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INTEREST RATE SURPRISES: A TALE OF TWO SHOCKS

By

Ricardo Nunes
(University of Surrey, CIMS and CfM),

Ali Ozdagli
(Federal Reserve Bank of Dallas)

&
Jenny Tang
(Federal Reserve Bank of Boston).

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School of Economics
University of Surrey
Guildford
Surrey GU2 7XH, UK
Telephone +44 (0)1483 689380
Facsimile +44 (0)1483 689548
Web https://www.surrey.ac.uk/school-economics
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Interest Rate Surprises: A Tale of Two Shocks

Ricardo Nunes
University of Surrey, CIMS, and CfM

Ali Ozdagli
Federal Reserve Bank of Dallas

Jenny Tang
Federal Reserve Bank of Boston

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Abstract

Interest rate surprises around FOMC announcements contain both pure policy shocks and interest rate movements driven by central bank information about the economy. By analyzing interest rate changes on days of macroeconomic data releases, the impact of the central bank's information shocks can be identified and separated from the pure policy shocks. Results show that there is a significant central bank information component in the widely used policy rate surprise measure. Removing this component reveals that the contractionary effects of a positive pure policy shock are more pronounced relative to those estimated using the entire policy rate surprise. A positive information shock, on the other hand, is expansionary.

Keywords: Monetary policy; central bank information; high frequency identification; proxy structural VAR; external instruments
JEL Codes: C36, D83, E52, E58

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Emails: ricardo.nunes@surrey.ac.uk, ali.ozdagli@dal.frb.org, jenny.tang@bos.frb.org.

1 Introduction

How to properly identify monetary policy shocks and their effects is a classic question in macroeconomics (Sims 1980; Bernanke and Blinder 1992; Christiano, Eichenbaum, and Evans 2005). To do so, one must first isolate the policy surprise by parsing out the anticipated component of policy changes. Second, it must be taken into account that such surprises in monetary policy rates are likely to stem from a combination of the policy stance itself and new information about the central bank's outlook on the economy (Romer and Romer 2000), each of which can have a very different effect on the economy.

There is now a large literature using high-frequency interest rate changes measured around FOMC announcements in event-study frameworks to identify the effects of monetary policy shocks. This literature goes back to Kuttner (2001) and Gürkaynak, Sack, and Swanson (2005a,b). A more recent very important development in the literature involves using this method to construct external instruments to identify monetary policy shocks in vector autoregressions (VARs), as done in Gertler and Karadi (2015) based on the method of Mertens and Ravn (2013) and Montiel Olea, Stock, and Watson (2021). This method improves on previous structural decompositions of VAR residuals, such as the commonly used Cholesky decomposition.[1]

Nevertheless, these interest rate shocks may capture not only financial market surprises due to deviations of a central bank's policy actions from its policy rule but also surprises due to a central bank's reactions to its private assessment of the economic outlook. In the former case, a negative interest rate surprise is expansionary, whereas in the latter case the same surprise can be contractionary, because the central bank communicates a negative economic outlook as the interest rate must be reduced to combat economic weakness. Hence, the external instruments widely used in the literature do not distinguish between these two

[1] Other external instruments include those based on narrative approaches (for example, Romer and Romer 2004). Both of these types of instruments have also been developed for other countries. For instance, for the United Kingdom, Cloyne and Hürtgen (2016) build a narrative measure, and Cesa-Bianchi, Thwaites, and Vicondoa (2020) consider high-frequency identification.

channels. The literature commonly refers to these as pure monetary policy channel versus central bank information channel (e.g. Romer and Romer 2000, Jarociński and Karadi 2020, Miranda-Agrippino and Ricco 2021).[2]

Our paper disentangles these two channels by using changes in interest rate expectations not only around FOMC announcements but also around macroeconomic data releases. We use both types of events in order to distinguish between the information component and the pure monetary policy shock component in the same VAR framework. We aim to obtain pure monetary policy shocks that are clean of central bank information and, therefore, can be directly compared with monetary policy shocks in standard models.

When macroeconomic data are released, this information becomes public and markets parse out how the Federal Reserve will change monetary policy in response to the new data. Thus, market interest rates at maturities covering the subsequent FOMC meetings react immediately and unveil the typical reaction of monetary policy to developments in the economy. These macroeconomic data release dates offer two important advantages for disentangling the pure monetary policy and central bank information channels. First, these release days are pre-determined and usually do not overlap with FOMC meetings.[3] Therefore, the movements in interest rates are due to the expected policy response to the data release itself; that is, we identify the endogenous (systematic) component of monetary policy. Second, a macro release day helps identify the effect of such information becoming public, and it is precisely this information effect that we are interested in. For instance, if a release announces that GDP is higher than expected, it is not because productivity jumped on that particular day; rather, productivity already was higher but this information has become public. Therefore, the macro release day can isolate the effect of this information becoming public, which is analogous to the effect of the central bank's private information about the economy

[2]Analogously, the Odyssean and Delphic terminology is used in the context of forward guidance at the zero lower bound and the commitment issues that arise in that context. For a discussion, see Campbell et al. (2012), Bodenstein, Hebden, and Nunes (2012), Del Negro, Giannoni, and Patterson (2012), and Andrade et al. (2019).

[3]Some data releases coincide with FOMC meetings, and we exclude those from our analysis.

becoming public. Using the interest rate surprises on macro release days, we can identify an information shock and use this shock to purge the information component from interest rate surprises on FOMC announcement days, leaving only the pure monetary policy shock.

Using the *interest rate* movements, rather than the macroeconomic data releases surprises themselves, has several advantages. First, this allows for time-variation in the underlying interest rate policy rule. In other words, the Fed may be more or less reactive at certain points in time and as such it is important to allow a flexible relationship between macroeconomic data and interest rate movements. Second, instead of focusing on subjective surveys and their participants, the interest rate surprises more accurately reflect the thinking and expectations of financial market participants, namely the same individuals whose expectations are captured in measures of interest rate surprises around policy announcements. Third, since we aim to clean the interest rate surprise in FOMC days, it is more natural to immediately use an interest rate movement analog on macroeconomic data releases days. By using these interest rate movements during macroeconomic announcement releases in an external-instruments VAR, we can decompose monetary and information shocks that occur with FOMC policy announcements.

Our results imply that interest rate surprises around FOMC announcements have both a pure monetary policy shock and an information shock confounded within them. After the two components are separated, the estimated effects of the pure monetary policy shock are more pronounced than the estimated response to the composite overall FOMC announcement interest rate surprise. We find that a properly identified contractionary monetary policy shock leads to lower inflation, lower economic activity, lower stock prices, and higher bond risk premia, with all of these effects being fairly precisely estimated. The information shock that manifests as a positive interest rate surprise leads to higher prices, higher activity, and dampened responses of bond risk premia and stock prices.

Literature Review — Our paper is related to the literature using interest rate futures and financial data to identify monetary policy shocks. This approach was introduced by Kuttner (2001), Cochrane and Piazzesi (2002), Bernanke and Kuttner (2005), and Gürkaynak, Sack, and Swanson (2005a,b), among others.[4] More recently, Gertler and Karadi (2015), Campbell et al. (2017), Nakamura and Steinsson (2018), and Paul (2020) extended this type of analysis by embedding the framework into VARs, making use of more financial data, examining the effects on more variables, and estimating effects over different subsamples.[5]

The literature examining the effect of various macroeconomic announcements on financial markets and the economy is vast (for example, Boyd, Hu, and Jagannathan 2005; Gürkaynak, Sack, and Swanson 2005b; Andersen et al. 2007; Faust et al. 2007; Savor and Wilson 2013; Tang 2017; Gürkaynak, Kisacikoglu, and Wright 2020; Bauer and Swanson 2023, among others). We contribute to this literature by introducing the use of interest rate movements around these events, not the surprises in the macro announcements themselves, to flexibly identify the effects of exogenous shocks to information through the systematic component of monetary policy.

Our work is also related to the empirical literature on information asymmetry between the central bank and private agents. Romer and Romer (2000) show compelling evidence that the Federal Reserve may have more updated, private information on the economy and that the private sector may try to infer such information. Barakchian and Crowe (2013) show evidence that the public can use FOMC policy actions to infer the Federal Reserve's private information. Ellingsen and Soderstrom (2001), Tang (2015), Mertens (2016), and Melosi (2017) provide theoretical models that explore the information channel (also referred to as the signaling channel).[6]

[4]Rudebusch (1998) also proposed using futures data to measure monetary shocks.

[5]Ozdagli (2018) examines the effects on the cross section of firms. Hamilton, Pruitt, and Borger (2011) estimate directly the policy rule that agents use to form their expectations by linking the effects of news on forecasts of both economic conditions and monetary policy. Gilchrist, López-Salido, and Zakrajšek (2015) and Caldara and Herbst (2019) further stress changes in corporate credit spreads and borrowing costs in the transmission of monetary policy.

[6]Blinder et al. (2008) provide an excellent survey on central bank communication. Hansen and McMahon (2016) and Lunsford (2020) examine the linguistic aspects of central bank announcements. Lunsford (2020) and Stavrakeva and Tang (2021) identify periods during which information shocks were prominent, namely the early 2000s and the Great Recession, respectively. See also Mankiw and Reis (2010) and Gaspar, Smets, and Vestin (2010) for a review of models of imperfect information.

Several recent papers provide empirical methods for separating information and monetary policy shocks. Cieslak and Schrimpf (2019), Jarociński and Karadi (2020), Andrade and Ferroni (2021) use sign restrictions to disentangle the two shocks. Unlike this literature, we do not impose any sign restrictions on stock prices' reaction to information shocks because such a restriction is not a clear implication of the theory and the empirical literature has not yet found a consensus.[7] In a parallel strand of literature, Miranda-Agrippino and Ricco (2021) project the high-frequency surprises on observable measures of central bank information to obtain a pure monetary policy surprise.[8] These works are complementary to ours, and our work differs from them by making use of the information content of macro releases.[9]

The remainder of the paper proceeds as follows. In Section 2, we describe the identification method and the data. Section 3 presents the estimated impulse responses along with some robustness checks. Section 4 concludes.

2 Identification Method

This section describes how we estimate responses to FOMC information shocks and monetary shocks using a VAR identified with high-frequency external instruments. To start, consider the following expression describing the behavior of policy rates:

$$i_t = \phi_t' X_t + \varepsilon_t^m. \tag{1}$$

The first term $\phi_t' X_t$ reflects the systematic policy response to a set of economic fundamentals X_t. The coefficients ϕ_t can be constant but can also change over time due to the zero lower

[7]Theoretically, the net effect of a rate hike revealing positive economic news could be positive or negative for stock prices due to competing effects on discount rates and cash flows. Accordingly, empirical studies on stock price responses to information shocks and monetary policy shocks have been shown to be of ambiguous sign or to be state-dependent (Boyd, Hu, and Jagannathan 2005; Galí 2014; Galí and Gambetti 2015; Lakdawala and Schaffer 2019; Yaron, Law, and Song 2019; Gardner, Scotti, and Vega 2021).

[8]See also Thapar (2008), Barakchian and Crowe (2013), and Lakdawala (2019) for works using central bank's information and forecasts. Altavilla et al. (2019) use factor analysis to measure monetary policy and quantitative easing in the euro area.

[9]Section 2.2 contains more in-depth discussion comparing our method with the ones that use central bank forecasts.

bound, the Fed changing its preferences when faced with the data, or conditional dependence of ϕ_t on X_t.[10] The fundamentals X_t driving the systematic response can include indicators of current or past economic outcomes or current assessments of future fundamentals. The second term is an exogenous shock to the policy rate that is orthogonal to the systematic response. According to standard theories, a positive shock to ε_t^m should have a contractionary effect on the economy, while a positive shock to beliefs about the economic fundamentals in X_t would have an expansionary effect for empirically plausible policy rate reaction functions.

Some of the earliest works using high-frequency identification estimate the response of economic variables to the shock ε_t^m by studying changes in expected policy rates that are measured in tight windows around FOMC announcements.[11] Because it's measured around the announcement of a policy decision, the policy shock ε_t^m is certainly reflected in these high-frequency interest rate surprises. This identification assumes, crucially, that these interest rate surprises do not also contain a change in beliefs about the systematic response component of policy, $\phi_t' X_t$, or the so-called information component of interest rate surprises. Despite the measurement of these surprises in a tight window around FOMC announcements, the interest rate surprises can contain an information component if financial market participants interpret the announcement itself as revealing FOMC's private information about the economic fundamentals X_t. Even if the FOMC is not perceived to have an informational advantage over the market as a whole, the announcement can still impact market participants' beliefs through two channels. One is by serving as a public signal that coordinates individuals' dispersed information. Another is by influencing how market participants interpret other publicly available information, including past information.[12] Indeed, several recent papers present evidence suggesting that this information component is present in the form of estimated responses to interest rate surprises that are opposite of those predicted by

[10] Our sample includes the zero lower bound period and also periods where monetary policy was explicitly made conditional on the data as reflected in the Federal Reserve Press release of December 12, 2012. See also Engen et al. (2012).

[11] See Kuttner (2001), Bernanke and Kuttner (2005), and Gürkaynak, Sack, and Swanson (2005a). Gertler and Karadi (2015) and Nakamura and Steinsson (2018) are two more recent examples.

[12] See Tang (2017) and Schmanski, Scotti, and Vega (2023).

theory.[13]

Earlier literature attempted to isolate ε_t^m by using the part of interest rate surprises that is orthogonal to changes in central bank forecasts and/or private forecasts (see Campbell et al. 2017; Miranda-Agrippino and Ricco 2021). This approach presumes that FOMC announcements accurately communicate central bank forecasts to markets. Another strategy for dealing with this issue, proposed by Jarociński and Karadi (2020), is to use both interest rate surprises and stock price changes over the same narrow windows around FOMC announcements in combination with sign restrictions to separately identify the effects of monetary shocks and the information component of interest rate surprises. One potential concern with this approach is that it requires the assumption that a positive information shock increases stock prices. Standard theory does not imply that this would necessarily be the case, because even if there is a positive effect of good news about economic fundamentals on expected future dividends, the positive reaction of the policy rate also increases the discount rate for those dividends.

Our proposed identification strategy does not rely on these assumptions. Instead it relies on the fact that the monetary shock, ε_t^m, does not occur on the dates of macroeconomic news.[14] With this assumption, we can use changes in expected policy rates measured around major macroeconomic news events—specifically, data releases for important economic variables—as external instruments to identify changes due to the systematic component of monetary policy on FOMC announcement days. Note that our instrument is not the change in economic fundamentals but instead the change in the interest rate, which, to a first-order approximation, is:

$$\Delta_D i_t = \phi_t' \Delta_D X_t + \Delta_D \phi_t' X_t, \tag{2}$$

where i_t is a market interest rate, the operator Δ_D refers to the change in the event window

[13] See Campbell et al. (2012), Tang (2015), Nakamura and Steinsson (2018), and Stavrakeva and Tang (2021), among others.

[14] Though there are some FOMC announcements that occur on dates of important macroeconomic news, we exclude these dates from our analysis so that this assumption holds over our sample.

around the macro-data release. The advantage is that macro data news, $\Delta_D X_t$, are translated into interest rate changes based on the monetary policy coefficients at that specific time, ϕ_t, thus allowing for different coefficients in different time-periods in the sample. A second advantage is that by using $\Delta_D i_t$, we measure directly the movements in financial markets whose participants have skin in the game. If we had used $\Delta_D X_t$, we would need to rely on *subjective* survey responses of what is generally a different set of individuals. Finally, to the extent that ϕ_t' may change endogenously with the state of the economy, we capture changes in ϕ_t that are correlated with changes in X_t, as shown in the last term of equation (2). Notably, our instrument does not contain orthogonal changes in ϕ_t, which may have a different impact on the economy than shocks to beliefs about X_t. Our approach is a safe and clean methodology to account for information effects, allowing time-variation in the monetary policy reaction function.

This approach then allows us to isolate the effects of FOMC information shocks from the effects of pure monetary shocks, both of which enter into interest rates surprises around FOMC announcements. When the FOMC decides on monetary policy, it also releases a statement mentioning the economic data and its interpretation. Since we know exactly how markets react when there are macro data announcements, we can parse out the economic response in FOMC days and therefore disentangle the monetary policy shock ε_t.

To be more precise, we estimate a structural VAR that contains both macroeconomic and financial variables. The reduced form of the VAR is:

$$y_t = \lambda_1 y_{t-1} + ... + \lambda_p y_{t-l} + u_t,$$

where the residuals u_t are mean zero with covariance matrix $\Sigma \equiv E\left[u_t u_t'\right]$. These reduced-form residuals are linear in the structural shocks,

$$u_t = [B_p \quad B_q][\varepsilon_t^{p\prime} \quad \varepsilon_t^{q\prime}]',$$

where we've partitioned the shocks into a 2-element vector, ε_t^p, which contains our FOMC information and monetary shocks, and a vector of the remaining shocks ε_t^q. In order to identify the effects of the shocks ε_t^p, we need to obtain estimates of B_p.

To do so, we use a method that relies on two main assumptions, motivated by the discussion above:

1. We have a vector of two instrumental variables Z_t that satisfies the relevance and exclusion conditions of being correlated with the shocks of interest ε_t^p and uncorrelated with the remaining shocks ε_t^q:

$$E\left[Z_t \varepsilon_t^{p\prime}\right] = \psi \quad (3)$$

$$E\left[Z_t \varepsilon_t^{q\prime}\right] = 0 \quad (4)$$

2. The monetary shock is not correlated with one of the instrumental variables Z_t; in our case, the interest rate surprises on macro news announcement dates. Accordingly, ψ contains one zero element and becomes triangular.

These two assumptions are sufficient for us to recover an estimate of B_p based on estimates of $E\left[Z_t u_t'\right]$ and Σ.[15] In fact, we show in Appendix A that, with a standard normalization of the shocks so that they have a unitary contemporaneous effect on one of the variables in the VAR, the estimates for B_p can be obtained from IV regressions involving the reduced-form residuals, analogous to the case of a single shock in Gertler and Karadi (2015) or Miranda-Agrippino and Ricco (2021).

More specifically, suppose that, without loss of generality, we arrange the structural shocks, instrumental variables, and VAR variables such that (1) the first shock is the information shock and the second is the monetary shock, (2) $Z_{1,t}$ is the instrument that is uncorrelated with the monetary shock, and (3) $y_{1,t}$ is the variable upon which the shocks have a contemporaneous effect of 1. Then the response of variable $j \neq 1$ to the information shock is given by the following IV estimates of reduced-form residual j regressed on the first

[15] Another paper that uses a similar method of identifying two shocks with two instruments is Lakdawala (2019).

residual instrumented by $Z_{1,t}$:

$$B_{j1} = \frac{E\left[Z_{1,t}u_{j,t}\right]}{E\left[Z_{1,t}u_{1,t}\right]}.$$

This is analogous to the case of a single shock in Gertler and Karadi (2015).

The response of variable j to the monetary shock is given by the following IV estimates of reduced-form residual j regressed on the first residual now instrumented by a transformed instrumental variable $\tilde{Z}_{2,t}$ that is $Z_{2,t}$ purged of the identified information shock:

$$B_{j2} = \frac{E_t\left[\tilde{Z}_{2,t}u_{j,t}\right]}{E_t\left[\tilde{Z}_{2,t}u_{1,t}\right]} \quad \text{where } \tilde{Z}_{2,t} \equiv Z_{2,t} - \frac{E\left[Z_{2,t}\varepsilon_{1,t}\right]}{E\left[\varepsilon_{1,t}^2\right]}\varepsilon_{1,t}.$$

The identified information shock itself is given by:

$$\varepsilon_{1,t} = \frac{B_1'\Sigma^{-1}}{B_1'\Sigma^{-1}B_1}u_t.$$

We now describe how we construct instrumental variables that satisfy our two main assumptions.

2.1 High-Frequency Instruments

The instrument $Z_{2,t}$ is standard in the literature, the change in the three-month-ahead federal funds rate future (FF4) in the one-hour window around scheduled FOMC announcements. This instrument captures the change in the expected average federal funds rate level over the third calendar month out from the day of the announcement, a horizon that also covers the following FOMC meeting.[16] As discussed above, this instrumental variable is correlated with both the information shock and monetary shock.

The instrument $Z_{1,t}$ is the change in the same FF4 future on the days of releases of two major labor market reports: the Bureau of Labor Statistics' monthly employment report, which contains the unemployment rate and the widely followed change in nonfarm payrolls,

[16]The choice of this particular interest rate future follows Gertler and Karadi (2015) and Jarociński and Karadi (2020). These futures also contain risk premia but Piazzesi and Swanson (2008) show that using high-frequency differences in these prices effectively cleans out risk premia, which predominantly vary at lower frequencies.

and the Department of Labor's weekly unemployment claims report.[17] To maintain our assumption that monetary shocks do not enter into interest rate surprises on these labor market news dates, we exclude days on which there were coincident FOMC announcements. Instead, the interest rate surprises that occur during these labor market announcements reflect the change in the expected policy rate as a result of new information about the economy in the form of this macro release. Importantly, despite being driven by news about other economic variables, we argue, this instrument is not correlated with other shocks to the economy, such as direct shocks to labor markets, because these announcements merely reveal information about labor market outcomes that had already occurred over the past month.

We focus on labor market news because they are the most watched indicators by financial markets, on par with FOMC announcements (see Table A1 in Appendix B). We later present results of robustness checks in which we include a wider range of macro announcements, including those for GDP, inflation indicators, business and consumer confidence indicators, and house sales (see again Table A1 for the full list).

2.2 Intuition and Comparison with Previous Literature

With the instruments defined, we can now provide some clear economic intuition for this identification strategy. Recall that the main problem faced when using methods involving high-frequency interest rate surprises around FOMC announcements to identify monetary shocks is that these surprises are contaminated by shocks to information about the systematic component of policy. Rather than using *proxies* for FOMC private information to "clean" the information shock from FOMC announcement interest rate surprises, as is done by, for example, Campbell et al. (2017) and Miranda-Agrippino and Ricco (2021), we clean an *identified* information shock out of these FOMC announcement surprises, where the information shock is itself identified using high-frequency macro announcement interest rate

[17]Note that we are not using the commonly used (survey-based) surprises in these macroeconomic data releases themselves, but rather the interest rate changes around these announcements.

surprises.

Finally, we highlight a few key aspects of this identification strategy. First, unlike the earlier literature that examines the response of variables to macroeconomic surprises, defined as the actual releases of macroeconomic variables less forecasts for those variables, we do not use these surprises in the macroeconomic variables as our instruments. Our measure instead captures the movements in market expectations of future interest rates around these announcements. And to our knowledge, this measure is not used in previous work that identifies the effects of either pure policy or information shocks.[18] This, in our view, is a more direct and flexible measure of changes in expectations of the systematic component of policy whose validity does not rely on particular assumptions about the functional form of this systematic response.

Second, our estimated responses to the information shock implicitly assume that the information shock is one dimensional in the sense that, regardless of whether the information about the systematic component of policy comes from the FOMC announcement or macroeconomic data releases, the information component part has the same effect. This implies that we are identifying the responses to exogenous changes in the systematic monetary policy response. As mentioned already, we conduct robustness exercises relative to the type of macro data releases that we include. As we will show later, the results are quite similar when different macro news days are included.[19]

Related to this last point, the information shock we identify is a broad information shock. It includes the revelation of information regarding the state of the economy in the last month. Such an information shock is not specific to the FOMC interest rate decision, but it is key in purging the information shock in FOMC days and, therefore, in obtaining a pure monetary policy shock.

[18]Ozdagli and Velikov (2020) use the change in policy expectations around inflation and employment data releases in a study of the monetary policy exposure of firms' stock prices.

[19]These results are consistent with the findings of Gürkaynak, Kisacikoglu, and Wright (2020) who find that the inclusion of a single latent factor to headline news explains essentially all yield curve variance in event windows.

3 Impulse Responses

This section summarizes the results from our benchmark VAR model and robustness tests. Our benchmark model uses the identification method discussed in the preceding section with interest rate surprises, on both FOMC announcement and labor market news dates, as instrumental variables. This VAR includes the one-year Treasury yield, the personal consumption expenditures price index (PCE) in logarithms, the industrial production index in logarithms, the excess bond premium (EBP) from Gilchrist and Zakrajšek (2012), and cumulative (dividend-inclusive) returns on the S&P 500 index in logarithm.

These last two variables summarize financial conditions in the economy. The EBP is the component of the average spread between corporate bond yields and matched-duration synthetic risk-free rates that remains after the contribution of expected default risk is removed. Accordingly, Gertler and Karadi (2015) interpret the EBP as a measure of the spread between yields on private versus public debt that is due to investor sentiment or risk appetite. Gilchrist and Zakrajšek (2012) show that the EBP has strong forecasting ability for economic activity. The reaction of stock prices to monetary policy has become a very popular research topic in macroeconomics and finance since the publishing of work by Bernanke and Kuttner (2005). Moreover, we use the responses of stock prices to the information and monetary shocks to compare our identification method with the sign restrictions in Jarociński and Karadi (2020).

We estimate the VAR at a monthly frequency with 12 lags using Bayesian methods with standard macroeconomic priors whose tightness is chosen by the procedure of Giannone, Lenza, and Primiceri (2015), as in Miranda-Agrippino and Ricco (2021).[20] We aggregate our high-frequency instruments to the monthly frequency using the method of Gertler and

[20]More specifically, this procedure uses Minnesota, sum-of-coefficients, and dummy-initial-observation priors. The hyperparameters are chosen to maximize the marginal likelihood. Giannone, Lenza, and Primiceri (2015) show that this method improves the accuracy of impulse response estimates relative to a VAR estimated with a flat (uninformative) prior.

Karadi (2015), which takes into account the timing of the surprise within the month.[21] The VAR is estimated from January 1980, while the instrument sample is only available from February 1990.

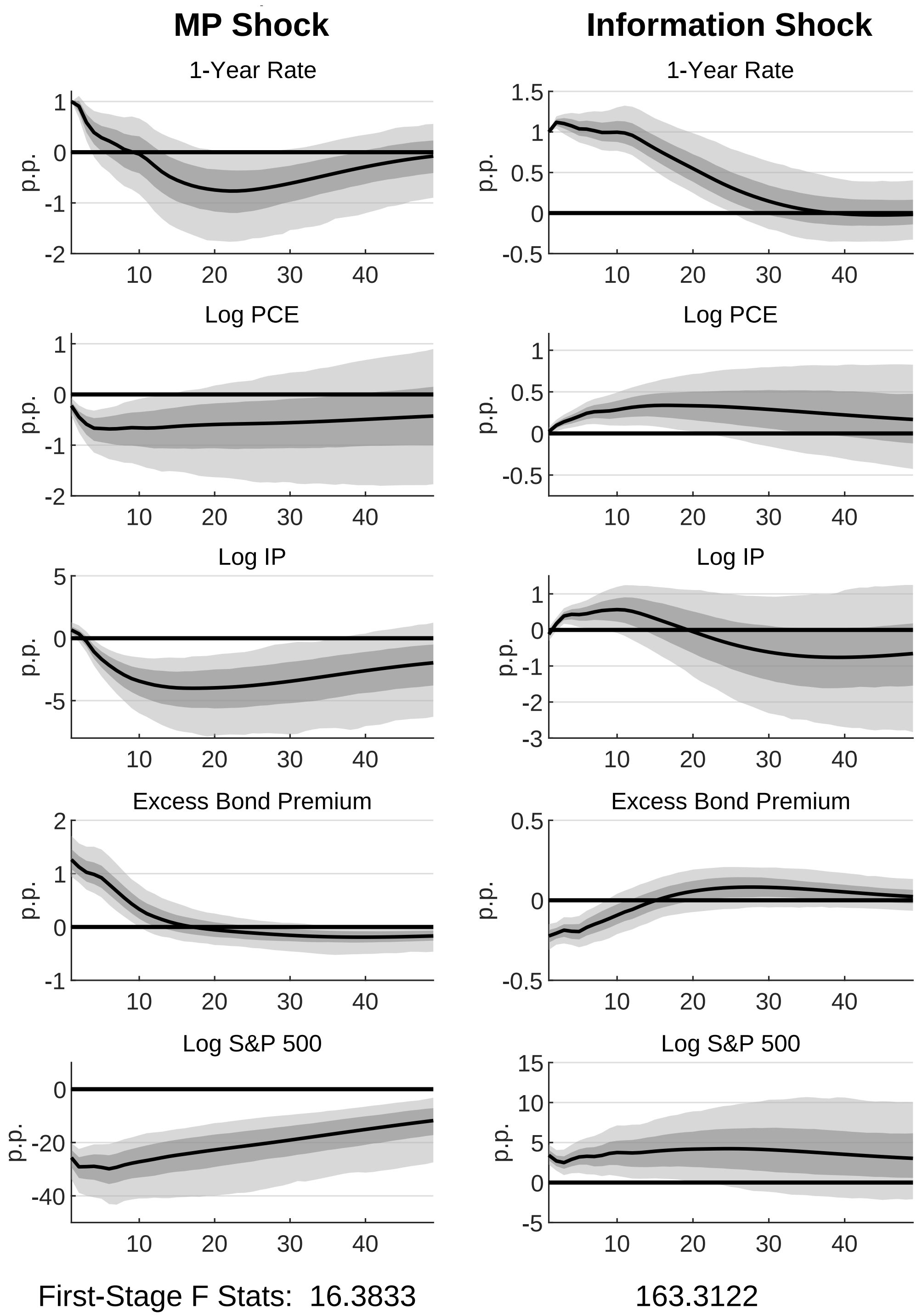
The left (right) panel of Figure 1 shows the dynamic response of the variables in our VAR to a pure policy (information) shock that increases the one-year Treasury yield by 1 percentage point. As a check to ensure that the instruments are relevant, we present the F-statistics from the first-stage regressions of the one-year Treasury yield reduced-form VAR residuals on labor-market-news interest rate surprise and the FOMC announcement surprise cleaned of the identified information shock. We find F-statistics of 16 and 163, respectively. Both of these values are higher than the threshold of 10 suggested by Stock, Yogo, and Wright (2002), thus indicating that the instruments are not weak.

Overall, these impulse responses are very intuitive: Both the pure policy shock and the information shock lead to higher short-term Treasury yields. However, their effects on other variables differ significantly. The pure policy shock decreases consumer prices and production, consistent with the conventional implications of a tighter monetary policy. The EBP increases substantially in response to a pure policy shock, which is consistent with the argument that such a shock would tighten the credit market conditions. Lastly, stock prices react very negatively to pure policy shocks, which is expected because pure policy shocks increase the discount rate and decrease future cash flows (Bernanke and Kuttner 2005).

On the other hand, the information shock reveals new positive information about the economy, which leads to increases in consumer prices and production. The EBP response is slightly negative, as the increased optimism about economic conditions more than offsets the tighter credit conditions generated by higher interest rates. Lastly, stock prices have a small positive reaction to the information shock because the negative effect of higher discount rates is slightly dominated by the higher expected future cash flows due to positive news about

[21] More specifically, the monthly surprises are an average over the month of a 31-day moving sum of daily surprises.

Figure 1: Impulse responses to monetary and information shocks



Note: Shaded areas denote posterior coverage bands for the 16th to 84th percentiles (darker gray) and the 5th to 95th percentiles (lighter gray). Responses to the information shock are identified using an instrument based on changes in the FF4 futures price on the days of labor market news (excluding days that overlap with FOMC announcements). Responses to the monetary shock are identified using an instrument based on the component in changes in the FF4 futures price over a one-hour window around FOMC announcements that is orthogonal to the identified information shock.

the economy. Note that we obtain this result without imposing the restriction of a positive stock price response to identify information shocks, the method of Jarociński and Karadi (2020).

Last, but not least, we are not assuming that the interest rate surprises on macro news dates are uncorrelated with the interest rate surprises on FOMC dates. Therefore, our approach also allows for the possibility of "Fed response to news" component described in Bauer and Swanson (2023), in which the market persistently underestimates the Fed's reaction to the economy and this underestimation leads to predictability of interest rate surprises on FOMC dates by macroeconomic news preceding the FOMC date. Nevertheless, we find that the monetary policy shock cleaned using our procedure leads to stronger IRFs relative to those cleaned using the procedure in Bauer and Swanson (2023).[22] The response of EBP is more positive, and the responses of inflation, output, and the stock market are more negative. We also find that with our FF4 measure there is no evidence that on FOMC days the market updates its beliefs of the monetary policy coefficients.[23]

3.1 Comparison with single-instrument VAR

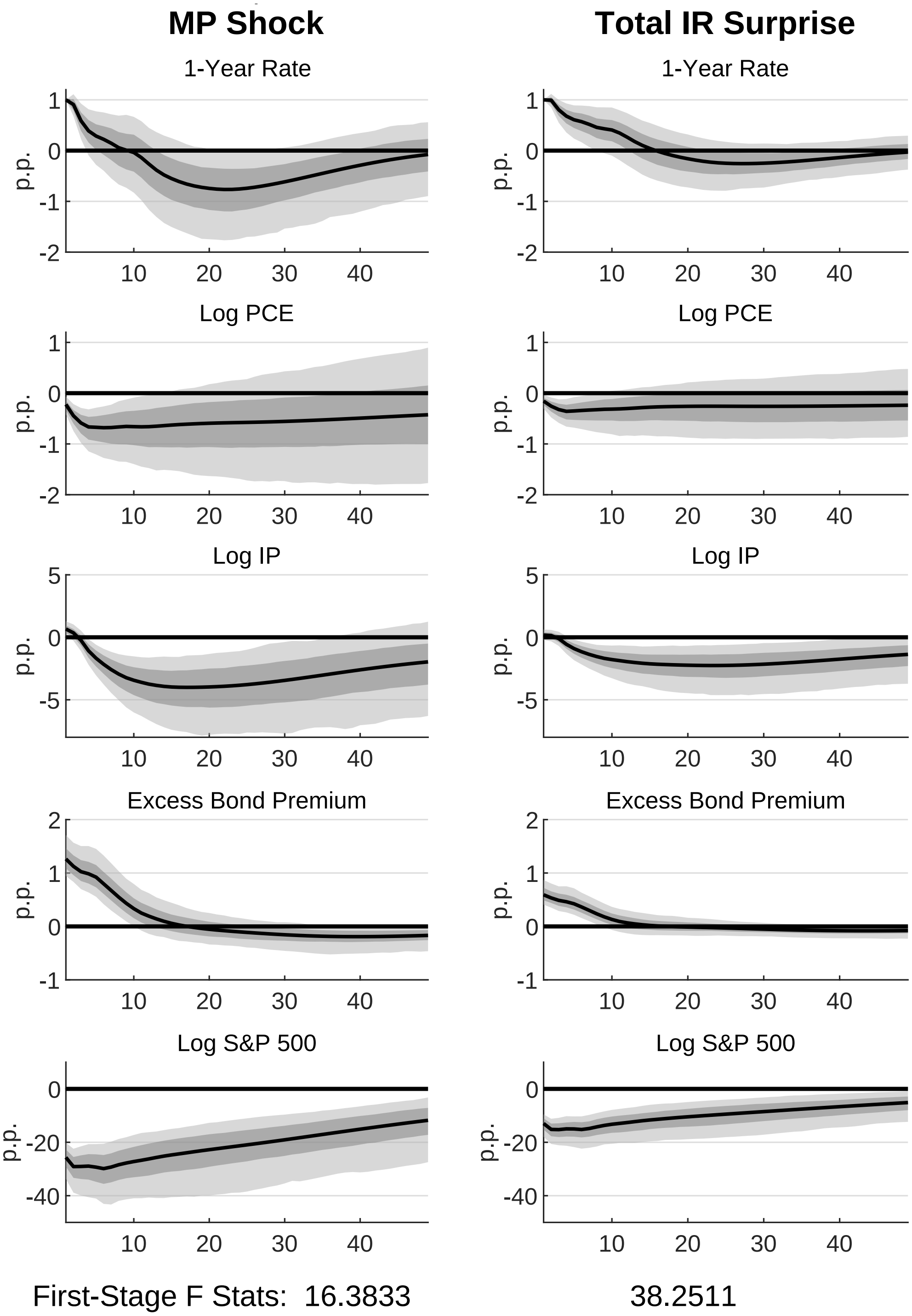
As the next step, we compare the impulse responses to the pure policy shock we have identified with the impulse responses to the overall (total) interest rate surprise, which is not purged of the information effect. The left panel of Figure 2 reproduces the effect of pure policy shock from Figure 1. The right panel of Figure 2 is the impulse response to the total interest rate surprise, calculated using the same VAR but with only interest rate surprises on FOMC announcement dates as instruments, as in Gertler and Karadi (2015).

We see that the peak effects of the pure policy shock on consumer prices, production, EBP, and stock prices are all about two times as large as the effect of the policy shock that is identified without taking the information effect into account. For example, the estimated

[22] Specifically, Bauer and Swanson (2023) use interest rate surprises on FOMC announcement dates as instruments, as in Gertler and Karadi (2015), but orthogonalize those surprises to macroeconomic news surprises preceding the FOMC announcement.

[23] Results are available upon request.

Figure 2: Comparison of impulse responses to standard external instruments identification

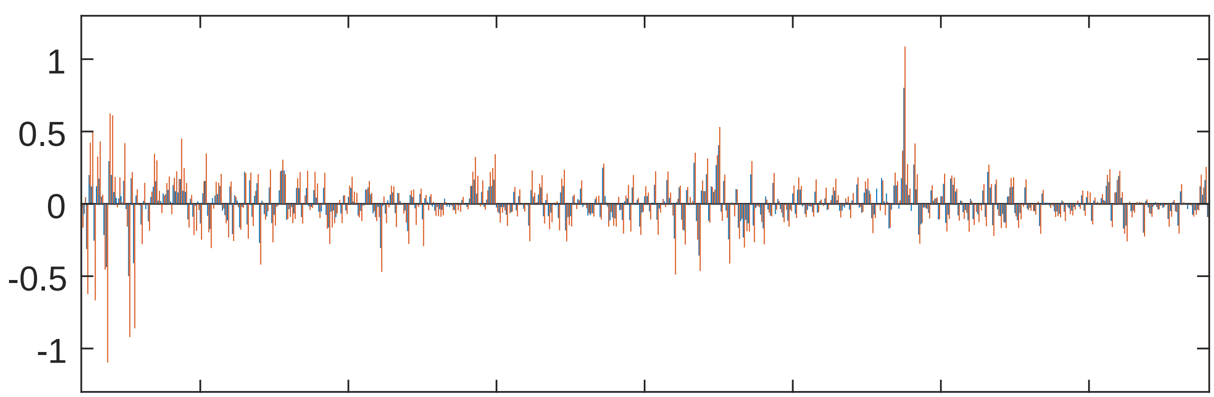


Note: Shaded areas denote posterior coverage bands for the 16th to 84th percentiles (darker gray) and the 5th to 95th percentiles (lighter gray). Responses to the (pure) monetary policy shock are identified using an instrument based on the component in changes in the FF4 futures price over a one-hour window around FOMC announcements that is orthogonal to the identified information shock. Responses to the total interest rate surprise are estimated using the overall changes in the FF4 futures price over a one-hour window around FOMC announcements as an instrument.

initial stock price response to the total interest rate surprise is a 12.9 percent decrease (bottom right panel in Figure 2). This result is in line with the results from the finance literature that uses similar high-frequency monetary policy surprises, such as Bernanke and Kuttner (2005) and Gürkaynak, Sack, and Swanson (2005a,b).[24] In contrast, the stock price decreases by more than 25 percent in response to the pure monetary policy shock we identified.

These results are in line with the recent literature that argues for the importance of the information channel of monetary policy (Ellingsen and Soderstrom 2001; Tang 2015; Mertens 2016; Melosi 2017; Nakamura and Steinsson 2018; Lunsford 2020; Stavrakeva and Tang 2021). In particular, if all of the effect of monetary policy were to operate through the conventional channels, we would see no difference in the impulse responses after accounting for the information channel. However, Figure 2 shows that the two sets of impulse responses in the left and right panels are far from identical.

Figure 3: Comparison of policy shocks to standard external instruments identification



Note: The figure compares the pure policy shock we have identified (blue bars) with the overall interest rate surprise, calculated as in Gertler and Karadi (2015), which is not purged of the information effect (orange bars). See also notes to Figure 2.

[24]These studies find that a surprise increase of 1 percentage point in the federal funds rate would reduce stock prices by about 4 to 5 percent within minutes. Ozdagli (2013) finds that such a surprise would increase the two-year (six-month) Treasury yield by about 38 (51) basis points. This implies a range of estimates in our setting with the shock normalized to move the one-year Treasury yield by 1 percentage point of (4%/0.51=7.8% to 5%/0.38=13.2%).

Figure 3 shows our pure policy shock and the total interest rate surprise, calculated as in Gertler and Karadi (2015). The figure shows that, as expected, the two shocks are highly correlated ($\rho = 0.95$). One can also observe that the magnitude of our pure policy shock is around 60% smaller. Nevertheless, the pure policy shock is not simply a rescaled version of the total interest rate shock. In particular, the information shock in our procedure is also positively correlated with total interest rate surprise of Gertler and Karadi (2015) ($\rho = 0.3$).[25] Accordingly, the effect of pure policy shocks are more than 60% larger than the effect of total interest rate surprises.

This phenomenon makes sense because our procedure disentangles the policy shock from the information component. An econometric methodology that does not properly take into account the information shock tends to partially include it inside a composite (or contaminated) monetary policy shock. The variance of such a composite monetary policy shock is overestimated and the resulting impulse response functions (IRFs) are a mix between pure policy and information shocks. Indeed, the IRFs in the right panel of Figure 2 seem to be a mixture between the pure policy and information shocks shown in Figure 1. In contrast, our refinement leads to a purified shock that is better defined and more contractionary, as shown in Figure 2.

3.2 Responses of Additional Variables

While it is customary in this literature to examine the responses of prices and activity to these shocks, a reasonable alternative VAR specification is to use a labor market variable as a measure of activity instead of industrial production, since we are using labor market news to identify the information shock. For this purpose, we examine a specification using an index of aggregate weekly hours for production and nonsupervisory employees in the private nonfarm sector (in logarithms). We choose this measure rather than a measure of

[25]Note that by construction, the pure policy and information shocks that we identify are uncorrelated, but that is not the case regarding the correlation between the total interest rate surprise and our information shock.

employment (or unemployment) since it more comprehensively captures variation in both the intensive and extensive margins of labor. Figure 4 shows that the negative response to pure monetary shocks and positive response to information shocks that we observed with industrial production are also reflected in the responses of hours.

As another check on the mechanism, we can additionally examine the response of growth forecasts, as theory predicts that these should rise with a shock delivering positive information about the economy and fall with a contractionary monetary shock. For this exercise, we use consensus (mean) one-quarter-ahead forecasts of GDP growth from *Blue Chip Economic Indicators*. Figure 5 shows that this is indeed the case.

3.3 Robustness

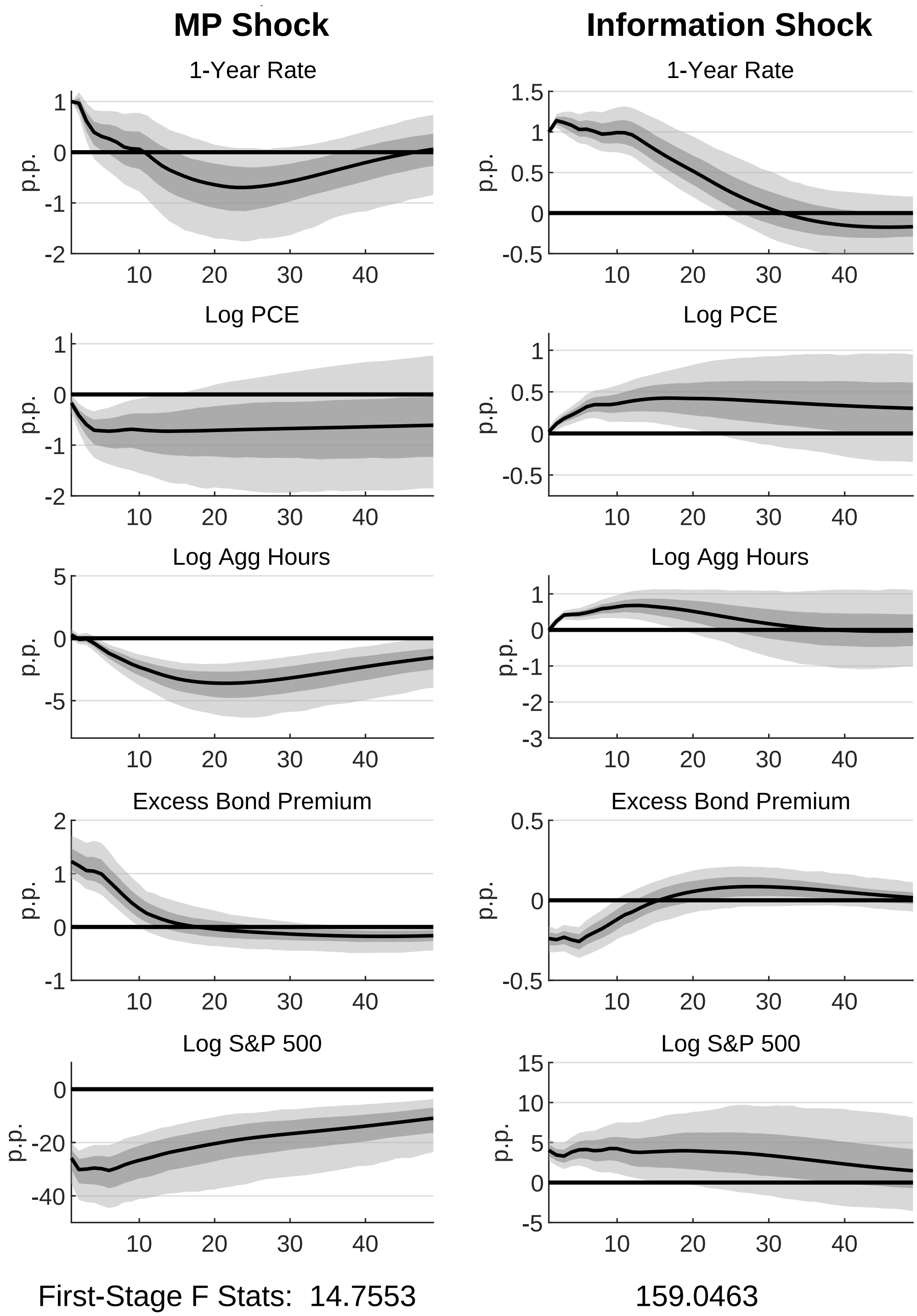
3.3.1 Using a larger set of macro announcements

Our results so far are based on the scheduled FOMC announcement dates and the dates of labor market data releases by the Bureau of Labor Statistics and the Department of Labor. Figure 6 shows our results when we use a broader set of macroeconomic news announcements detailed in Table A1 of Appendix B instead of only labor market news.[26] Using more macro news announcements effectively identifies an information shock that captures interest rate reactions to a broader array of exogenous information about the macroeconomy. We see that the effects of both the information and pure policy shocks are qualitatively similar to those reported in Figure 1. The responses to information shocks remain largely the same.

There are, however, two striking differences. First, there is more information content in these more broadly defined macro announcement interest rate surprises for the information shock, as seen in the increase in the F-statistic for this instrument from 163 to 268; and less remaining information content for the one-year yield after the (more broadly defined) information shock is purged from the FOMC announcement surprise, as seen in the fall

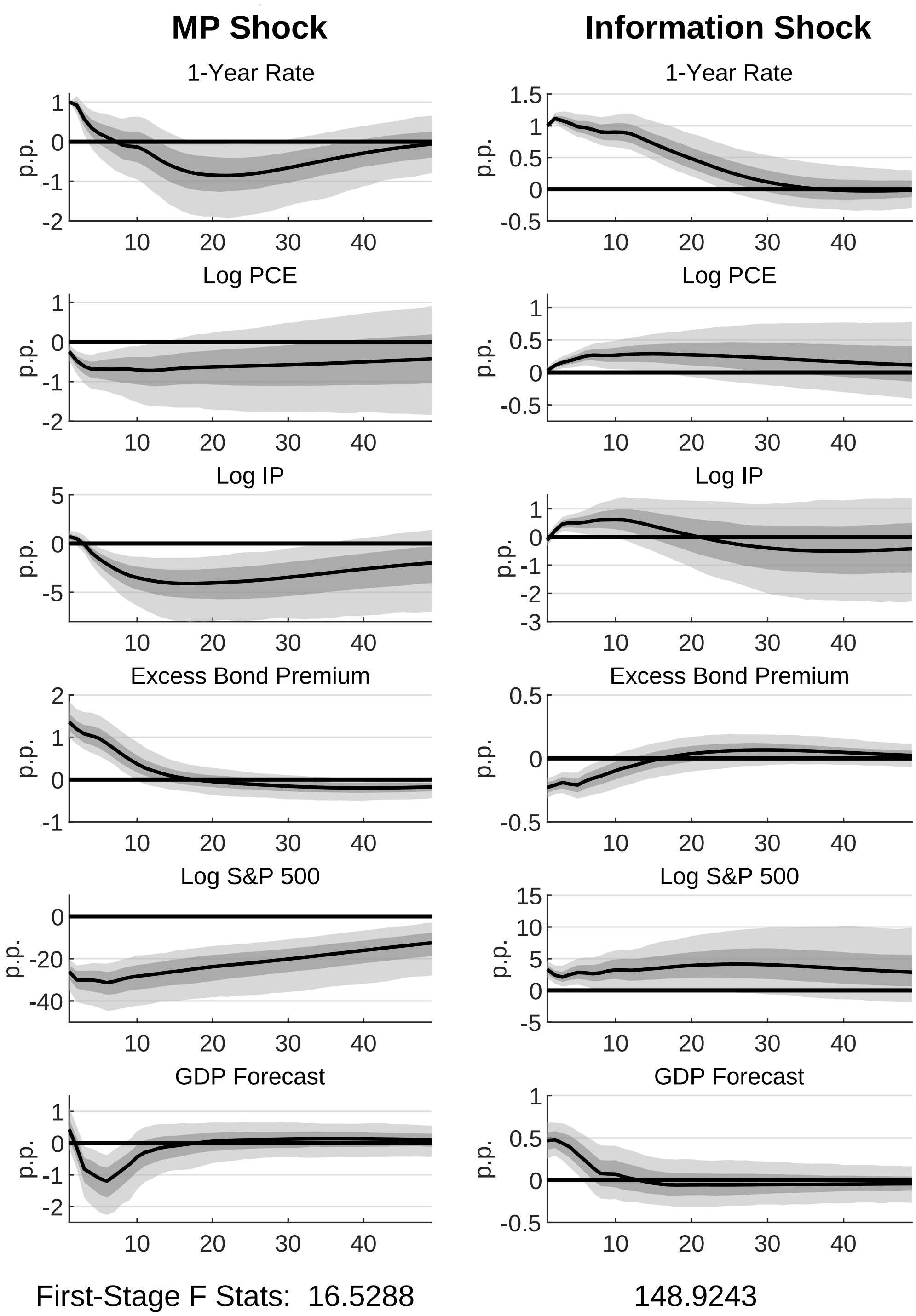
[26] Using all of the additional news announcements *except for* labor market news days leads to similar results.

Figure 4: Impulse responses to monetary and information shocks (Hours)



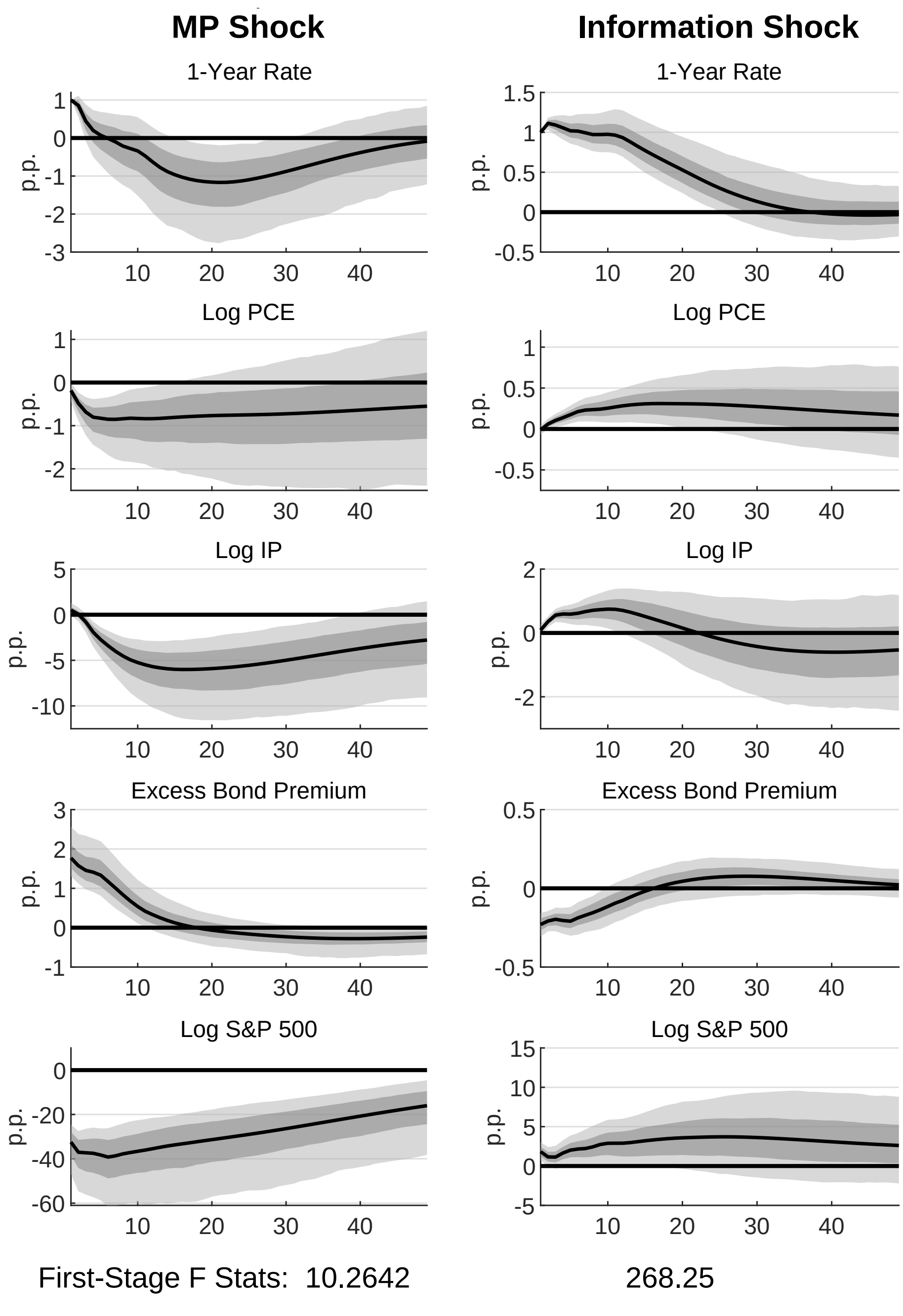
Note: Shaded areas denote posterior coverage bands for the 16th to 84th percentiles (darker gray) and the 5th to 95th percentiles (lighter gray). Responses to the information shock are identified using an instrument based on changes in the FF4 futures price on the days of labor market news (excluding days that overlap with FOMC announcements). Responses to the monetary shock are identified using an instrument based on the component in changes in the FF4 futures price over a one-hour window around FOMC announcements that is orthogonal to the identified information shock.

Figure 5: Impulse responses to monetary and information shocks (Forecasts)



Note: Shaded areas denote posterior coverage bands for the 16th to 84th percentiles (darker gray) and the 5th to 95th percentiles (lighter gray). Responses to the information shock are identified using an instrument based on changes in the FF4 futures price on the days of labor market news (excluding days that overlap with FOMC announcements). Responses to the monetary shock are identified using an instrument based on the component in changes in the FF4 futures price over a one-hour window around FOMC announcements that is orthogonal to the identified information shock.

Figure 6: Impulse responses to monetary and information shocks identified using a wider set of macro announcements



Note: Shaded areas denote posterior coverage bands for the 16th to 84th percentiles (darker gray) and the 5th to 95th percentiles (lighter gray). Responses to the information shock are identified using an instrument based on changes in the FF4 futures price on the days of labor market news in addition to the days of releases of jobless claims, advance GDP estimates, CPI, the ISM Report on Business, Conference Board Consumer Confidence, retail sales, new home sales, the Conference Board Leading Economic Index, the employment cost index, PPI, and capacity utilization (excluding days that overlap with FOMC announcements). Responses to the monetary shock are identified using an instrument based on the component in changes in the FF4 futures price over a one-hour window around FOMC announcements that is orthogonal to the identified information shock.

in the F-statistic for this instrument from 16 to 10. This weakening of the monetary shock instrument leads to larger posterior coverage bands for the estimates. However, the estimated responses to the pure monetary shocks are also now slightly larger for all variables so that a zero response remains outside the 90 percent posterior coverage band in the short or medium term.

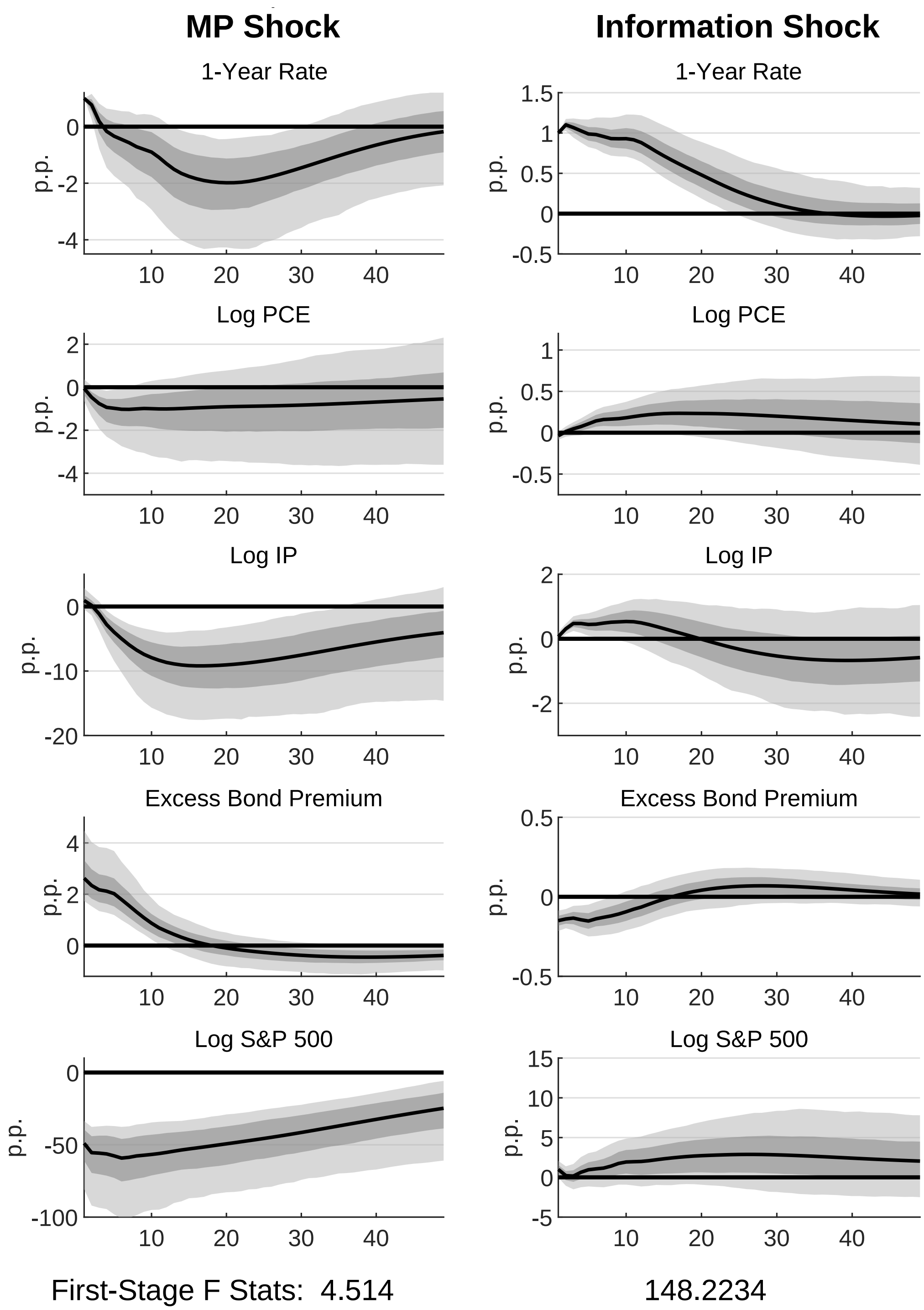
3.3.2 Using different interest rate futures

As an additional robustness check, we substitute the three-quarter-ahead euro dollar future (ED4) for FF4 when constructing our labor market news interest rate surprise in our benchmark VAR model. The results are presented in Figure 7. We see that the effects of both information shocks and pure policy shocks are again qualitatively similar to those reported in our benchmark model in Figure 1. However, as with the case involving additional macro announcements, the responses to pure monetary shocks again become larger and with wider posterior coverage bands, as the F-statistic for the (still FF4-based) FOMC announcement surprise purged of the signaling shock falls to about 4.5.

3.3.3 Excluding the Zero Lower Bound Period

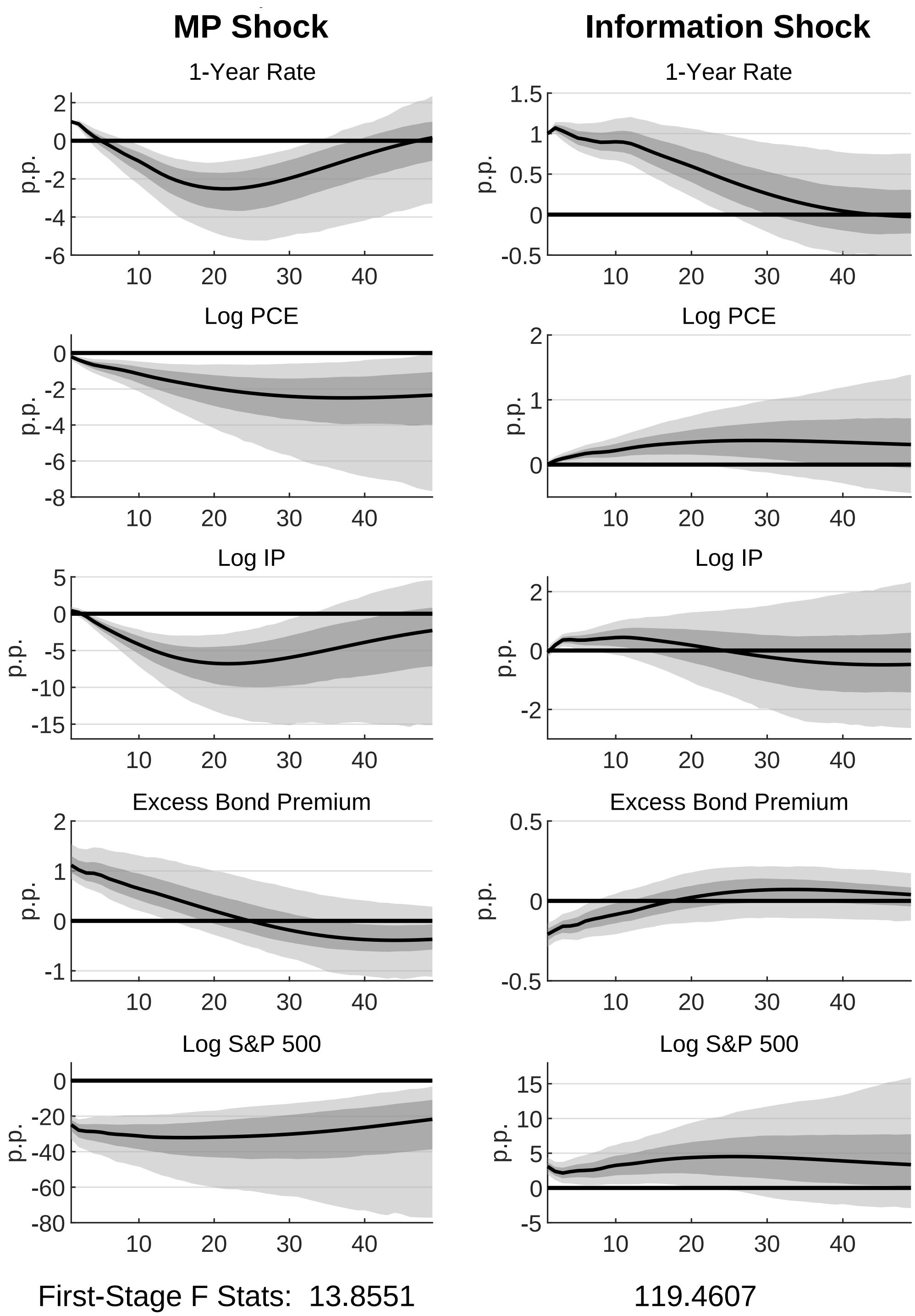
Lastly, to ensure that our estimates are not unduly influenced by the period when short-term interest rates were constrained by the zero lower bound, we exclude the December 2008–November 2015 period, when the federal funds rate target was at zero. Though excluding seven years from our sample does result in slightly less precise estimates, the results remain qualitatively the same, as shown in Figure 8.

Figure 7: Impulse responses to monetary and information shocks identified using an alternative futures contract



Note: Shaded areas denote posterior coverage bands for the 16th to 84th percentiles (darker gray) and the 5th to 95th percentiles (lighter gray). Responses to the information shock are identified using an instrument based on changes in the ED4 futures price on the days of labor market news (excluding days that overlap with FOMC announcements). Responses to the monetary shock are identified using an instrument based on the component in changes in the FF4 futures price over a one-hour window around FOMC announcements that is orthogonal to the identified information shock.

Figure 8: Impulse responses to monetary and information shocks (excluding the period from Dec 2008 through Nov 2015)



Note: Shaded areas denote posterior coverage bands for the 16th to 84th percentiles (darker gray) and the 5th to 95th percentiles (lighter gray). Responses to the information shock are identified using an instrument based on changes in the FF4 futures price on the days of labor market news (excluding days that overlap with FOMC announcements). Responses to the monetary shock are identified using an instrument based on the component in changes in the FF4 futures price over a one-hour window around FOMC announcements that is orthogonal to the identified information shock.

4 Conclusion

This paper introduces a novel method for separating the pure policy shocks and central bank information shocks that jointly enter into interest rate surprises. The key to this method is the use of high-frequency instruments that enable information shocks to be cleanly identified in isolation, which thereby allows us to parse these shocks out of high-frequency interest rate surprises. Relative to previously introduced methods, our method does not require assumptions about the signs of responses to either of these shocks nor assumptions about the nature of the central bank private information that is conveyed to the public during policy announcements.

Applying our method produces estimated responses to pure policy shocks and information shocks that are consistent with standard theories. The responses to pure policy shocks tend to be stronger than those identified using interest rate surprises without taking into account the presence of information shocks. Moreover, though we do not impose the sign restrictions used to achieve identification in some previous studies, we still find a clear positive response of stock prices to expansionary information shocks. This is consistent with the negative effects of higher discount rates (due to systematic policy response to this information) being smaller than the positive effects of higher expected future cash flows (due to good economic news).

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Appendix

A Identifying multiple shocks in an external instruments SVAR

This section provides the derivations underlying the identification scheme in our SVAR.[27] Consider the reduced-form representation of a structural VAR:

$$y_t = \lambda_1 y_{t-1} + ... + \lambda_l y_{t-l} + u_t,$$

where the reduced-form residuals are linear in a set of structural shocks,

$$u_t = B\varepsilon_t, \text{ with } \Sigma \equiv E\left[u_t u_t'\right]. \tag{5}$$

This can be written in a one-lag companion form by stacking lags of y as follows:

$$\left[\begin{array}{c} y_t \\ \vdots \\ y_{t-l+1} \end{array}\right] = \underbrace{\left[\begin{array}{ccc} \lambda_1 & ... & \lambda_l \\ I & 0 & 0 \\ 0 & I & 0 \end{array}\right]}_{\Lambda} \left[\begin{array}{c} y_{t-1} \\ \vdots \\ y_{t-l} \end{array}\right] + \left[\begin{array}{c} u_t \\ 0 \\ 0 \end{array}\right]$$

Impulse responses to shock j are determined by B_j, which is the j-th column of B. Estimates of $\{\Lambda, \Sigma\}$ can be obtained using a variety of methods including standard OLS or Bayesian estimation. The classic SVAR identification issue is that we have $E[u_t u_t'] = BB' = \Sigma$, but since this matrix is symmetric, we don't have enough equations to identify all the elements of the matrix B. Therefore, we need to impose additional restrictions to obtain the structural coefficients.

For the derivations, we partition variables and matrices into policy and non-policy blocks:

$$\varepsilon_t = \left[\begin{array}{c} \varepsilon_t^p \\ \varepsilon_t^q \end{array}\right], \quad \text{and } B = \left[\begin{array}{cc} B_p & B_q \end{array}\right],$$

$$\text{with } B_p = \left[\begin{array}{c} B_{pp} \\ B_{pq} \end{array}\right] \text{ and } B_q = \left[\begin{array}{c} B_{qp} \\ B_{qq} \end{array}\right].$$

ε_t^p and ε_t^q are our policy shocks of interest and the remaining shocks, respectively. We will apply this same partitioning convention later to other related matrices as well.

To identify the impulse responses to any of the structural shocks, ε_t, we need to identify the columns B_p of the matrix B. We use external instruments as in Mertens and Ravn (2013), Gertler and Karadi (2015), and more recently Lakdawala (2019). Let Z_t denote the set of instruments that satisfy:

$$E\left[Z_t \varepsilon_t^{p\prime}\right] = \psi \text{ and } E\left[Z_t \varepsilon_t^{q\prime}\right] = 0$$

[27] One version of this method is also outlined in Lakdawala (2019).

We denote the diagonal shock variance-covariance matrix by $\Omega \equiv E\left[\varepsilon_t \varepsilon_t'\right]$. The number of VAR equations is n. There are $n_p = 2$ policy shocks (as well as instruments) and $n_q = n - n_p$ non-policy shocks.

Note that given the conditions above, we have

$$
\begin{aligned}
E\left[Z_t u_t'\right] &= E\left[Z_t\left(B_p \varepsilon_t^p + B_q \varepsilon_t^q\right)'\right] = \psi B_p', && (6)\\
E\left[Z_t u_t'\right]\left(E\left[u_t u_t'\right]\right)^{-1} E\left[u_t Z_t'\right] &= \psi B_p' \left(E\left[\left(B\varepsilon_t\right)\left(B\varepsilon_t\right)'\right]\right)^{-1} B_p \psi' \\
&= \psi B_p' \left(B'\right)^{-1} \Omega^{-1} B^{-1} B_p \psi' \\
&= \psi \Omega_{pp}^{-1} \psi', && (7)\\
\text{since } B^{-1} B &= \begin{bmatrix} B^{-1} B_p & B^{-1} B_q \end{bmatrix} = I_n \Rightarrow B^{-1} B_p = \begin{bmatrix} I_{n_p} \\ 0_{n_q \times n_p} \end{bmatrix},
\end{aligned}
$$

where I_j denotes an identity matrix of size j, and $0_{i \times j}$ denotes a zero matrix of size $i \times j$.

Equations (6) and (7) together add up to $\frac{n_p(n_p+2n+1)}{2}$ equations with $(n+n_p)\,n_p$ unknowns. Thus, we need $\frac{n_p(n_p-1)}{2}$ additional restrictions.

Our assumption that the macro news interest rate surprise does not correlate with the monetary shock amounts to restricting one of the elements of ψ to be zero. We can then order instruments and shocks such that ψ is lower triangular. Then, $\tilde{\psi} \equiv \psi \Omega_{pp,root}^{-1}$, where $\Omega_{pp,root}$ denotes an element-wise square root of the diagonal variance matrix Ω_{pp}, will also be lower-triangular and can therefore be obtained by a Cholesky decomposition of $E\left[Z_t u_t'\right]\left(E\left[u_t u_t'\right]\right)^{-1} E\left[u_t Z_t'\right]$.

Given a solution for $\tilde{\psi}$, we can obtain the following:

$$
B_p \Omega_{pp,root} = E\left[u_t Z_t'\right]\left(\tilde{\psi}'\right)^{-1}.
$$

Lastly, we normalize the shocks so that each has a unit effect on one of the VAR variables such that B_p has a row of ones. Since $\Omega_{pp,root}$ is diagonal, the above expression becomes a system of nn_p equations with nn_p unknowns, thus allowing us to solve for the shock variances and the response matrix B_p.[28]

A.1 Historical Decomposition

Using this identification procedure, we are able to obtain the historical series of the identified structural shocks.

To see this, first note that we can obtain the variance of the j-th structural shock using

[28]It is more common in the external instruments SVAR literature to apply a slightly different unit-effect normalization such that the diagonal elements of B are ones. This alternate normalization or a unit variance normalization that scales shocks such that the diagonal elements of Ω_{pp} are just alternate ways to scale the structural shocks and, correspondingly, the impulse responses.

the following relationship:

$$
\begin{aligned}
B_j'\Sigma^{-1}B_j &= B_j'\left(B\Omega B'\right)^{-1}B_j \\
&= B_j'B'^{-1}\Omega^{-1}B^{-1}B_j \\
&= e_j'\Omega^{-1}e_j \\
&= \frac{1}{\omega_j^2},
\end{aligned}
$$

where e_j is a column selection vector with a one in the j-th position and zeros elsewhere, and we again use the fact that $B^{-1}B_j = e_j$ since $B^{-1}B = I_n$.

We can obtain the standardized structural shock as follows:

$$
\begin{aligned}
B_j'\Sigma^{-1}u_t &= B_j'\left(B\Omega B'\right)^{-1}u_t \\
&= B_j'B'^{-1}\Omega^{-1}B^{-1}u_t \\
&= e_j'\Omega^{-1}\varepsilon_t \\
&= \frac{\varepsilon_{j,t}}{\omega_j^2},
\end{aligned}
$$

and therefore,

$$
\varepsilon_{j,t} = \frac{B_j'\Sigma^{-1}}{B_j'\Sigma^{-1}B_j}u_t. \tag{8}
$$

A.2 IV interpretation

In this section, we derive the IV interpretation of our identification. We do so for our specific case of $n_p = 2$, though we note that this method can be extended to the case of more shocks. For notational simplicity and without loss of generality, we also assume that the vector of structural shocks is ordered such that our two shocks of interest are the first two; that is, $B_p = [B_1 B_2]$.

Then, using our assumption of ψ being lower triangular and our unit-effect normalizations of $B_{11} = B_{12} = 1$, we obtain the following relationship:

$$
E\left[Z_t u_t'\right] = \psi B_p' = \begin{bmatrix} \psi_{11} & 0 \\ \psi_{21} & \psi_{22} \end{bmatrix} \begin{bmatrix} B_1' \\ B_2' \end{bmatrix}. \tag{9}
$$

Focusing first on the first rows of the matrices in this expression, we have:

$$
\begin{aligned}
E\left[Z_{1,t}u_t'\right] &= \psi_{11}B_1' \\
\Rightarrow \psi_{11} &= E\left[Z_{1,t}u_{1,t}\right] \quad \text{and} \quad B_{j1} = \frac{E\left[Z_{1,t}u_{j,t}\right]}{E\left[Z_{1,t}u_{1,t}\right]}.
\end{aligned}
$$

Thus, the contemporaneous response of variable j to the first shock, B_{j1}, can be interpreted as IV estimates of the j-th reduced-form residual regressed on the first reduced-form residual instrumented by $Z_{1,t}$. This is the same as in the single shock, single instrument case, as we assume that $Z_{1,t}$ is correlated only with the first shock.

To derive the responses to the second shock, B_2, we use the second row from equation (9) and the following additional equations coming from the relationship between the variances of the shocks and reduced-form residuals.

$$\begin{aligned} E\left[Z_t u_t'\right]\left(E\left[u_t u_t'\right]\right)^{-1} E\left[u_t Z_t'\right] &= \begin{bmatrix} \psi_{11} & 0 \\ \psi_{21} & \psi_{22} \end{bmatrix} \begin{bmatrix} B_1' \\ B_2' \end{bmatrix} \Sigma^{-1} \begin{bmatrix} B_1 & B_2 \end{bmatrix} \begin{bmatrix} \psi_{11} & \psi_{21} \\ 0 & \psi_{22} \end{bmatrix} \\ &= \begin{bmatrix} \psi_{11} & 0 \\ \psi_{21} & \psi_{22} \end{bmatrix} \begin{bmatrix} \omega_{11}^{-2} & 0 \\ 0 & \omega_{22}^{-2} \end{bmatrix} \begin{bmatrix} \psi_{11} & \psi_{21} \\ 0 & \psi_{22} \end{bmatrix} \\ &= \psi \Omega_{pp}^{-1} \psi \end{aligned}$$

This relationship between symmetric matrices yields three scalar equations that give the following solutions for the variances of the two shocks and another condition involving B_2:

$$\omega_{11}^{-2} = B_1' \Sigma^{-1} B_1$$

$$\begin{aligned} \psi_{11}\psi_{21}\omega_{11}^{-2} &= \psi_{11}\left[\psi_{21} B_1' \Sigma^{-1} B_1 + \psi_{22} B_1' \Sigma^{-1} B_2\right] \\ &= \psi_{11}\psi_{21}\omega_{11}^{-2} + \psi_{11}\psi_{22} B_1' \Sigma^{-1} B_2 \\ &\Rightarrow B_1' \Sigma^{-1} B_2 = 0 \end{aligned}$$

$$\begin{aligned} \psi_{21}^2\omega_{11}^{-2} + \psi_{22}^2\omega_{22}^{-2} &= \psi_{21}^2 B_1' \Sigma^{-1} B_1 + 2\psi_{21}\psi_{22} B_1' \Sigma^{-1} B_2 + \psi_{22}^2 B_2' \Sigma^{-1} B_2 \\ &\Rightarrow \omega_{22}^{-2} = B_2' \Sigma^{-1} B_2 \end{aligned} \tag{10}$$

Combining equation (10) with the second row of equation (9) and using our solution for the first structural shock in equation (8) gives

$$\psi_{21} = \frac{B_1' \Sigma^{-1} E\left[u_t Z_{2,t}\right] - \psi_{22} B_2' \Sigma^{-1} B_1}{B_1' \Sigma^{-1} B_1} = \frac{E\left[Z_{2,t} B_1' \Sigma^{-1} u_t\right]}{B_1' \Sigma^{-1} B_1} = E\left[Z_{2,t}\varepsilon_{1,t}\right].$$

From here, we can substitute this solution for ψ_{21} into each element in the second row of equation (9) to obtain the following solutions for ψ_{22} and the remaining responses B_{j2} for

$j \in 2, ..., n$:

$$
\begin{aligned}
\psi_{22} &= E\left[Z_{2,t} u_{1,t}\right] - \psi_{21} \\
&= E\left[Z_{2,t} u_{1,t}\right] - E\left[Z_{2,t} \varepsilon_{1,t}\right], \\
B_{j2} &= \frac{E\left[Z_{2,t} u_{j,t}\right] - \psi_{21} B_{j1}}{\psi_{22}} \\
&= \frac{E\left[Z_{2,t} u_{j,t}\right] - E\left[Z_{2,t} \varepsilon_{1,t}\right] B_{j1}}{E\left[Z_{2,t} u_{1,t}\right] - E\left[Z_{2,t} \varepsilon_{1,t}\right]} \\
&= \frac{E\left[Z_{2,t} u_{j,t}\right] - E\left[Z_{2,t} \varepsilon_{1,t}\right] \frac{E_t\left[\varepsilon_{1,t} u_{j,t}\right]}{E\left[\varepsilon_{1,t}^2\right]}}{E\left[Z_{2,t} u_{1,t}\right] - E\left[Z_{2,t} \varepsilon_{1,t}\right] \frac{E_t\left[\varepsilon_{1,t} u_{1,t}\right]}{E\left[\varepsilon_{1,t}^2\right]}} \\
&= \frac{E_t\left[\tilde{Z}_{2,t} u_{j,t}\right]}{E_t\left[\tilde{Z}_{2,t} u_{1,t}\right]} \quad \text{where } \tilde{Z}_{2,t} \equiv Z_{2,t} - \frac{E\left[Z_{2,t} \varepsilon_{1,t}\right]}{E\left[\varepsilon_{1,t}^2\right]} \varepsilon_{1,t}.
\end{aligned}
$$

To obtain the final expression, we use the fact that $B_{j1} = \frac{E_t[\varepsilon_{1,t} u_{j,t}]}{E[\varepsilon_{1,t}^2]}$ based on the relationship defined in (5), and that $B_{11} = 1$ based on our unit effect normalization. Note that this final expression shows that B_{j2} is the population IV estimate of $u_{j,t}$ regressed on $u_{1,t}$ instrumented by an instrumental variable that is constructed as the residual of $Z_{2,t}$ regressed on the identified shock $\varepsilon_{1,t}$.

In other words, we can identify the first structural shock $\varepsilon_{1,t}$ using an instrument correlated only with that shock. Then using this estimate, we can purge the shock from the instrumental variable $Z_{2,t}$ that is correlated with both shocks of interest. Doing so creates an instrument that is valid for identifying the second shock of interest $\varepsilon_{2,t}$ using the same IV method as the single shock case.

Note that equation (8) yields the solution for any shock j once its response vector B_j is identified. Thus, this method can be extended sequentially to an arbitrary number of shocks as long as ψ is triangular.

This method parallels the case of assumptions that yield zero restrictions on B, which then allows internal instruments for structural shocks to be created using the reduced-form VAR residuals.

B Data details

Table A1: Macro news indicator Bloomberg relevance indices

Event	Bloomberg Ticker	Relevance Index
Change in Nonfarm Payrolls	NFP TCH Index	99.2
Initial Jobless Claims	INJCJC Index	98.4
FOMC Rate Decision	*FDTR Index*	*97.6*
GDP Annualized QoQ	GDP CQOQ Index	96.9
CPI MoM	CPI CHNG Index	96.1
ISM Manufacturing	NAPMPMI Index	95.3
Conference Board Consumer Confidence	CONCCONF Index	93.7
Retail Sales Advance MoM	RSTAMOM Index	92.9
New Home Sales	NHSLTOT Index	90.6
Unemployment Rate	USURTOT Index	89.3
Leading Index	LEI CHNG Index	83.5
CPI Ex Food and Energy MoM	CPUPXCHG Index	76.9
Employee Cost Index QoQ	ECI SA% Index	74.8
PPI Ex Food and Energy MoM	FDIDSGMO Index	66.1
Capacity utilization	CPTICHNG Index	63.9

Note: This table contains Bloomberg relevance indices for the full set of macroeconomic announcements that we consider in constructing our macro news interest rate surprise instrumental variable. The FOMC rate decision (italicized) is included for reference only and is not in our set of macroeconomic announcements. These relevance indices are the percentage of Bloomberg users that signed up for automatic notifications of the release of each macro indicator.