal funds futures.

As an alternative measure of the stock price surprises we take the first principal component of the surprises in the S&P500, Nasdaq Composite and Wilshire 5000. Nasdaq Composite is based on about 4000 stocks skewed towards the technology sector, and Wilshire 5000 is based on 7000 stocks of essentially all publicly listed companies headquartered in the US. All three indices are market capitalization-weighted. Our dataset has many missing values for Nasdaq and Wilshire, so we use the alternating least squares (ALS) algorithm that simultaneously estimates the missing values while computing principal components.

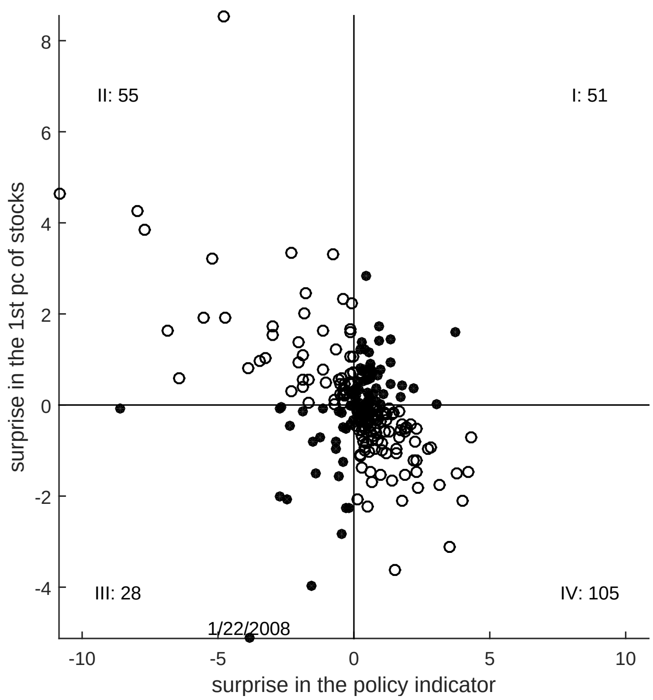
Table A.1 reports the correlations between the 3-months fed funds futures surprises, S&P500 surprises and the two alternative measures of surpries just discussed. The correlation between the surprises in the 3-month fed funds futures and the policy index is 0.89. The correlation between S&P500 and the first principal component of the three stock indices is higher, 0.96. The correlations between interest surprises and stock price surprises is negative, but quite weak, around -0.4,-0.5.

Table A.1: Correlations between surprises

	3-m fff	SP500	policy indicator	1st p.c. of stocks
3-m fff	1.00			
SP500	-0.46	1.00		
policy indicator	0.89	-0.53	1.00	
1st p.c. of stocks	-0.40	0.96	-0.47	1.00

Figure A.1 shows that when we use the alternative measures of surprises, the lessons on the 'wrong-signed' responses of stock prices to interest rates hold. Still, in 33% of the cases the correlation between interest rates and stock price surprises is positive. This confirms the lessons from Figure 1.

Figure A.1: Scatter plot of interest rate and stock price surprises. The policy indicator and the 1st principal component of stock indices.



Note: Black filled circles highlight the data points where both surprises have the same sign. The number in each quadrant is the number of data points in the quadrant (not counting the data points for which one of the surprises is zero).

Appendix B Bayesian estimation

This section explains how we estimate the VAR in (1). This VAR has two non-standard features. First, a subset of variables m_t is assumed to be i.i.d. which implies that the corresponding VAR parameters are restricted to 0. Second, due to data limitations some of the observations on m_t are missing.

It is convenient to introduce some notation: a) write down the VAR in (1) in matrix notation, b) partition the variance matrix Σ and c) introduce notation for the missing values of m_t.

a) The VAR in (1) in matrix notation is

$$\begin{pmatrix} M & Y \end{pmatrix} = X \begin{pmatrix} 0 & B \end{pmatrix} + \begin{pmatrix} U^m & U^y \end{pmatrix}. \tag{B.1}$$

where $M = (m_1, ..., m_T)'$, $Y = (y_1, ..., y_T)'$, X is a matrix that collects the right-hand-side variables, with a typical row $x_t' = (m_{t-1}' \, y_{t-1}' \dots m_{t-P}' \, y_{t-P}' \, 1)$, $B = \left(B_{YM}^1, B_{YY}^1, ..., B_{YM}^P, B_{YY}^P, c_y\right)'$, $U^m = (u_1^m, ..., u_T^m)'$, and $U^y = \left(u_1^y, ..., u_T^y\right)'$.

b) We partion Σ as follows

$$\Sigma = \begin{pmatrix} \Sigma_{MM} & \Sigma_{MY} \\ \Sigma_{YM} & \Sigma_{YY} \end{pmatrix}. \tag{B.2}$$

c) We introduce notation for missing observations on m_t. In some periods all of m_t or its subset is unobserved. Let $(\tau_1, ..., \tau_{T^*})$ denote the time periods in which all or part of m_t is unobservable. Let m_t^*, $t \in (\tau_1, ..., \tau_{T^*})$, denote the unobserved m_t. Let M^* be the set of the unobserved m_t^* and let M^o be the set of the observed m_t.

The likelihood function of M, Y is

$$p(Y, M|B, \Sigma) \propto |\Sigma|^{-T/2} \exp\left(-\frac{1}{2} \operatorname{tr}\left(\left(\begin{pmatrix} M & Y \end{pmatrix} - X \begin{pmatrix} 0 & B \end{pmatrix}\right)' \left(\begin{pmatrix} M & Y \end{pmatrix} - X \begin{pmatrix} 0 & B \end{pmatrix}\right) \Sigma^{-1}\right)\right). \tag{B.3}$$

We introduce an independent normal-inverted Wishart prior, $p(B, \Sigma) = p(B)p(\Sigma)$, where

$$p(\Sigma|\underline{S}, \underline{v}) = \mathcal{IW}\left(\underline{S}, \underline{v}\right) = \propto |\Sigma|^{-\underline{v}/2} \exp\left(-\frac{1}{2} \operatorname{tr} \underline{S}\Sigma^{-1}\right), \tag{B.4}$$

$$p(vecB|\underline{B}, \underline{Q}) = \mathcal{N}(\operatorname{vec} \underline{B}, \underline{Q}) \propto \exp\left(-\frac{1}{2} \operatorname{vec}(B - \underline{B})' \underline{Q}^{-1} \operatorname{vec}(B - \underline{B})\right), \tag{B.5}$$

$\mathcal{IW}$ denotes the Inverted Wishart distribution and $\mathcal{N}$ denotes the normal distribution.

The prior about the unobserved surprises is noninformative,

$$p(m_t^*) \propto 1 \text{ for all } t \in (\tau_1, ..., \tau_{T^*}) \tag{B.6}$$

and therefore we ignore it further.

The posterior is obtained as the product of the likelihood and the prior,

$$p(B, \Sigma, M^*|Y, M^o) \propto p(Y, M|B, \Sigma)p(B)p(\Sigma). \tag{B.7}$$

We use a Gibbs sampler to compute posterior. The Gibbs sampler consists of drawing in turn Σ, B and m_t^* for $t = \tau_1, ..., \tau_{T^*}$ from their conditional posteriors until the sampler converges. Convergence means that the obtained sequence of draws approximates a sample from the posterior (B.7).

B.1 The conditional posteriors

The conditional posteriors are as follows.

- The conditional posterior of Σ:

$$p(\Sigma|Y, M, B) = \mathcal{IW}\left(\overline{S}, \overline{v}\right) \tag{B.8}$$

where

$$\overline{S} = \left(\begin{pmatrix} M & Y \end{pmatrix} - X\begin{pmatrix} 0 & B \end{pmatrix}\right)' \left(\begin{pmatrix} M & Y \end{pmatrix} - X\begin{pmatrix} 0 & B \end{pmatrix}\right) + \underline{S}, \tag{B.9}$$

$$\overline{v} = T + \underline{v}. \tag{B.10}$$

- The conditional posterior of B:

$$p(\operatorname{vec} B|Y, M, \Sigma) = \mathcal{N}\left(\overline{B}, \overline{Q}\right) \tag{B.11}$$

where

$$\overline{Q} = \left(\underline{Q}^{-1} + \Sigma_{YY.1}^{-1} \otimes X'X\right)^{-1}, \tag{B.12}$$

$$\operatorname{vec} \overline{B} = \overline{Q}\left(\underline{Q}^{-1} \operatorname{vec} \underline{B} + \left(\Sigma_{YY.1}^{-1} \otimes X'\right) \operatorname{vec}\left(Y + M\Sigma_{MM}^{-1}\Sigma_{MY}\right)\right) \tag{B.13}$$

and $\Sigma_{YY.1} = \Sigma_{YY} - \Sigma_{YM}\Sigma_{MM}^{-1}\Sigma_{MY}$. The computation of matrix $\overline{Q}$ involves an inverse of a large matrix. To reduce the computational cost, we follow Clark et al. (2016) and draw coefficients B equation by equation, sequentially.

- The conditional posterior of m_t^*:

$$p(m_t^*|M^{t-1}, Y, B, \Sigma) = \mathcal{N}\left(\Sigma_{MY}\Sigma_{YY}^{-1}u_t, \Sigma_{MM.1}\right), \tag{B.14}$$

where $\Sigma_{MM.1} = \Sigma_{MM} - \Sigma_{MY}\Sigma_{YY}^{-1}\Sigma_{YM}$, M^{t-1} denotes the matrix $(m_{t-1}, ..., m_0)'$ and $u_t = y_t - B'x_t$. Note that x_t contains elements from M^{t-1}, that's why we make the conditioning on M^{t-1} explicit.

B.2 Derivation of the conditional posteriors

The conditional posterior of Σ is standard.

To obtain the conditional posterior of B decompose the likelihood as follows:

$$p(Y, M|B, \Sigma) = p(Y|M, B, \Sigma)p(M|B, \Sigma) \tag{B.15}$$

where

$$p(M|B, \Sigma) = p(M|\Sigma_{MM}) \propto |\Sigma_{MM}|^{-T/2} \exp\left(-\frac{1}{2} \operatorname{tr} M'M\Sigma_{MM}^{-1}\right) \tag{B.16}$$

and

$$p(Y|M,B,\Sigma) \propto |\Sigma_{YY.1}|^{-T/2}$$
$$\exp\left(-\frac{1}{2}\operatorname{tr}\left(Y-XB+M\Sigma_{MM}^{-1}\Sigma_{MY}\right)'\left(Y-XB+M\Sigma_{MM}^{-1}\Sigma_{MY}\right)\Sigma_{YY.1}^{-1}\right) \quad \text{(B.17)}$$

with $\Sigma_{YY.1} = \Sigma_{YY} - \Sigma_{YM}\Sigma_{MM}^{-1}\Sigma_{MY}$. See e.g. Bauwens et al. (1999) Section A.2.3.

We notice that the second term in the likelihood does not involve B, i.e. the only terms in the posterior that involve B are $p(Y|M,B,\Sigma)p(B)$. We do the product and collect the terms involving B in the standard way.

To obtain the conditional posterior of M^* decompose the likelihood as follows:

$$p(Y,M|B,\Sigma) = p(M|Y,B,\Sigma)p(Y|B,\Sigma) \quad \text{(B.18)}$$

where

$$p(Y|B,\Sigma) = \mathcal{MN}\left(XB, \Sigma_{YY}\otimes I_T\right) \propto |\Sigma_{MM}|^{-T/2}\exp\left(-\frac{1}{2}\operatorname{tr}\left(Y-XB\right)'\left(Y-XB\right)\Sigma_{YY}^{-1}\right) \quad \text{(B.19)}$$

and

$$p(M|Y,B,\Sigma) = \mathcal{MN}\left((Y-XB)\Sigma_{YY}^{-1}\Sigma_{YM}, \Sigma_{MM.1}\otimes I_T\right) \quad \text{(B.20)}$$

with $\Sigma_{MM.1} = \Sigma_{MM} - \Sigma_{MY}\Sigma_{YY}^{-1}\Sigma_{YM}$.

We notice that the only term in the posterior that involves M is $p(M|Y,B,\Sigma)$. Moreover, we notice that a term involving m_t^* depends only on the earlier values of m^*, M^{t-1} and does not depend on the future values m_τ^* for $\tau > t$. This justifies drawing m_t^* sequentially over time, using (B.14).

Appendix C Additional results for the US

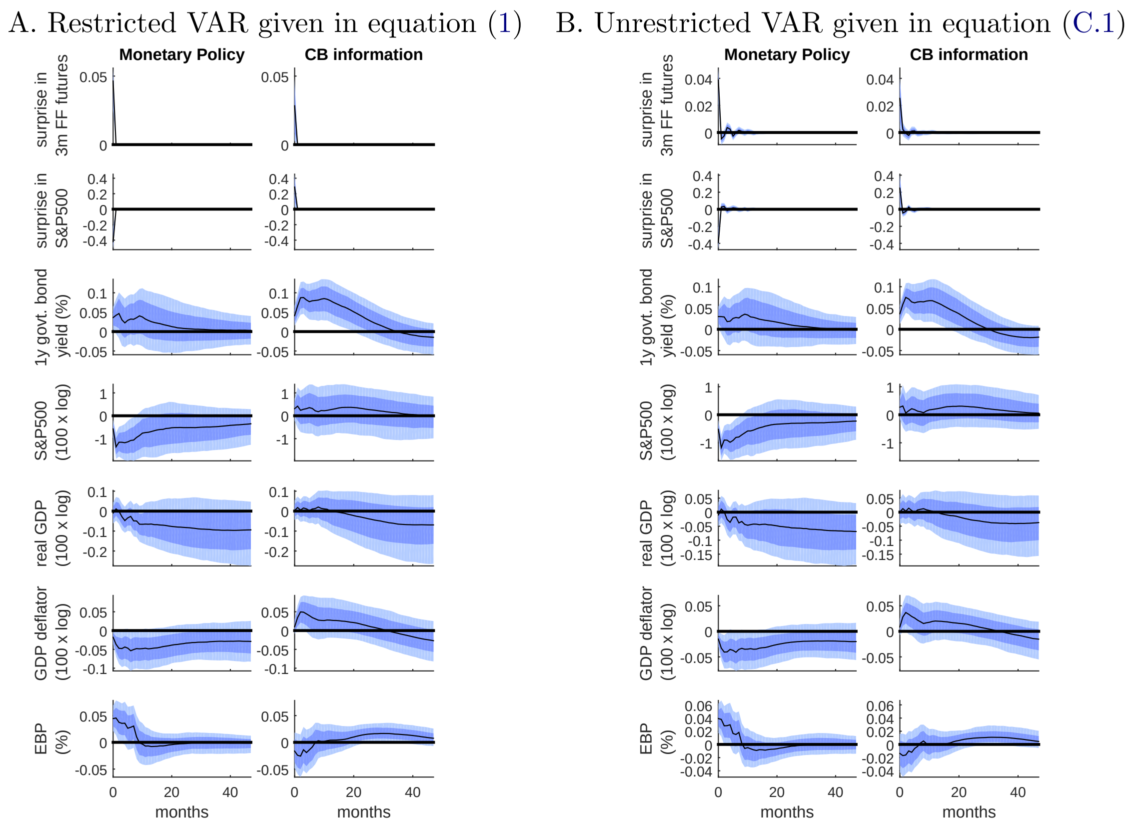
C.1 Relaxing the restrictions on the dynamics of m_t

In this subsection we show that our results are robust to relaxing the restrictions on the dynamics of m_t in the VAR. The unrestricted VAR is

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

For the comparison of the restricted and the unrestricted VAR we use the sample without the missing values in m_t, i.e. starting in February 1990. Furthermore, we replace the missing observation in September 2001 with zero. This is because handling missing data on m_t becomes more involved when the dynamics of m_t is unrestricted. Panel A of Figure C.1 reports the impulse responses obtained with the restricted VAR given in equation (1). We can see that they are quite similar to the impulse responses in Figure 2. Panel B of Figure C.1 reports the impulse responses obtained with the unrestricted VAR given in equation (C.1). We can see that relaxing the zero restrictions in the VAR hardly affects the impulse responses.

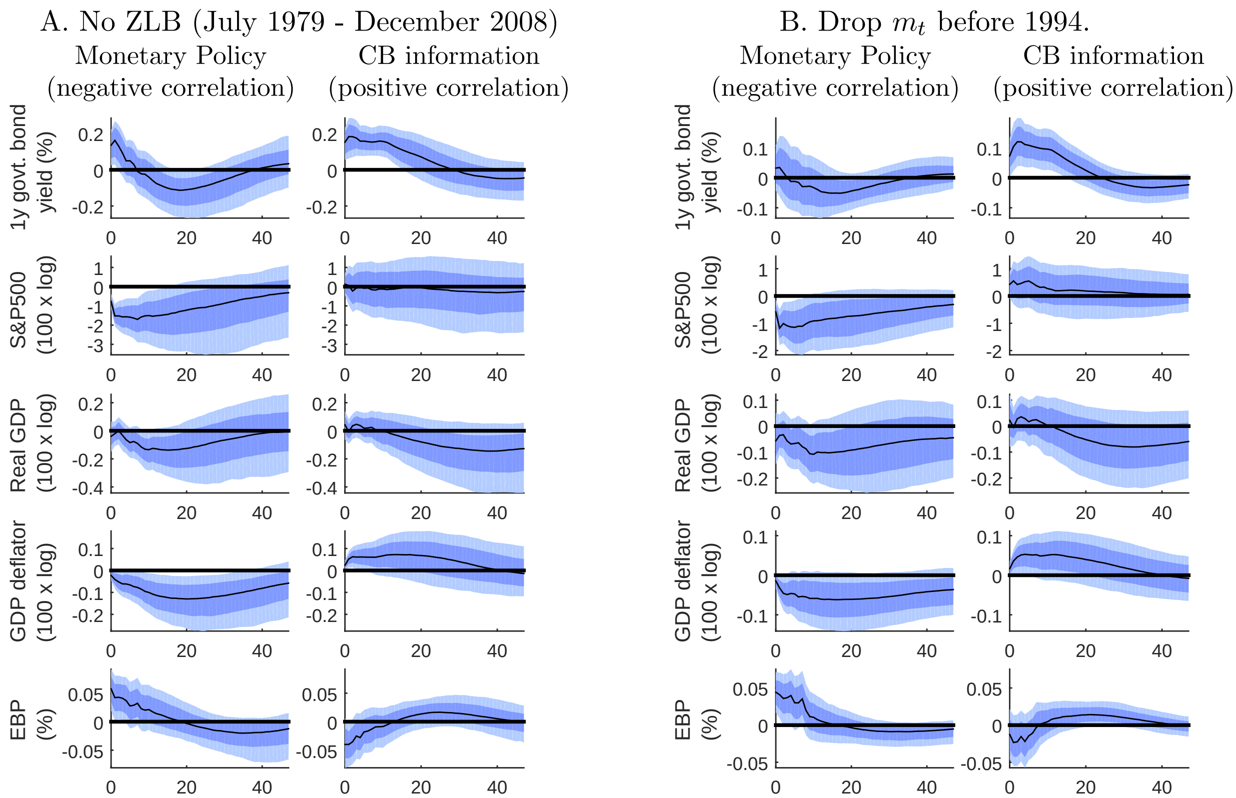
Figure C.1: Impulse responses in the restricted and in the unrestricted VAR. Sample February 1990 to August 2016. Impulse responses to one standard deviation monetary policy and central bank information shocks. Median (line), percentiles 16-84 (darker band), percentiles 5-95 (lighter band).



C.2 Results on other subsamples

Figure C.2 shows that the findings continue to be similar when we estimate the VAR on a sample ending on December 2008, i.e. before the interest rates hit the zero lower bound (ZLB) in January 2009 (Panel A). Furthermore, the findings continue to be similar when we omit the high-frequency surprises before February 1994 (Panel B). The motivation to omit these surprises is that the Fed did not issue a press release about FOMC decisions until February 1994, so the earlier surprises might be coming from a different regime.

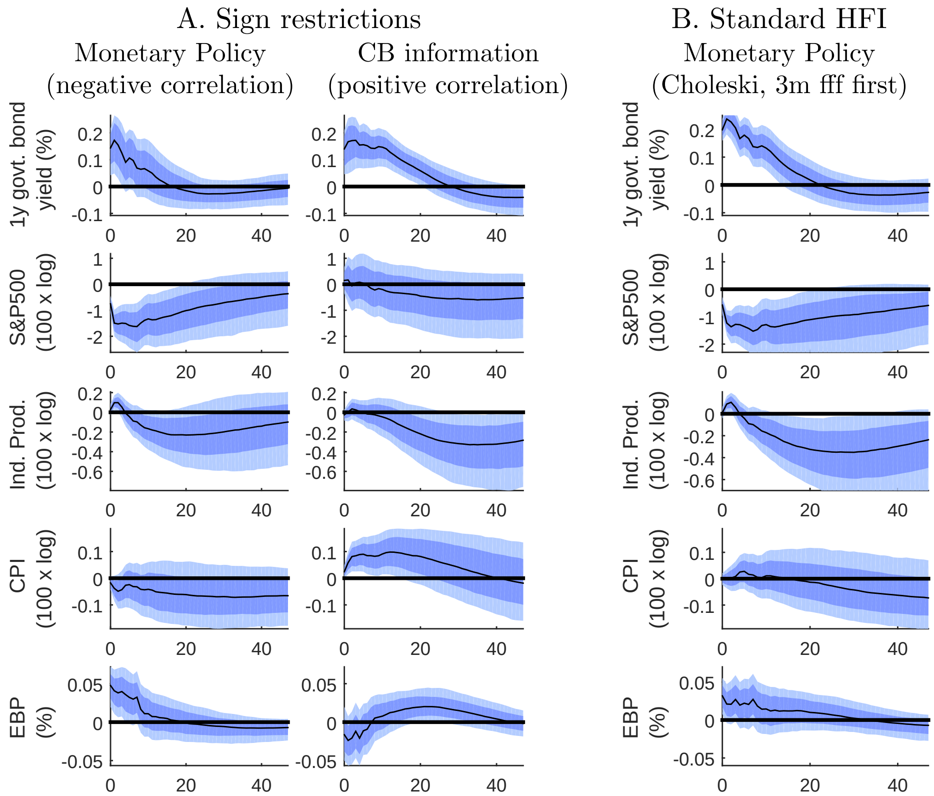
Figure C.2: Impulse responses of y_t to monetary policy and central bank information shocks: results for subsamples. Median (line), percentiles 16-84 (darker band), percentiles 5-95 (lighter band).



C.3 Results with Industrial Production and CPI

Figure C.3 shows that when we replace the real GDP and GDP deflator with the industrial production and the CPI index, the standard high-frequency identification yields a small price puzzle, and our sign restrictions eliminate it.

Figure C.3: Impulse responses of y_t to monetary policy and central bank information shocks, model with Industrial Production and Consumer Price Index. Median (line), percentiles 16-84 (darker band), percentiles 5-95 (lighter band).

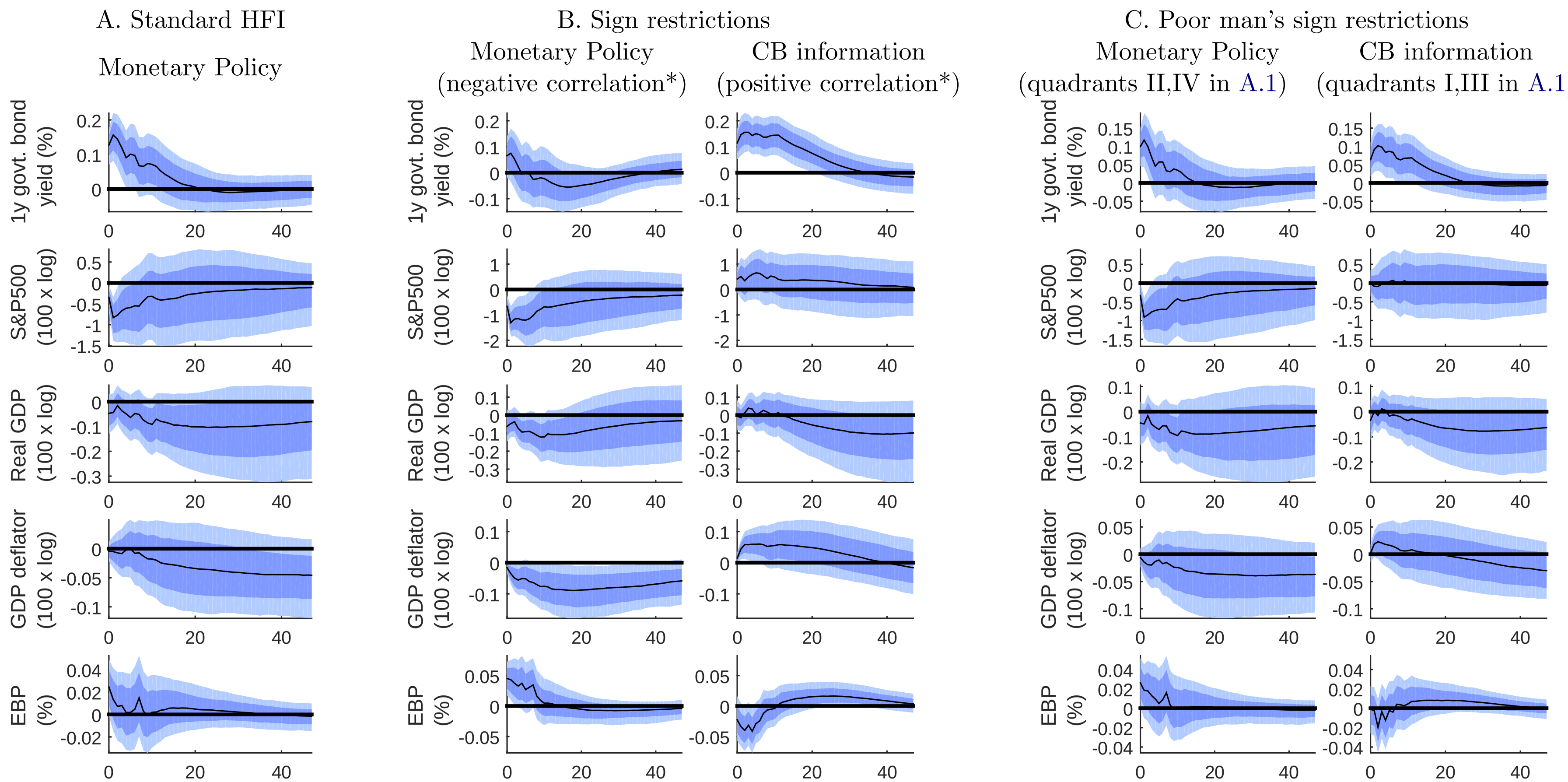


C.4 VAR with factors of high-frequency surprises

In an alternative specification we use factors extracted from multiple interest rate and stock market surprises, instead of the 3-month fed funds futures and S&P500. Specifically, we summarize interest rate surprises with a 'policy indicator' obtained as the first principal component of the surprise in the current month fed funds futures, 3-month fed funds futures, and the eurodollar futures at the horizons of 2, 3 and 4 quarters. We summarize the stock market surprises with the first principal component of the S&P500, Wilshire and Nasdaq surprises.

Figure C.4 shows that using factors changes very little in the impulse responses. The main difference is that the monthly S&P500 index now responds positively to the central bank information shock.

Figure C.4: Impulse responses to one standard deviation shocks, VAR with factors of surprises. Median (line), percentiles 16-84 (darker band), percentiles 5-95 (lighter band). Months on the horizontal axis.



C.5 Robust error bands of Giacomini and Kitagawa (2015)

This section shows that the impulse responses to the two shocks we identify continue to be very different from each other irrespective of the prior on the rotation matrices Q. We make this point using the 'multiple priors' approach of Giacomini and Kitagawa (2015).

The prior on Q might be important, because the sign restrictions in Table 1 provide only a set identification, not a sharp identification. That is, for every nonsingular variance matrix Σ there is a continuum of rotation matrices Q that are consistent with the sign restrictions. Since the sample carries no information about Q, the weights on different values of Q are determined by the prior. As most of the literature, we use the uniform prior on the space of rotation matrices (Rubio-Ramirez, Waggoner and Zha, 2010). How much could the impulse responses change if we used some other, non-uniform prior on Q?

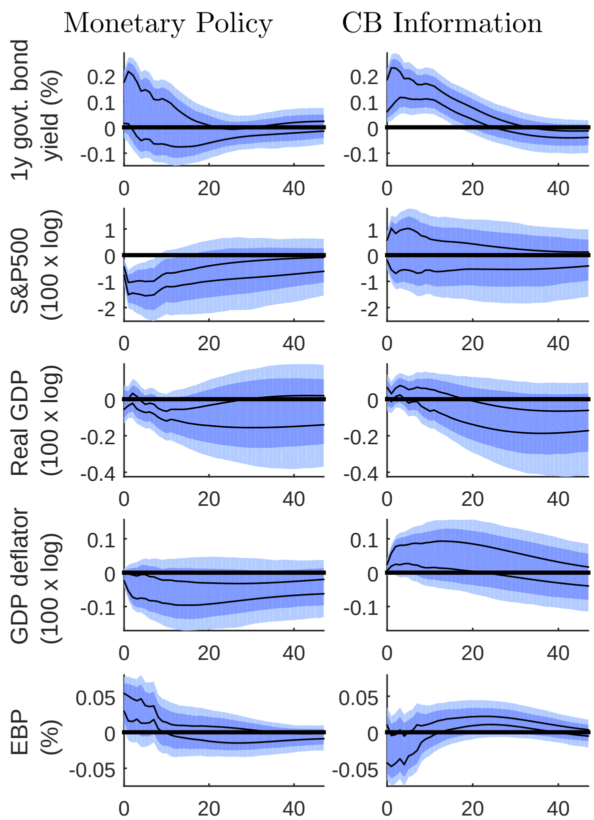
To answer this question we compute the 'robust' uncertainty bounds following Giacomini and Kitagawa (2015). In this approach, the *posterior mean bounds* delineate the range of the posterior means of the impulse responses across all possible priors on Q. The *X% robustified region* is the envelope of the X% highest probability regions obtained across all possible priors on Q. For example, to construct the 90% robustified region for the impact response of the BAA bond spread to the central bank information shock, we find for each draw of Σ the Q that yields the lowest response and the Q that yields the highest response across all Qs that satisfy the sign restrictions. The 90% robustified region is delimited by the 5th percentile of the lowest responses and the 95th percentile of the highest responses. This region is necessarily wider than the usually reported region delimited by the 5th and the 95th percentiles of all the draws of the responses from the posterior, where we also draw Q.

Figure C.5 reports the robust bounds for the impulse responses of all variables y_t at all horizons. The bounds are wider and include zero more often than the bounds in Figure 2, but the different nature of the monetary policy and central bank information shocks remains clear. Furthermore, let us make two comments related to the width of the bounds. First, the robust bounds are conservative because the search for the 'worst-case' Q is performed separately for each variable, shock and horizon. Any single prior on Q will produce narrower bands. Second, there are many ways to refine the sign restriction identification by postulating further reasonable restrictions on the impulse responses. Our point in this paper is that the simple sign restriction we propose is enough to separate two shocks of very different nature.

Appendix D Surprises and proxies for Fed private information

For every scheduled FOMC meeting, the Federal Reserve staff prepares nowcasts and forecasts for the expected dynamics of the price level and economic activity. These forecasts do not directly influence private forecasts, because they are made public only with a 5 year delay. However, they are made available to the FOMC members, who can take them into account when setting the course of policy and formulating official communication. The staff forecasts

Figure C.5: Impulse responses to one standard deviation shocks, baseline VAR, with 'robust' error bands of Giacomini and Kitagawa (2015). Posterior mean bounds (line), 68% robustified region (darker band), 90% robustified region (lighter band).



have been shown to have superior forecasting ability relative to private forecasts (Romer and Romer, 2000). The difference between the staff forecasts and forecasts of private forecasters, therefore, is a popular proxy for the private information of the FOMC. Controlling for private information using these proxies has been shown to influence predictions about the effects of monetary policy shocks (Gertler and Karadi, 2015; Campbell et al., 2016).

It is far from clear, however, how much of the FOMC private information is actually revealed through a policy change and the accompanying communication. FOMC decision makers might not share the views of the staff about the economy, and even if they do their communication might not be detailed enough to explain all the assumptions behind their choices. Therefore, instead of using such proxies, we use market-price reactions to the announcements to learn about the information content of the FOMC statements in our baseline regressions. Changes in asset prices provide more first-hand signal about the extent of new information in the statement as assessed by market participants (and not just economic forecasters), who can be expected to have key influence on market prices that drive economic fundamentals. Still, it is worthwhile to assess how well our measures line up with private information proxies. Is it true that FOMC private information is associated more with central bank information shocks?

To this end, we regress the monthly 3-months ahead federal funds futures surprise and the median monetary policy and central bank information shocks as measured by their impact on the 3-month-ahead fed funds futures surprise on standard measures of the FOMC private information. In particular, we link the staff forecasts on scheduled FOMC meetings with the last preceding forecasts surveyed by the Blue Chip Economic Indicators. We use the current, and the one- and two-quarters ahead GDP deflator and real GDP growth forecasts and the current month unemployment forecasts. We take a simple difference between the staff and private forecasts for each variables. The regression results are shown in Table D.1.

Table D.1: Surprises and proxies for Fed private information

	(1)	(2)	(3)
VARIABLES	FF4	FF4 MP	FF4 INFO
π	0.00203	0.00209	0.000288
	(0.330)	(0.383)	(0.0660)
$\pi(+1)$	0.00623	0.00163	0.00497
	(0.474)	(0.201)	(0.776)
$\pi(+2)$	-0.00799	-0.00514	-0.00363
	(-0.835)	(-0.849)	(-0.717)
dy	0.0181***	0.0183***	-0.00141
	(2.893)	(3.119)	(-0.388)
dy(+1)	0.0140	0.000733	0.0143***
	(1.379)	(0.0886)	(3.078)
dy(+2)	-0.00758	-0.00220	-0.00671
	(-0.891)	(-0.341)	(-1.643)
u	-0.0279	-0.0256	-0.00629
	(-0.630)	(-0.796)	(-0.296)
Observations	180	180	180
R-squared	0.117	0.116	0.070

Robust t-statistics in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The results are mixed. We find that private information about the one-quarter-ahead real GDP growth influences the central bank information shocks significantly. At the same time, we do not find that private information about prices or the unemployment would influence the same shock; and we also find that private information about the current-quarter real GDP growth influences our monetary policy measure.

Appendix E High-frequency euro area data

We use high-frequency data on euro area asset prices to build our dataset of high-frequency asset price responses to the ECB policy announcements, analogous to the Gürkaynak et al. (2005b) dataset for the US. We take the high-frequency asset price data from the Thomson Reuters Tick History database. Our dataset has two kinds of assets: interest rate swaps and stock prices.

Stock prices. For the stock prices it is straightforward to obtain high-frequency data, since stocks are traded in centralized markets. The stock index we use is Euro Stoxx 50. The Thomson Reuters includes its price 4 times a second.

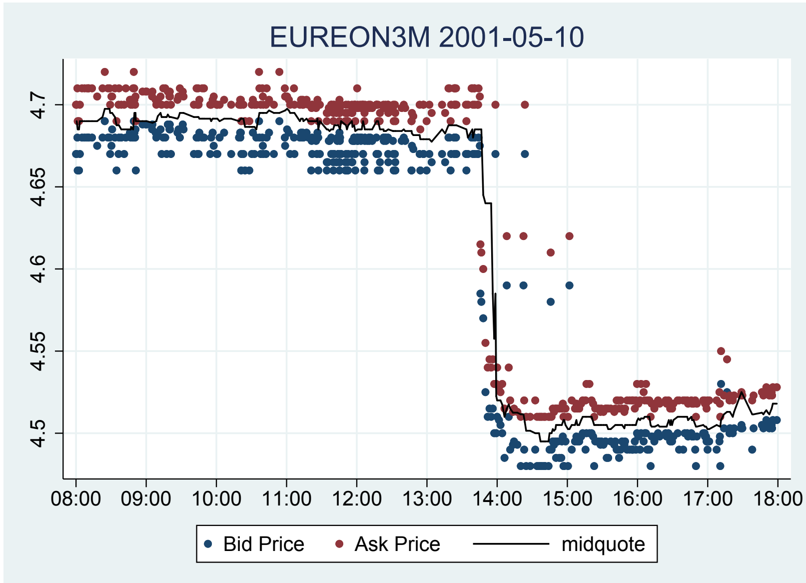
Interest rate swaps. In the euro area we use the interest rate swaps instead of the futures, as in the euro area the swap market is more liquid and has a longer history. We use the Overnight Indexed Swaps (OIS), based on the Eonia rate. In this swap contract the parties exchange the variable, overnight Eonia rate for the fixed swap rate. We focus on the 3-month swap.

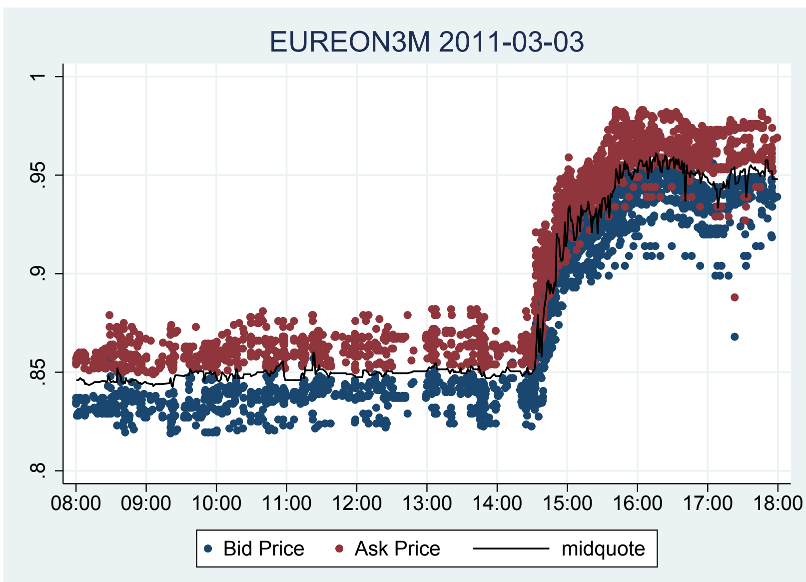
Measuring the Eonia OIS rate is more difficult than measuring stock prices, because these swaps are traded in over-the-counter markets. We do not observe the prices. Thomson Reuters only provides the quotes posted by individual traders. The quotes consist of a bid rate and an ask rate, and the trades are concluded over the phone. The database includes bid and ask quotes with time stamps (at the millisecond level) and with the identity of the posting institution. Some quotes are outliers that cannot reasonably reflect actual trades (e.g. they differ from the other quotes at that time by orders of magnitude). To clean the data from the outliers, for each day, we exclude the lowest and highest 1 percents of bid and ask quotes. In some instances, we eliminate further outliers if they are very far from the outstanding quotes (sometimes 5-6 standard deviations away) making it unreasonable to assume that any trade was conducted at the quoted price.

We measure the market price as the average of the highest bid and lowest ask prices out of the most recent five quotes made by distinct institutions. Furthermore, we disregard quotes posted more than 15 minutes ago, even if this reduces the number of available quotes below 5. Our choices are informed by our aim to obtain an accurate and timely proxy for market valuation. Choosing the five latest quotes balances timeliness with accuracy: if after a market news 5 institutions modified their quotes, we would like our measure to reflect the change, even if some still outstanding quotes (possibly posted before the news) suggest different valuations. We disregard quotes older than 15 minutes altogether, because quotes can not be directly traded on. They are indicative of the valuation of the posting institution only when they were made, and can lose their actuality over time. The 15 minutes limit guarantees that our baseline surprise measure, which reads the asset price 20 minutes after the monetary policy news, does not include quotes made before the news.

Figure E.1 shows two examples of how we process the data. Each quote consists of a pair of dots: a blue dot, showing the bid rate, and a red dot, showing the ask rate. The outliers

Figure E.1: Construction of high-frequency surprises for the 3-month Eonia swap rate.





are already removed, as they would distort the scale of the picture. The black line shows the midquote, which is our measure of the market rate. The first panel presents the market for the 3-months Eonia OIS on May 10th, 2001. On that day the ECB announced a 25 basis point cut in its policy rates. The press release was issued at 13:45. We can see that around 13:45 the quotes drop by about 20 basis points. The midquote we compute follows the lower quotes. The second panel shows the data for March 3rd, 2011. The activity in the market is higher in 2011 than in 2001, as witnessed by a much larger number of quotes posted. On this particular day the ECB Governing council decided to keep the policy rates unchanged, as anticipated, so the press release at 13:45 did not contain any surprises. However, during the press conference that started at 14:30 and lasted about an hour, the ECB President Jean-Claude Trichet delivered a hawkish message. He highlighted the upwards risks to inflation coming from an increase in commodity prices, and concerns about second-round effects (i.e. the price increases fuelling wage increases). By the end of the press conference the 3-months Eonia OIS was about 10 basis points higher, reflecting expectations of future interest rate increases.

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