Identifying Communication Surprises in ECB Monetary Policy

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Abstract

In this paper, we offer a novel approach to identify monetary policy communication surprises and examine their impact on macroeconomic and financial variables. We estimate a Proxy SVAR in which monetary policy actions and communication are characterized using two separate policy variables. The first policy variable is the main refinancing operations rate and the second one a monetary policy communication index. To identify policy action and communication surprises in both policy variables, we employ a high-frequency data approach using EONIA OIS forwards. We find that communication shocks lead to significant responses in production and inflation, which is not the case when a recursive identification strategy is used. Also, this approach enables us to examine reactions of fast-moving variables, such as the exchange rate and stock prices. Following both positive monetary policy action and communication shocks the nominal effective exchange rate appreciates on impact, while stock prices fall in the middle to long run, consistent with economic theory.

Keywords: Monetary Policy Transmission, Communication, Proxy SVAR, High-Frequency identification

JEL Codes: E43, E44, E52

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1 Introduction

Over the last two decades, central bank communication has gradually become an essential part of the central bankers' toolkit. In crisis periods, when the binding zero lower bound renders the traditional reaction function in the form of the Taylor rule less effective as a means of predicting the future policy rate, the importance of communication increases. The increase in frequency and clarity of central bank communication has reemphasized an important task for the researcher - examining the role of monetary policy communication for the economy. In that respect, Eggertsson and Woodford (2003) showed that credible communication could be used for the conduct of optimal monetary policy when the interest rates are at the ZLB. In DSGE models, forward guidance is shown to have strong real effects. However, Del Negro et al. (2012) coined the term "forward guidance puzzle" to point out that communication stemming from these models overestimates the impact of forward guidance on the economy. Empirically, Gürkaynak et al. (2005) were among the first to disentangle action from communication effects of FED monetary policy on financial markets. Therefore with advances on both the theoretical and empirical front, recent years have led to a flourishing literature concerning central bank communication.[1]

In this paper, we aim to set up a euro-area VAR, that incorporates both ECB action and policy communication variables. Additionally, we use a high-frequency identification approach that facilitates the separation of both policy action and communication surprises. We follow the work of Neuenkirch (2013) and use the Swiss Economic Institute's Monetary Policy Communicator (MPC, henceforth) as a measure of ECB future policy communication. According to KOF (2007a), the MPC anticipates changes in the marginal refinancing operations rate (MRO, henceforth) by two to three months. Employing, as in Neuenkirch (2013), a recursive identification scheme in such a model is, however, challenging. The ordering of the MRO rate and the MPC variable inevitably assumes a specific timing of responses to the thereby identified shocks. To avoid this problem, we use market-based monetary policy surprises as a means of identification.

More specifically, we follow the work of Andrade et al. (2016) and use changes in EONIA Overnight Index Swaps (OIS, henceforth) to identify ECB monetary policy surprises. Following the methodology of Gürkaynak et al. (2005), we apply a principal components

[1] See, e.g. Blinder et al. (2008) for an early overview of the literature.

analysis to the term structure of EONIA OIS forwards and generate orthogonal "target" and "path" factors. Herein, the target factor tracks changes in current forward rates during monetary policy announcements days, whereas the path factor tracks changes in expected forward rates during policy announcement days. We use these factors within a Proxy SVAR framework, as used, for example, in Gertler and Karadi (2015). To identify monetary policy action surprises, we instrument action surprise via the target factor. We use the path factor to instrument communication surprises. The novelty lies in our use of the MPC index. We argue that changes in the path factor can explain variation in the MPC index. The rationale is that a part of the reduced-form error of the MPC index should be correlated with communication surprises, for which surprise changes in interest rate expectations, i.e. the path factor, serve as an instrument.

Our analysis provides several interesting insights. Responses of inflation and production to both ECB action and communication surprises prove to be significant. This contrasts the results obtained using the recursive identification scheme, where the influence of communication appears to be weak. Further, in our analysis, we do not find any evidence for the exchange rate puzzle, i.e. lack of exchange rate appreciation as a result of policy tightening. Indeed, (contractionary) policy action and communication surprises lead to a significant exchange rate appreciation on impact. The recursive identification, however, again yields insignificant results. Furthermore, we compare our identified communication surprise with the "information shock" by Jarocinski and Karadi (2018), and find some similarities.

We add to the literature in two ways. First, concerning the literature, which attempts to identify monetary policy communication surprises, Nakamura and Steinsson (2018) document a FED information effect. Therein, policymakers announce higher future interest rates while believing the economy is strong enough to cope with possible adverse effects. Market participants might therefore become more optimistic concerning the path of the economy, which leads to positive output forecasts. This resembles short-run impulse responses of industrial production using our communication surprise. Jarocinski and Karadi (2018) propose a decomposition of monetary policy surprises into monetary policy shocks and information shocks. Whereas the former is identified by negative co-movement of interest rates and stock prices during policy announcement, the former is

identified by positive co-movement of both. We compare our methodology more closely to the approach by Jarocinski and Karadi (2018) at the end of this paper. Here we also establish similarities between their "information shock" and our identified communication surprise.

Second, we re-evaluate results by Neuenkirch (2013), who tackles the problem by building a euro-area VAR model that contains both the ECB MRO rate and a future monetary policy communication variable, i.e. the MPC index. He makes use of a timing assumption, implemented via a Cholesky decomposition, as a means of identification. His results suggest that there is a need for including the communication variable into a euro-area VAR to fully capture ECB monetary policy effects. We deviate from the use of a timing assumption and instead employ high-frequency identification using exogenous variation in OIS forwards and find ECB communication effects different to those found in Neuenkirch (2013). We compare our identification approach with a Cholesky approach to be comparable.

The paper will continue as follows: In Section 2 we describe the communication variable included in our VAR model. Section 3 introduces our econometric model and identification strategy of policy surprises. Results are then presented in Section 4. In Section 5 we compare our approach to Jarocinski and Karadi (2018). We conclude in Section 6.

Note concerning this draft: In this version we make use of daily-data changes in interest rate swaps. In the future version we will be redoing the analysis using a more narrow time window around announcements would increase the "quality" of our high-frequency, in terms of their exogeneity. Such intra-day tick data was, however, unavailable to us while writing this version of the paper. Due to the ECB's announcement structure, it would then be possible to measure high-frequency responses around interest rate announcements and the press conference, separately. The decision regarding changes in key interest is announced at 13:45, meaning that the time window from 13:30 to 14:00 can be used to collect market responses to key interest rate surprises. As the press conference starts at 14:30, the time window from 14:15 to 15 minutes after the end of the conference end might be used to measure financial markets' reaction to unexpected changes in communication. Similar to the approach presented in this paper, the high-frequency measure around press releases could be used as an instrument for policy action surprises, and the

measure around the press conference as an instrument for communication surprises. We are confident that such an exercise would yield interesting additional insights.

2 Communication Variable

Our contribution relies mostly on combining the MPC-augmented VAR approach introduced by Neuenkirch (2013) with a high-frequency identification strategy to disentangle policy action from communication effects. For this reason, we begin our exposition in this section by discussing the communication variable that we include in the VAR. In our view, a policy variable tracking central bank communication should fulfill three criteria. First, the communication variable should be forward-looking. As such, it should provide information about the upcoming macroeconomic situation and on upcoming ECB monetary policy and thus complement the MRO rate when included in the model. Second, the variable should be based on price developments. This mirrors the ECB's prime objective of price stability. In that respect, ECB officials spare no words when it comes to explaining that their future policy guidance is always conditional on future price developments. This is nicely pictured in the following excerpt from Benoit Coeure's[2] speech: "At any rate, for our forward guidance, both on rates and the APP, to be credible, we need to keep our policy expectations well aligned with our evolving assessment of the balance of risks and the outlook for inflation – this is the Delphic part of our forward guidance. We would pay a high price in terms of our credibility if we failed to adapt our forward guidance once we had changed our views on the outlook", ECB (2017). Finally, as can already be ascertained from this citation, the measure should encompass a variety of instruments. Central bank communication is not exclusively focused on the future interest rate path, especially in turbulent times. For example, regarding the recent period, ECB's forward guidance "[...] encompasses a carefully expounded series of expectations involving both key policy rates and asset purchases", ECB (2017). For this reason, using a measure of communication that focuses exclusively on the future interest rate changes would omit a significant fraction of useful future policy information.[3] We now elaborate on the measure we use in this paper and to which extent it has the outlined characteristics.

[2]Member of the Executive Board of the ECB.
[3]This does not exclude, though, that communication in that respect might affect interest rate expectations.

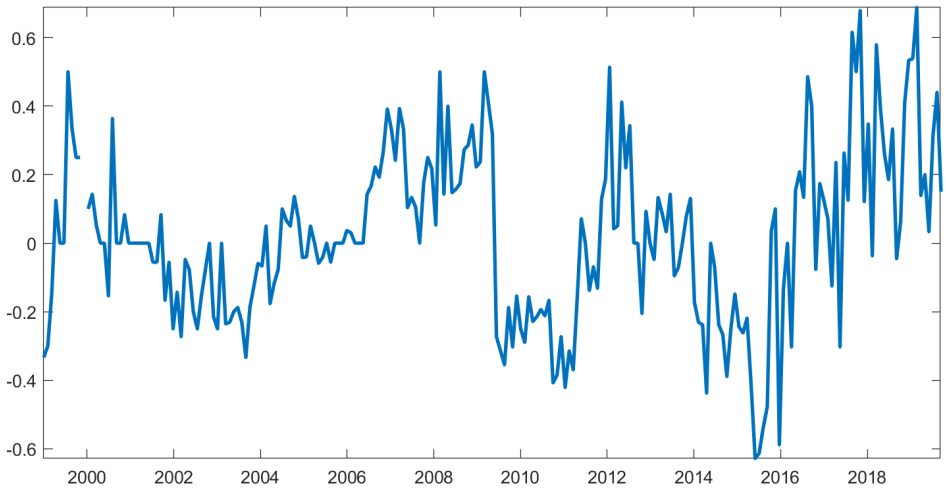


Figure 1: KOF Monetary Policy Communicator

The primary communication tool used by the ECB are monthly press conferences held after the ECB Governing Council meeting. Each conference consists of an introductory statement and Q&A session. The opening statement provides a comprehensive summary of ECB decisions and economic developments of importance for monetary policy. To generate the quantitative communication index, the specialist media research institute, Media Tenor, reads the text of the introductory statement sentence by sentence and codes all the statements. Each statement is treated as an observation and classified into one of the four sections (real, prices, monetary, other). Additional attributes are assigned to each statement such as tense (past, present, future), the tendency (decrease, no change, increase), judgment (bad, neutral, good) and ambiguity (unambiguous, conditional, restricted/conjecture). The KOF Swiss Economic Institute exclusively uses forward-looking statements regarding price stability to construct the KOF Monetary Policy Communicator. While statements from all four sections are used, comments from the section on price development appear to be most relevant (KOF 2007b). The coding is aggregated into an index by taking balances of the statements that reveal that the ECB sees upside risks to price stability and statements that show that the ECB sees downside risks to price stability, relative to all statements about price stability (including neutral). By construction, the values of the MPC are restricted to be in the range from -1 to 1. The larger a positive (negative) value of the MPC, the more the ECB emphasized that there are upside (down-side) risks for price stability. Therefore more positive (negative) value implies more

pronounced expected tightening (easing) of ECB monetary policy in the near future. For example, as can be seen in Figure 1, during the Great Financial Crisis down-side risks for price stability dominated ECB communication, as the ECB was worried about the euro-area economy falling into a deflationary period.

When considering our three characteristics, the MPC is forward-looking and, while containing information about aggregates besides prices, is mostly based on statements regarding price stability. It is not constrained to a single policy instrument. Instead, through its focus on future price stability, it can be interpreted as predicting a future likely "course" of monetary policy. KOF (2007a) estimates show that the MPC anticipates changes in the MRO rate by two to three months. In addition, we find that the correlation coefficient between both policy variables is as low as 0.12 for the sample used in this paper, implying that the communication variable captures additional information regarding ECB monetary policy.[4] These properties will help identify monetary policy communication surprises but also create some challenges. The advantage is that the MPC contains information about ECB communication, which the MRO rate can not convey. The disadvantage is that movements in the communication indicator must not necessarily reflect communication surprises. In the same way, market participants at times succeed to anticipate changes in the MRO rate, the same might hold true for statements made during the press conference. Communication surprises in that context would be unexpected changes in the wording or new information communicated during the press conference. We aim to tackle this issue using our identification strategy.

3 Methodology

In this section, we set up a euro-area VAR model and then explain our identification strategy of monetary policy action and communication surprises.

[4]More details concerning the MPC can be found on: https://www.kof.ethz.ch/en/forecasts-and-indicators/indicators/kof-monetary-policy-communicator.html

3.1 The Euro-Area VAR

As a baseline we estimate the following VAR:

$$Y_t = A(L)Y_{t-1} + u_t, \tag{1}$$

$$u_t \sim \mathcal{N}(0, \Sigma),$$

where reduced form errors u_t can be linked to structural shocks ϵ_t via the relation

$$u_t = B\epsilon_t, \quad \text{with} \quad \epsilon_t \sim \mathcal{N}(0, I) \quad \text{and} \quad B'B = \Sigma. \tag{2}$$

The vector Y = [IP, INF, M3, MRO, MPC] is the vector of endogenous variables representing the euro-area economy, where IP is the industrial production index, INF is the y-o-y inflation rate based on the HICP, M3 tracks the monetary aggregate M3, MRO is the ECB main refinancing operations rate, and MPC is the KOF monetary policy communicator. The sample consists of monthly data starting in January 2002 and ending in January 2015. In later sections, we expand the model by additional variables such as the nominal effective exchange rate and stock prices to examine their reactions to ECB monetary policy shocks. At first, however, we exclude them from the baseline specification. The lag length is set to three as proposed by the majority of lag-length selection tests. All VAR models estimated in this paper satisfy the stability condition.

Ultimately, we are interested in uncovering the influence of specific structural shocks in ϵ_t on macroeconomic variables such as industrial production and inflation. To extract monetary policy action and communication surprises, we need to identify the matrix of structural coefficients B, which is generally unknown and can not be deduced from data alone. Additional identifying assumptions are necessary, which we discuss in the following sub-sections.

3.2 Identification & High-frequency Measures

Reduced form VARs can only deliver estimated forecast errors. However, equation (2) shows that each forecast error consists of a linear combination of structural shocks. It is usually not possible to infer these structural shocks from the VAR alone. Additional

structural assumptions are necessary. In his seminal article, Sims (1980) initiated the use of VARs to asses macroeconomic models. This can be achieved by imposing identifying assumption, reflecting model properties, on the VAR, and assess the resulting responses. A common procedure is a recursive identification approach, which assumes that there is a natural lag between the moment a structural shock impacts one variable and the time it translates to other variables.[5] For example, in such an approach, a contractionary monetary policy rate surprise increases the policy rate today, while other macroeconomic aggregates react with a lag. This is usually justified by recognizing that the effects of monetary policy surprises on GDP and inflation take more than one month to transmit. Such an identification scheme implies a triangular form for matrix B, which can be computed using a Cholesky decomposition of the reduced form error covariance matrix.[6] However, such recursive identification schemes often yield non-intuitive "puzzling" results and are also not suited for models including financial variables due to endogeneity issues, as the timing assumption is often not valid.[7] Also, in the context of this paper, where two ECB policy variables are involved, the "correct" ordering of the MRO and MPC variable in the model would be unclear. To avoid any assumption on the timing of monetary policy action and communication surprises, we make use of the Proxy SVAR approach using high-frequency narrative measures.

The general idea here is to find an external instrument, which on the one hand is highly correlated with the respective structural shock, but is on the other hand uncorrelated with any other structural shock. Such a measure in hand, we are then able to identify elements of matrix B, so that we can link structural shocks to the VAR's endogenous variables. First, we introduce the high-frequency narrative measures for monetary policy action and communication surprises, respectively. Second, we will explain how to apply these measures to arrive at our desired shock identification.

3.2.1 High-frequency Measures

A prominent approach that has received attention over the last years is the use of high-frequency data as narrative measures to identify monetary policy surprises. Among the

[5] See for example **?**.

[6] This would give $B = chol\,(\Sigma)$.

[7] Some puzzling results are the rise in prices and exchange rate depreciation after a positive interest rate shock.

first to utilize a high-frequency identification approach was Kuttner (2001) who used daily changes in the FED funds futures rate and Gürkaynak et al. (2005) who used intra-day data.[8] Gertler and Karadi (2015) go a step further and employ high-frequency measures within a Proxy SVAR to elicit the responses of macroeconomic and financial variables following a monetary policy shock in the U.S. Similarly, Andrade et al. (2016) make use of the term structure of EONIA OIS forward rates to construct monetary policy innovations and apply the Proxy SVAR methodology similar to that of Gertler and Karadi (2015) to examine the ECB monetary policy transmission. To identify policy surprises, we will closely follow the procedure laid out in Gürkaynak et al. (2005).

Gürkaynak et al. (2005) use changes in the FED funds futures rates around FOMC policy announcements to obtain a series of exogenous monetary policy innovations. As immediately before the central bank announcement financial markets reflect all publicly available information and expectations, high-frequency changes around the policy announcements reflect a surprise component of the central bank's monetary policy. Gürkaynak et al. (2005) collect such innovations in FED funds futures markets for a range of different maturities for a set of FED monetary policy announcement days. They use principal components to extract two factors that explain a large fraction of the variation in the data. They then rotate these factors such that one factor, i.e. the "future path of policy factor", explains variation in all but the shortest maturity (current month) FED funds future. The remaining factor explains the variation in the current month future, i.e. the "current FED funds rate target factor".[9] Following the authors' interpretation, the target factor captures innovations in the FED funds rate, i.e. policy actions, while the path factor captures innovations in FOMC communication. In what follows, we will elaborate in detail how we employ this method to construct similar factors describing ECB monetary policy.

Constructing Euro-Area High-Frequency Measures

We construct our shock measures by combining the approach of Gürkaynak et al. (2005) and more recently Andrade et al. (2016). We consider daily data (end of day values) on

[8] In their paper Gürkaynak et al. (2005) show that the same results are obtained using the daily data frequency. Intra-day data, however, yields statistically more significant results as it reduces financial markets noise.

[9] For the sake of expediency we will refer to these two factors as the target and the path factor.

EONIA OIS contracts from January 2002 until January 2015.[10] Following Andrade et al. (2016) for nine maturities (one week to two years) we first construct daily OIS forward rates using

$$r_{t_1,t_2} = \left(\frac{(1+r_2)^{d_2}}{(1+r_1)^{d_1}}\right)^{\frac{1}{d_2-d_1}} - 1. \tag{3}$$

The main reason for doing this is that while the OIS swap itself is a swap contract with a maturity of, for example six months, the six months forward rate we construct is the short-run rate expected by market participants to prevail in six months from now. This is an exercise which more closely resembles the one done using the FED funds futures in the U.S. For each ECB press conference day (157 days in total) we construct differences of that day and the previous day's closing value. We interpret this difference as the exogenous market reaction to ECB monetary policy. From this set of OIS forward differences calculated for nine maturities, we extract the first two factors that explain 70% of variation using principal component analysis. Following Gürkaynak et al. (2005) we rotate the factors in such a way that one factor explains the variation in all longer maturities but is orthogonal to the shortest duration (one week) forward.[11] As previously mentioned we will refer to the factor capturing variation in longer maturities as path factor, and to the factor capturing variation in short maturities as target factor.

3.2.2 Identification

We perform identification using a Proxy SVAR approach, as introduced in Stock and Watson (2008). This approach has been used in multiple papers such as Gertler and Karadi (2015) to identify monetary policy or in Mertens and Ravn (2013) to identify fiscal policy surprises. An overview and detailed exposition of the Proxy SVAR and other similar approaches can be found in Stock and Watson (2018).[12]

As stated at the beginning of this section we estimate a VAR(p) where reduced form errors u_t and structural shocks ϵ_t are linked via:

$$u_t = B\epsilon_t. \tag{4}$$

[10] Intra-day high-frequency tick data is only available commercially via the Thomson Reuters Tick History Database. We therefore resort to the use of daily data extracted from Bloomberg.

[11] See Section 8.2 in the appendix for details.

[12] Note that Stock and Watson (2018) refer to the approach as SVAR-IV, as we are in principle using an instrumental variables approach within a SVAR framework.

We aim at identifying a latent structural monetary policy shock ϵ_t^x, where x is a placeholder for either the policy rate (target) or communication (path) shock. Following Stock and Watson (2018), the high-frequency measure m_t for e_t^x has to satisfy the following conditions:[13]

$$E\left[m_t \epsilon_t^x\right] = \phi \neq 0 \tag{5}$$

$$E\left[m_t \epsilon_t^{non-x}\right] = 0. \tag{6}$$

Here, condition (5) establishes relevance of the measure in the sense that it must be correlated with the structural policy shock of interest. Condition (6) establishes exogeneity, ensuring that the high-frequency measure is not correlated with remaining structural shocks. Using these conditions, we can estimate the initial impacts of the respective policy shocks on all variables in the VAR using instrumental variable estimators, which provides the columns of matrix B corresponding to the respective structural shocks.

We proceed in the following way. As a proxy for a monetary policy action shock, we use the target factor. The target factor tracks exogenous movements in the current forward rate, which should be correlated with surprise movements in the MRO rate. As a proxy/instrument for monetary policy communication surprises, we make use of the path factor. We argue that relevance of this instrument is a reasonable assumption. Since the MPC tracks changes in monetary policy communication, its reduced form error in a VAR represents unexplained variation in the communication indicator. Surprises in ECB communication concerning price stability should affect interest rate expectations, which are proxied by our path factor. We compute coefficients of matrix B using the Proxy SVAR approach, which satisfies equations (5) and (6), using code provided by Gertler and Karadi (2015).[14]

A further advantage of this identification strategy is that it also allows for the inclusion of fast-moving variables for which the recursive identification would lead to simultaneity issues. In this way, we can examine the reaction of such variables to both monetary policy

[13] w.l.o.g. $E\left[m_t\right] = 0$

[14] In a first stage regression to identify action surprises, we regress the MRO rate reduced form error on the target factor and the reduced form error of the MPC index on the path factor. For a closer look at the algorithm used for the IV estimation see Gertler and Karadi (2015), page 9.
We use the MATLAB estimation code which is made public here: https://sites.google.com/site/pkaradi696/research

shocks. Having explained the methodology and the high-frequency measures we use, in the following section we will turn to present our final results.[15]

4 Results

We now turn to the main findings of our paper. The main results are split into several sections. First, we analyze responses following a ECB policy action surprise and continue to explain our findings concerning the policy communication shock. We further address results concerning the addition of supplementary financial variables in the econometric model.

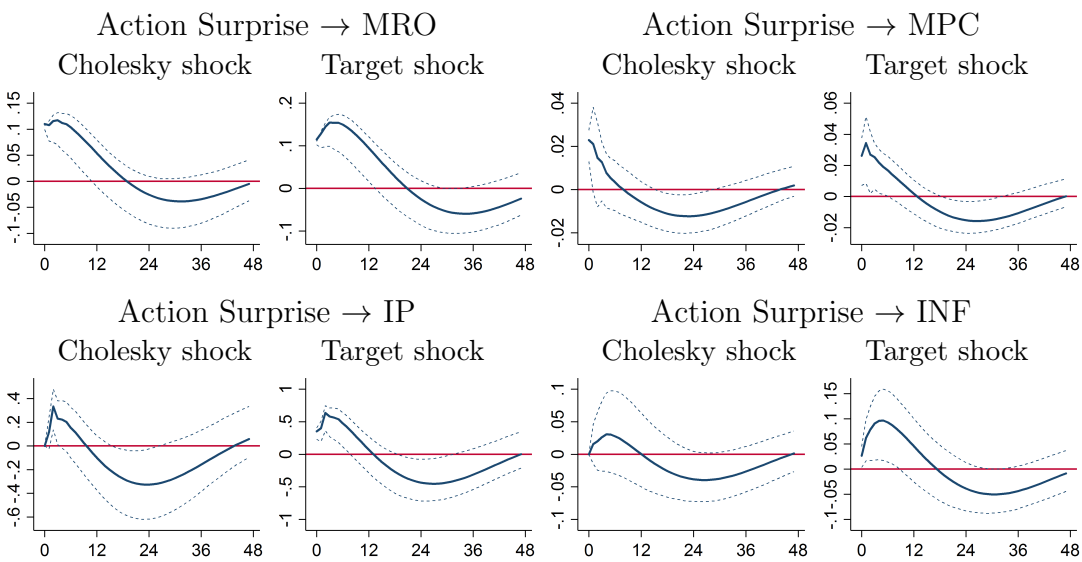
4.1 Policy Action Surprises

We first turn to interpret results in Figure 2, which pictures the reactions of the main macroeconomic variables in response to ECB policy action shocks. We also present the results obtained using the recursive identification scheme, i.e using the Cholesky decomposition. The notation "Action Surprise $\rightarrow Y$" reads: "Response of the variable Y to a positive one standard deviation policy action surprise". The "Cholesky shock" then refers to the recursive identification strategy, and "Target shock" refers to the High-frequency/Proxy SVAR approach. Responses of MRO, MPC, IP, and INF are estimated using the baseline model as described in equation (1).[16]

Considering ECB action surprises, Figure 2 shows that the high-frequency approach yields similar results to those of the traditional Cholesky decomposition in terms of sign, magnitude, and statistical significance. A positive monetary policy action surprise leads to an increase in the MPC, which can be interpreted as the ECB communicating higher future inflation risks when tightening monetary policy today. This holds for both types of shocks – Cholesky and high-frequency. Further, industrial production and inflation both unintuitively jump on impact and then fall in the middle run. These results have already been documented in other euro-area VARs, see e.g. Peersman and Smets (2001) and

[15] Following Andrade et al. (2016) and Miranda-Agrippino (2016) we also check for the unpredictability of our high-frequency measures and respective reduced-form errors. See Section 8.1 in the appendix.

[16] When using Cholesky decomposition, ordering in the baseline model is IP, INF, M3, MRO, MPC. The ordering of the MRO rate and the MPC variable are the same as in the baseline specification of Neuenkirch (2013).



Notes: Bootstrapped 90% confidence intervals

Figure 2: Impulse response functions for monetary policy action surprises

Neuenkirch (2013). Here, there are no significant differences when considering different identification approaches. The price puzzle also characterizes results from papers similar to ours that use high-frequency data but coupled with one-policy-variable VAR, see e.g. Jarocinski and Karadi (2018) and Andrade et al. (2016). The inclusion of the MPC variable does not help to deal with the issue.

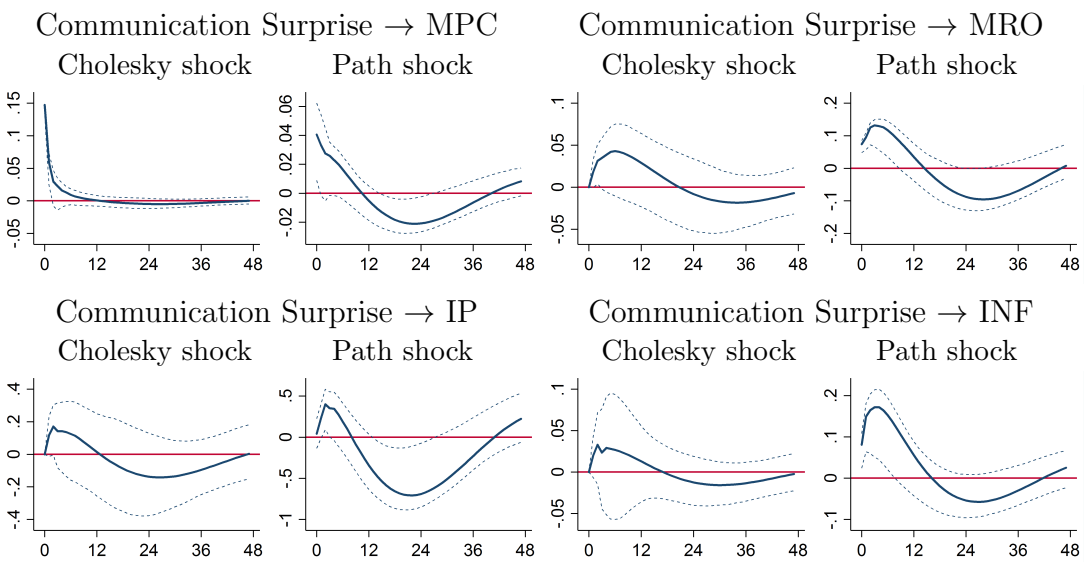
4.2 Policy Communication Surprises

We now turn to Figure 3, which represents the influence of ECB communication surprises on the main macroeconomic variables. Notation used is analogous to that in Figure 2.[17] As before, results stemming from the recursive identification approach are offered for comparison.

Figure 3 shows responses to ECB communication surprises. When comparing Cholesky and the high-frequency identification approaches, significant differences appear. When using a recursive identification strategy with the MPC variable ordered last, the response of the MRO rate is zero by construction.[18] However, in the high-frequency case, a pos-

[17]The notation "Communication Surprise → Y" reads: "Response of the variable Y to a positive one standard deviation communication surprise". The "Cholesky shock" then refers to the recursive identification strategy, and "Path shock" refers to the High-frequency/Proxy SVAR approach.

[18]Ordering the MRO last in a recursive identification approach creates non-zero but insignificant responses



Notes: Bootstrapped 90% confidence intervals

Figure 3: Impulse response functions for monetary policy communication surprises

itive path shock significantly increases the MRO on impact which points to the timing assumption as being too restrictive.

Next, looking at industrial production and inflation, compared to Cholesky, the path shock responses are more pronounced and statistically significant.[19] Interpretation of the industrial production and inflation dynamics as a response to the communication shock is not trivial. Intuitively, responses of the MPC index to the communication surprise implies that during the monthly press conference, the ECB communicates unexpected, extraordinary higher price risks for months to come. Such a shock might be accompanied by a contemporaneous interest rate hike to fight such an unfavorable outlook (for the central bank) – which is indeed the case in our response functions. However, as economic theory suggests, monetary policy affects macro-variables only with a lag. Hence, we could observe industrial production and inflation rising in the short run before the policy starts having any restrictive effects. In case of such an interpretation, the short-run increases in industrial production and inflation are not puzzling; they are a mere consequence of monetary policy lagging real effects.[20] Especially inflation is expected to increase in the short run as the MPC is a measure of ECB communication regarding future prices. Indeed,

in response to the communication surprise (a shock to the MPC variable).

[19]Responses to the path shock are more prominent in magnitude even though the shock itself is three times smaller than the Cholesky shock.

[20]Compare to Neuenkirch (2013)[p.4280].

while the IP variable jump is small and hardly significant, the inflation hike is much bigger and significant. Furthermore, these findings are also in line with results of Jarocinski and Karadi (2018) for the euro-area. They argue that monetary policy innovations are a construct of two different shocks, "monetary policy shocks" and "information shocks" that hit the market during the monetary policy announcement day. In their framework, monetary policy shocks are innovations that lead to a fall in industrial production, prices, and stock markets. However, during announcement days, central banks also provide information about the future economic outlook. This part of the policy innovation is called "information shocks" and a positive innovation in information, which is described as a positive communication of the central bank regarding the future economic outlook, induces a rise in industrial production, inflation and stock prices. Such a shock is accompanied by an increase in interest rates as a response to fighting the expected expansion. The impulse responses we obtain follow such a pattern. In a later section, we will further elaborate on that and introduce the communication measure into the Jarocinski and Karadi (2018) framework.

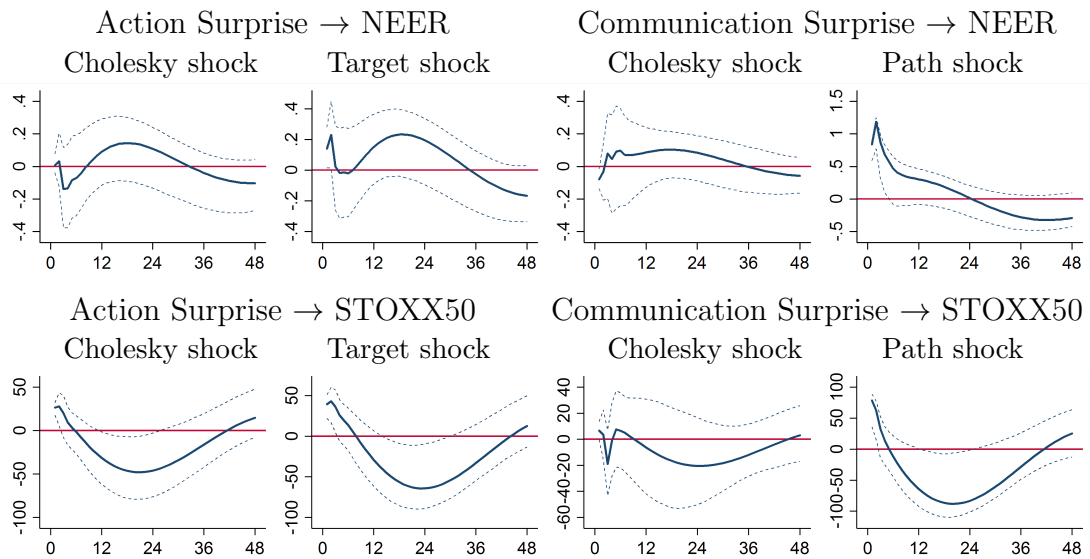
4.3 Exchange Rates and Stock Prices

Using timing assumptions for purposes of identifying structural shocks becomes problematic when fast-moving variables are introduced in the VAR. The main problem appears in situations in which the policy surprise not only affects a variable but when the policy variable also responds to other shocks within the same period, in this case within a month. The high-frequency approach to identification can mitigate such issues. For example, considering exchange rate responses, VAR models often yield puzzling results. As shown in Grilli and Roubini (1995), a positive innovation in the domestic interest rate leads to depreciation, instead of appreciation, of the exchange rate in the non-U.S. G7 countries, when Cholesky identification is used. Therefore, financial variables which are considered to be fast-moving seem to be reasonable candidates to be included in a Proxy SVAR.[21]

For these reasons, in this paper, we consider the following two variables: The nominal

[21] See for example Gertler and Karadi (2015) for the use of high-frequency approach to including the credit costs in a VAR framework

effective exchange rate (NEER) and stock prices (STOXX50).[22] Each of these variables is individually added at the end of the VAR in equation (1) and its responses to both action and communication shocks, using both the Cholesky and high-frequency approach, are computed. Results are presented in Figure 4.



Notes: Bootstrapped 90% confidence intervals

Figure 4: Fast-responding variables IRF.

Looking at the upper four graphs of Figure 4, we see that the high-frequency approach very much differs from results using the Cholesky approach. Using the high-frequency measures, a contractionary monetary policy action shock appreciates the nominal exchange rate initially, while the effect becomes insignificant shortly after. In the Cholesky approach, the appreciation is hardly noticeable, with effects being insignificant over the whole response period. Concerning a positive communication surprise, indicating surprise up-side risks to price stability or potential future contractionary policy action, the Cholesky and high-frequency identified responses of the exchange rate differ drastically. The Cholesky identified response is always insignificant. The high-frequency identified action and communication surprises lead to sizable initial appreciation, followed by a gradual depreciation, which is consistent with the uncovered interest rate parity. If the

[22]The nominal effective exchange rate (NEER) of the euro is a weighted average of nominal bilateral rates between the euro and a basket of foreign currencies. If this index rate goes up, more foreign currency can be obtained, on average, for one EUR. The STOXX50 Index is the leading blue-chip index for the euro-area. The index covers 50 stocks from 11 euro-area countries: Austria, Belgium, Finland, France, Germany, Ireland, Italy, Luxembourg, the Netherlands, Portugal and Spain.

uncovered interest parity holds and foreign interest rates remain constant, a positive innovation in domestic interest rates or even expectations of rising domestic interest rates lead to an initial appreciation of the exchange rate. As prices adjust in the long-run, this is followed by a depreciation of the exchange rate.[23] In total, this evidence implies that the high-frequency shock identification yields exchange rate dynamics consistent with standard theory, i.e. there is no exchange rate puzzle. Conrad and Lamla (2010) document a similar result concerning the EUR-USD nominal exchange rate. They, however, construct their own communication index using Context Analysis and employ the index within a GARCH-type model.

When considering the reaction of stock prices to a policy action shock, there is not much difference between the Cholesky and the high-frequency approach. In both cases, the STOXX50 index rises on impact and then falls in a medium to long run. While the longer-run fall is expected as the interest rate hike contracts the economy, the initial stock prices jump is in this context considered puzzling. A contractionary monetary policy shock should reduce stock prices, not increase them on impact. This puzzling result was also found by Jarocinski and Karadi (2018) in a one-policy-variable VAR, who then opted to further "deconstruct" the monetary policy shock into sub-components in an attempt to deal with the issue. Considering responses to communication innovations, theoretical predictions of the Jarocinski and Karadi (2018) model imply a positive impact of communication on stock markets on impact, because the information shock reveals favorable economic conditions in the near future. Simultaneously this leads to interest rates increase as a reaction of the central bank to fight the ongoing expansion and a fall of stock prices afterwards. The result of our high-frequency communication surprise is well in line with these predictions, while the Cholesky decomposition yields mostly insignificant results.

In summary, the application of our high-frequency approach showed, that it can deliver VAR responses of exchange rates and stock price, which are in line with standard theory, contrary to recursive identification strategies.

[23] See Kim and Roubini (2000).

5 Communication using Jarocinski and Karadi (2018)

In this section, we use the framework of Jarocinski and Karadi (2018) (JK, henceforth during this section) to shed some additional light on the role of communication in the monetary policy transmission mechanism. As we already argued, in reality, central banks' monetary policy announcements do not exclusively involve interest rate adjustments. Such adjustments are instead accompanied by the policymakers' explanations of the policy and the surrounding macroeconomic environment. For this reason, two monetary policy components (action and communication) may shock the markets in two different directions on the same monetary policy announcement date. JK provide an example for such a possibility: "On January 22, 2008 during the early phase of the 2007-2009 U.S. financial crisis, the U.S. 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."

JK try to disentangle the two components by relying on information in high-frequency co-movement of interest rates and stock prices around policy announcements. The main idea is that high-frequency co-movement of interest rate and stock prices reactions during a short window around the monetary policy announcement provides essential information on the nature of the monetary policy shock and thus on the long-run reactions of macroeconomic variables. They argue that for a broad set of models, monetary policy tightening leads to lower stock market valuation. If during the monetary policy announcement, market interest rates increase and at the same time stock prices fall, JK consider such behavior a "monetary policy shock", which has a contractionary nature. In other words, looking at the longer run, such a shock would lead to a contraction in output and a tightening

of financial conditions. In contrast, if during the monetary policy announcement, market interest rates increase and at the same time stock prices rise, JK consider this to be a "information shock", which has an expansionary nature. In other words, again looking at the longer run, such a shock would lead to rises in output and relaxation of financial conditions.

Following this line of thought, we repeat the exercise done in JK. By incorporating our MPC variable into their framework, we aim to compare their approach to ours.

5.1 Methodology & Identification

In their paper, JK estimate the following restricted VAR model:

$$\begin{pmatrix} m_t \\ y_t \end{pmatrix} = \sum_{p=1}^{P} \begin{pmatrix} \mathbf{0} & \mathbf{0} \\ B_{YM}^{p} & B_{YY}^{p} \end{pmatrix} \begin{pmatrix} m_{t-p} \\ y_{t-p} \end{pmatrix} + \begin{pmatrix} c_M \\ c_Y \end{pmatrix} + \begin{pmatrix} u_t^m \\ u_t^y \end{pmatrix}, \tag{7}$$

$$\begin{pmatrix} u_t^m \\ u_t^y \end{pmatrix} \sim \mathcal{N}(0, \Sigma),$$

where m_t is a block of fast-responding variables, and y_t is a block of slow-responding variables. More specifically, m_t consists of both (monthly) high-frequency innovations, i.e. OIS forward rate during policy announcement and STOXX 50 changes in policy announcement days. JK implement their empirical model using Bayesian estimation and identify monetary policy and information shock via a combination of high-frequency measures and sign restrictions. Within the empirical specification (7) identification via high-frequency measures is achieved by ordering the respective measure first in the VAR. Such a specification produces results, which are qualitatively similar to the Proxy SVAR used in this paper. However, the main difference is that in JK's specification high-frequency measures are not merely treated as instruments or proxies for structural shocks, but as direct representations of structural shocks.[24] For sake of comparability we use their approach.

The "monetary policy shock" is then identified by the negative co-movement of the EONIA OIS and the STOXX 50 during announcement days. The "information shock" is identified by positive co-movement of both EONIA OIS and the STOXX 50 during policy announcement days. The authors also show that their results are robust to using a

[24] Compare to Stock and Watson (2018)[p.936 ff.] for a discussion.

simpler identification strategy instead of standard sign-restrictions, which they refer to as poor man's sign restrictions. In that approach, high-frequency time series are created for both "monetary policy" and "information shocks". The underlying assumption is that at each policy announcement day, only one of these shocks materializes.[25] Since we are only interested in a qualitative comparison to our results, we proceed by using that approach. To construct high-frequency measure m_t, we compute two sets of high-frequency time series, one for the "monetary policy shock" and one for the "information shock".

Constructing Poor Man's Sign Restrictions

For each ECB policy announcement day we measure the daily interest rate surprise (end of day value minus the previous end of day value) and a corresponding daily stock prices surprise in the STOXX 50.[26] We then compare the two surprise series to construct the separate "monetary policy shock" and "information shock" series in the following way. To generate the "monetary policy shock" time series, we consider our daily surprises in the interest rate. For days where their value has a sign different than that of the stock market surprise, we leave the value of the interest rate surprise as it is, while for days where the signs are the same we set the value to zero. Therefore we construct a time series of interest rate shocks, which has a non-zero value only on dates where the interest rate innovation was of a different sign than the stock prices innovation. These "monetary policy shocks" are expected to have a contractionary nature. On the other hand, to generate the "information shocks" time series, we again consider our original (complete) daily surprises in interest rates. For days where their value has the same sign as the stock market surprise, we leave the value of the interest rate surprise as it is, while for days where the signs are different we set the value to zero. In this way, we attain a time series of interest rate shocks, which has a non-zero value only on dates where the interest rate innovation was of the same sign as the stock prices innovation.[27]

The y_t vector consists of monthly industrial production, the price level, STOXX50, and BBB-spread. JK also add a german one-year interest rate. We substitute the one-

[25] JK show that their results are robust in that respect.

[26] We use the 60 days OIS forward rate because this is the closest measure to the 90 days EONIA OIS used by JK.

[27] It should again be noted, that we are using daily data, instead of intra-day data as in JK, as these were not available to us at the time of writing this paper. However, our results are similar to results in JK.

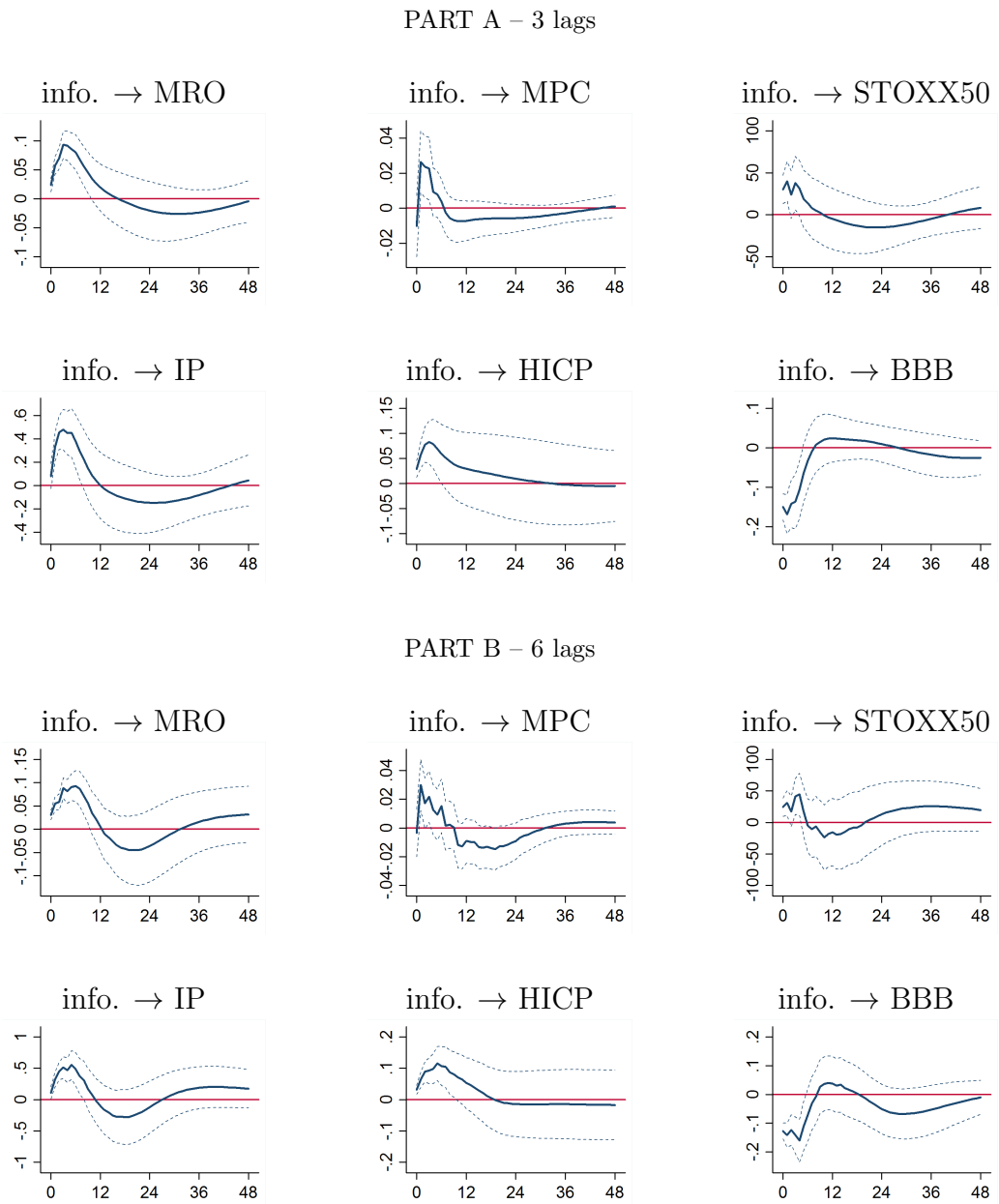
year interest rate by the MRO rate and the MPC index to gauge responses of both to "monetary policy" and "information shocks".

5.2 Results

We estimate the model firstly by using the "information shock" as the top variable in the VAR given by (7); we use three and six lags for robustness. Results are presented in Figure 5, which displays the orthogonalized impulse response functions of all the six variables (MRO, MPC, STOXX50, IP, HICP, and BBB-spread) to a positive one standard deviation "information shock'. Figure 5 shows that the responses of all variables are similar to those originally found by JK.[28] A positive "information shock" increases stock prices, industrial production, and inflation on impact and relaxes financial conditions, i.e. BBB-spread falls. As in JK, the central bank increases the interest rate to counter an overheating economy. The positive "information shock" induces a rise in the MPC variable in the very short-run, implying that the central bank is communicating increased inflation risks for months to come while increasing interest rates today. These results resemble our findings on macroeconomic variables' responses to the communication surprise (path shocks) in Figures 3 and 4. Positive ECB communication surprises regarding future prices were accompanied by an increase in the MRO rate and at the same time, a rise in prices and in the stock index in the short run. It seems that path shocks in our framework and the "information shocks" in the framework of JK are very similar.

We now turn to "monetary policy shocks". Figure 6 displays the orthogonalized impulse response functions of all variables from our model in equation (7) to a positive one standard deviation shock to the "monetary policy shock" variable which is now included at the top of the VAR instead of the "information shock". In contrast to the previous figure on "information shocks", positive "monetary policy shocks", while increasing the MRO rate now, reduce the MPC index, implying that the central bank communicates lower future prices as a result of tighter monetary policy. Production and prices fall on impact, while in the case of stock prices and BBB-spread negative and significant responses on impact are only obtained when six lags are used. Results are again similar to those of JK providing further assurance that our analysis using daily data is robust.

[28] Original results can be found in JK, page 29, Figure 8.



Notes: 90% confidence intervals

Figure 5: Orthogonalized impulse response functions, "Information Shocks"

6 Conclusions

In our paper, we propose a novel way of decomposing monetary policy shocks into policy and communication surprises by extending the work of Neuenkirch (2013). In our baseline specification, we show that the high-frequency methodology enables the incorporation of fast responding variables into a SVAR, which is usually problematic due to simultaneity issues. An attempt to introduce stock prices into the VAR has led us to compare our

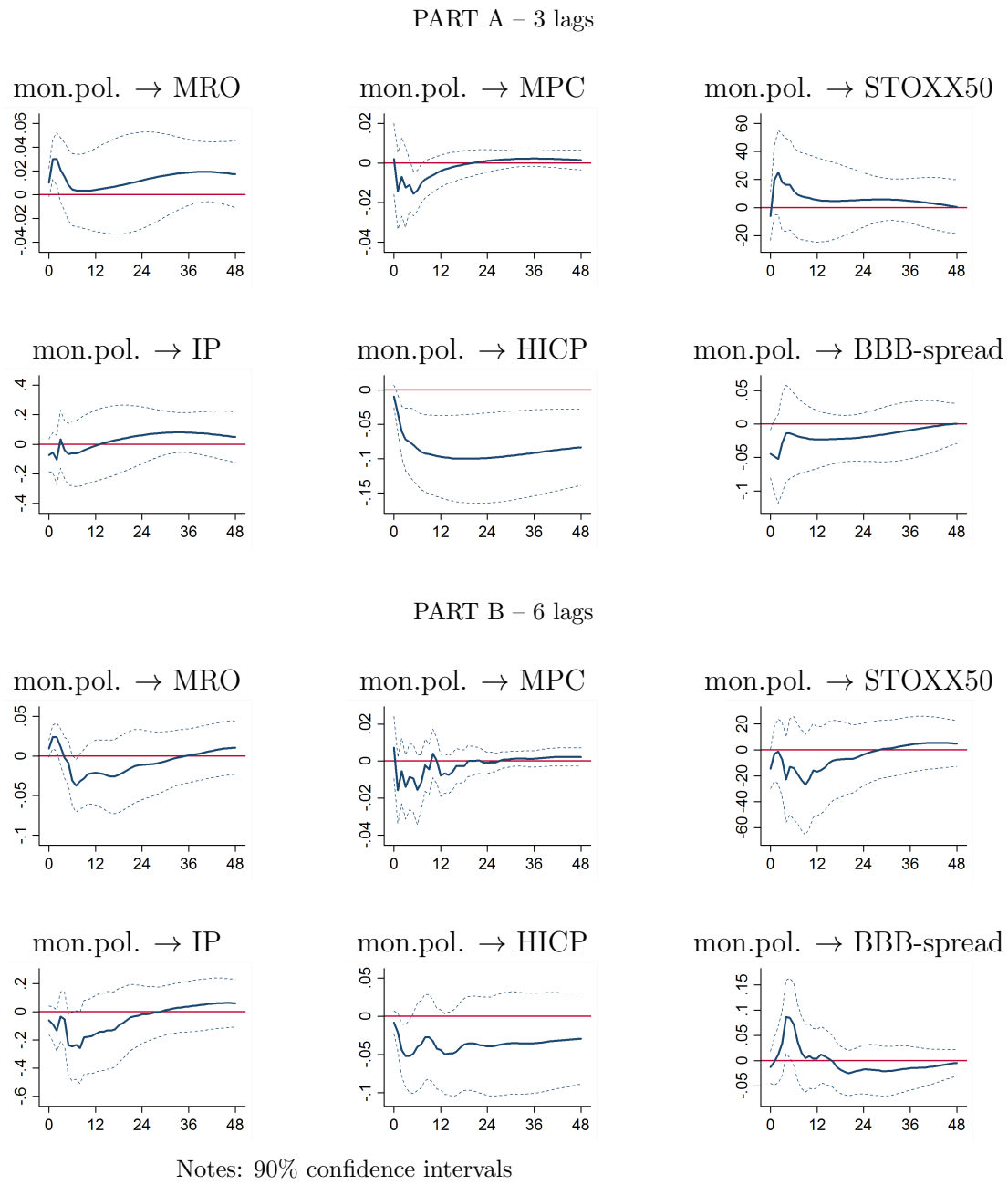


Figure 6: Orthogonalized impulse response functions, "Monetary Policy Shocks"

approach to that of Jarocinski and Karadi (2018), who also attempt to separate monetary policy shocks into its components. The analysis led to the conclusion that our identified communication shock is very similar to their "information shock". Both shocks can be interpreted as the ECB communicating favorable macroeconomic conditions in the near future and thus higher inflation risks. Also, both shocks lead to an increase in stock prices, inflation, industrial production, and an interest rate hike as the central bank fights the potential overheating of the economy.

Three avenues for future research are worth mentioning. First, the years following the Great Financial Crisis showed a substantial shift in the way money markets and monetary policy interact. Interest rates moved close to the zero lower bound, the ECB changed their tender system to fixed-rate full-allotment, and excess liquidity in reserve markets appears to have moved the EONIA away from the MRO rate closer to the deposit facility rate. These developments raise the question if the MRO rate is still able to capture key changes in monetary policy when included in a VAR.

Second, the monetary policy communication index as it is constructed by the KOF Swiss Economic Institute does not provide us with the possibility to assign different weights to specific sections of the ECB policy decision press conference. Computing our own index, with varying importance put on price, real and monetary developments, might be worthwhile to pursue. This would enable us to analyze the importance of price, real, and monetary categories in ECB communications regarding their effects on macroeconomic aggregates and financial variables.

Third, redoing the analysis using a more narrow time window around announcements would increase the "quality" of our high-frequency, in terms of their exogeneity. Such intra-day tick data was, however, unavailable to us while writing this version of the paper. Due to the ECB's announcement structure, it would then be possible to measure high-frequency responses around interest rate announcements and the press conference, separately. The decision regarding changes in key interest is announced at 13:45, meaning that the time window from 13:30 to 14:00 can be used to collect market responses to key interest rate surprises. As the press conference starts at 14:30, the time window from 14:15 to 15 minutes after the end of the conference end might be used to measure financial markets' reaction to unexpected changes in communication. Similar to the approach presented in this paper, the high-frequency measure around press releases could be used as an instrument for policy action surprises, and the measure around the press conference as an instrument for communication surprises. We are confident that such an exercise would yield interesting additional insights.

7 Appendix

7.1 Predictability

Whereas conditions (5) and (6) are necessary to compute the impulse response functions with respect to a structural shock, they do not ensure the instrument's validity. Given a data set X_{t-1}, not included in the VAR, a combination of reduced form errors u_t and instrument m_t is valid if at least one of the following conditions holds:

$$E\left[u_t X_{t-1}\right] = 0 \tag{8}$$

$$E\left[m_t X_{t-1}\right] = 0. \tag{9}$$

Conditions (16) and (17) imply the non-predictability of reduced form errors and instruments, respectively. As mentioned, it suffices if one of these conditions holds. If the reduced form errors are predictable, but the instrument is not, the part of the reduced form error, which is correlated with the instrument will be non-predictable.

This leads us to ask the following questions:

(a) To which extent are reduced form errors of MRO and MPC predictable?

(b) To which extent are our high-frequency measures predictable?

To check these conditions we follow procedures outlined in Andrade et al. (2016) and Miranda-Agrippino (2016). We use a set of euro-area and U.S. macroeconomic and financial variables not included in the VAR and extract principal components which explain 70% of variation in the data. The information set used to construct the principal components includes: U.S. industrial production, FED funds rate, commodity prices, EMU inflation expectations, euro-area real effective exchange rate, and the DAX stock market index.

We extract three principal components and run regressions of both high-frequency measures (target and path factor) and both reduced form errors (MRO, MPC) on these factors.

Table 2 shows the joint explanatory power of all three principal components using p-values of an F-test. Even though the principal components have explanatory power

for the target factor, this is not the case when looking at the corresponding reduced form error of the MRO variable. This is promising as in the attempt to compute the structural monetary policy shock, the target factor is projected onto the reduced form error. This means that the structural shock which will be used is uncorrelated with the information set. In addition, neither the path shock nor its corresponding reduced form error is predictable given the information set used.

Variable	P-Value
Target	0.071
Reduced form error MRO	0.570
Path	0.574
Reduced form error MPC	0.578

Notes: T = 157

Table 1: OLS regressions for testing predictability

7.2 Rotating Factors

To compute the target and path factor used in our high-frequency identification approach, we extract two rotated factors from a set of EONIA OIS forwards, closely following the approach outlined in Gürkaynak et al. (2005). To rotate the factor F into the new factor Z we set

$$Z = FU. \tag{10}$$

F consists of principal components extracted from the term structure of EONIA OIS forwards, and U is the (orthonormal) rotation matrix. Define the rotation matrix by

$$U = \begin{pmatrix} \alpha_1 & \beta_1 \\ \alpha_2 & \beta_2 \end{pmatrix}, \tag{11}$$

U is identified by four restrictions. First, all columns have to be normalized. Second the resulting new factors in Z must be orthogonal to each other. Therefore it follows that:

$$E\left(Z_1 Z_2\right) = \alpha_1\beta_1 + \alpha_2\beta_2 = 0. \tag{12}$$

It remains to impose the restriction that the second factor Z_2 does not affect innovations in the shortest maturity forward. Inverting equation (18) we can express principal components F as a function of parameters in U and of columns of the new factors Z:

$$F_1 = \frac{1}{\alpha_1\beta_2 - \alpha_2\beta_1}\left[\beta_2 Z_1 - \alpha_2 Z_2\right], \tag{13}$$

$$F_2 = \frac{1}{\alpha_1\beta_2 - \alpha_2\beta_1}\left[\alpha_1 Z_2 - \beta_1 Z_1\right]. \tag{14}$$

With γ_1 and γ_2 being the (known) loadings of the high-frequency measure on factors F, it follows that

$$\gamma_2\alpha_1 - \gamma_1\alpha_2 = 0, \tag{15}$$

which is the final restriction.

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8 Appendix

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Notes: T = 157

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$$Z = FU. \tag{18}$$

F consists of principal components extracted from the term structure of EONIA OIS forwards, and U is the (orthonormal) rotation matrix. Define the rotation matrix by

$$U = \begin{pmatrix} \alpha_1 & \beta_1 \\ \alpha_2 & \beta_2 \end{pmatrix}, \tag{19}$$

U is identified by four restrictions. First, all columns have to be normalized. Second the resulting new factors in Z must be orthogonal to each other. Therefore it follows that:

$$E\left(Z_1 Z_2\right) = \alpha_1\beta_1 + \alpha_2\beta_2 = 0. \tag{20}$$

It remains to impose the restriction that the second factor Z_2 does not affect innovations in the shortest maturity forward. Inverting equation (18) we can express principal components F as a function of parameters in U and of columns of the new factors Z:

$$F_1 = \frac{1}{\alpha_1\beta_2 - \alpha_2\beta_1}\left[\beta_2 Z_1 - \alpha_2 Z_2\right], \tag{21}$$

$$F_2 = \frac{1}{\alpha_1\beta_2 - \alpha_2\beta_1}\left[\alpha_1 Z_2 - \beta_1 Z_1\right]. \tag{22}$$

With γ_1 and γ_2 being the (known) loadings of the high-frequency measure on factors F, it follows that

$$\gamma_2\alpha_1 - \gamma_1\alpha_2 = 0, \tag{23}$$

which is the final restriction.