MICHAEL D. BAUER, ERIC T. SWANSON

A Reassessment of Monetary Policy Surprises and High-Frequency Identification

Institute for Monetary and Financial Stability
GOETHE UNIVERSITY FRANKFURT

WORKING PAPER SERIES NO. 165 (2022)

Institute for Monetary and Financial Stability
Goethe University Frankfurt
House of Finance
Theodor-W.-Adorno-Platz 3
D-60629 Frankfurt am Main
www.imfs-frankfurt.de | info@imfs-frankfurt.de

A Reassessment of Monetary Policy Surprises and High-Frequency Identification *

Michael D. Bauer
Universität Hamburg and CEPR

Eric T. Swanson
UC Irvine and NBER

March 15, 2022

Conference Draft

Abstract

High-frequency changes in interest rates around FOMC announcements are an important tool for identifying the effects of monetary policy on asset prices and the macroeconomy. However, some recent studies have questioned both the exogeneity and the relevance of these monetary policy surprises as instruments, especially for estimating the macroeconomic effects of monetary policy shocks. For example, monetary policy surprises are correlated with macroeconomic and financial data that is publicly available prior to the FOMC announcement. We address these concerns in two ways: First, we expand the set of monetary policy announcements to include speeches by the Fed Chair, which essentially doubles the number and importance of announcements in our dataset. Second, we explain the predictability of the monetary policy surprises in terms of the "Fed response to news" channel of Bauer and Swanson (2021) and account for it by orthogonalizing the surprises with respect to macroeconomic and financial data. Our subsequent reassessment of the effects of monetary policy yields two key results: First, estimates of the high-frequency effects on financial markets are largely unchanged. Second, estimates of the macroeconomic effects of monetary policy are substantially larger and more significant than what most previous empirical studies have found.

Keywords: FOMC, policy rule, monetary transmission, SVAR, external instruments

JEL Classifications: E43, E52, E58

*Draft prepared for the NBER Macroeconomics Annual Conference in Spring 2022. We thank Valerie Ramey for very helpful comments and suggestions. All remaining errors and all views expressed in the paper are ours and are not necessarily those of the individuals or groups listed above.
Bauer: michael.bauer@uni-hamburg.de, www.michaeldbauer.com.
Swanson: eric.swanson@uci.edu, www.ericswanson.org.

1 Introduction

Over the past two decades, high-frequency interest rate changes around the Federal Reserve's Federal Open Market Committee (FOMC) announcements, or *monetary policy surprises*, have become an important tool for identifying the effects of monetary policy on asset prices and the macroeconomy. For example, Kuttner (2001), Gürkaynak, Sack and Swanson (2005), Bernanke and Kuttner (2005), Hanson and Stein (2015), and Swanson (2021) use monetary policy surprises to estimate the effects of monetary policy on asset prices, while Cochrane and Piazzesi (2002), Faust et al. (2003), Faust, Swanson and Wright (2004), Gertler and Karadi (2015), Ramey (2016), and Stock and Watson (2018) use them to help estimate the effects of monetary policy on macroeconomic variables in a structural VAR or Jordà (2005) local projections framework.

Monetary policy surprises are appealing in these applications because their focus on interest rate changes in a narrow window of time around FOMC announcements plausibly rules out reverse causality and other endogeneity problems. For example, FOMC decisions are completed an hour or two before the decision is announced, implying that the FOMC could not have been reacting to changes in financial markets in a sufficiently narrow window of time around the announcement, so the asset price changes are clearly caused by the announcements themselves, rather than vice versa. For lower-frequency changes in monetary policy and asset prices, the direction of causality is generally not clear (see, e.g., Rigobon and Sack, 2003, 2004).

Monetary policy surprises are also typically viewed as being unpredictable with any publicly available information that predates the FOMC announcement. This view is supported by the standard argument that, otherwise, financial market participants would be able to trade profitably on that predictability and drive it away in the process. Thus, monetary policy surprises are plausibly exogenous with respect to all macroeconomic variables that are publicly known prior to the FOMC announcement itself, making them a valid instrument for the effects of monetary policy in structural VARs and local projections, as discussed in Stock and Watson (2018).

A few recent studies, however, have questioned whether monetary policy surprises possess these desirable properties to the extent that the litereature has typically assumed. For example, Cieslak (2018), Miranda-Agrippino and Ricco (2021), and Bauer and Swanson (2021) all document substantial predictability of monetary policy surprises with publicly available macroeconomic or financial market information that predates the FOMC announcement, with Bauer and Swanson (2021) reporting R^2 of 10–40 percent. These predictability results undermine the standard assumption that monetary policy surprises represent exogenous changes and call into question the results of the empirical studies cited above. In addition, Ramey (2016) finds that the macroeconomic effects of monetary policy are often poorly estimated in samples that begin after about 1984, likely because monetary policy was conducted more systematically over this period and thus the set of structural monetary policy shocks (estimated using high-frequency monetary policy surprises or other methods) is much smaller and less informative than for the years prior to 1984. In other words, the results in Cieslak (2018) and the other studies cited above question the *exogeneity* of high-frequency monetary policy surprises, while Ramey (2016) questions whether those surprises are sufficiently *relevant*. As discussed in Stock and Watson (2018), both conditions are required for monetary policy surprises to be a good instrument for estimating the effects of monetary policy.

In this paper, we address these challenges in two main ways. First, we improve the relevance of monetary policy surprises by substantially expanding the set of monetary policy announcement events to include press conferences, speeches, and testimony by the Federal Reserve Chair (which we will subsequently refer to as "speeches" for brevity) as well as FOMC announcements. As shown by Swanson and Jayawickrema (2021), speeches by the Fed Chair are even more important for financial markets than FOMC announcements themselves, and thus should more than double the relevance of the monetary policy variation in our analysis, relative to previous studies that focused on FOMC announcements alone. Thus, we respond to Ramey's (2016) critique by increasing the number and total variation of monetary policy announcement shocks in our sample. Moreover, Swanson and Jayawickrema extend the sample for all of these monetary policy announcements back to 1988, giving us a few more years of data during a period when monetary policy was more variable than in the 1990s, which increases the variation in our monetary policy surprise series further still.

Second, for this expanded set of monetary policy surprises, we address the exogeneity issue by removing the component of the monetary policy surprises that is predictable, following the recommendations of Bauer and Swanson (2021). In particular, we regress those surprises on the economic and financial variables that predate the announcements and have predictive power for them, and take the residuals. These orthogonalized monetary policy surprises should help to eliminate any attenuation bias or "price puzzle" types of effects in output, inflation, or other variables in a structural VAR or local projections framework, providing better estimates of monetary policy's true effects.

We thus produce a new measure of monetary policy surprises that is both more relevant and more exogenous than those used by previous researchers. We use our new measure to reassess previous empirical estimates of the effects of monetary policy on financial markets and the macroeconomy, using high-frequency event-study regressions, structural VARs, and local projections. Our reassessment leads to two main findings: First, estimates of the effects of monetary policy on financial markets with high-frequency event-study regressions are largely unchanged. The correlation of monetary policy surprises with macroeconomic and financial data that pre-date the announcements has essentially no effect on these estimates, consistent with theoretical arguments developed in the paper. Second, conventional estimates of the effects of monetary policy on the macroeconomy using high-frequency identification are substantially biased, due to the econometric endogeneity of the monetary policy surprises. Using our new, improved monetary policy surprise measure produces stronger, more plausible, and more precise estimates. In addition, our correction of monetary policy surprises uses *publicly available* data, so our results do not support the view that Fed information effects are an important confounding factor for monetary policy surprises, in contrast to Nakamura and Steinsson (2018), Miranda-Agrippino and Ricco (2021), and others.

We begin our analysis with a simple theoretical model of private-sector learning about the Fed's monetary policy rule in Section 2. The model extends an earlier model in Bauer and Swanson (2021) and helps to organize our thinking and make testable empirical predictions. In the model, the Fed's responsiveness to the economy is both time-varying and unobserved by the private sector, and the private sector must form beliefs about this parameter. A key result is that monetary policy surprises are due not only to exogenous monetary policy shocks, but also to imperfect information about the Fed's response parameter. As a consequence, monetary policy surprises can be correlated with economic variables observed priod to the policy announcements.[1] A precondition for this effect, which Bauer and Swanson (2021) termed the "Fed response to news" channel, is that the public systematically underestimated how strongly the Fed would respond to economic news. We provide empirical evidence that the Fed has become more responsive to the economy over our sample, 1988–2019, which can explain why the Fed responded more on average than the private sector expected. Additional evidence in Cieslak (2018) and Schmeling, Schrimpf and Steffensen (2021) also supports this view.[2] The model has additional implications for our subsequent empirical analysis: It predicts that monetary policy surprises can be used without correction for estimating asset price responses to monetary policy, but that they are unlikely to be valid instruments for monetary policy shocks in structural VARs or local projections.

In Section 3, we review and extend previous studies of the predictability of high-

[1]While there is *ex post* correlation between the policy surprises and economic variables predating the announcements, the monetary policy surprises were in fact unpredictable *ex ante* by financial market participants, according to this explanation. Imperfect information often leads to full-sample, *ex post* predictability even without any *ex ante* predictability (Lewellen and Shanken, 2002; Johannes et al., 2016).

[2]Bauer and Swanson (2021) show that controlling for the Fed response to news channel—by controlling for these macroeconomic and financial variables—eliminates the "Fed information effect" puzzle discussed by Romer and Romer (2000), Campbell et al. (2012), and Nakamura and Steinsson (2018).

frequency monetary policy surprises. We document strong predictability of monetary policy surprises with information that is publicly available prior to the FOMC announcements. We argue that this predictability is unlikely to be entirely driven by time-varying risk premia, since survey forecast errors for the federal funds rate are also significantly predictable using the same pre-announcement information. Instead, we aruge that a violation of the Full Information Rational Expectations (FIRE) hypothesis is a more likely explanation. Monetary policy surprises were likely unpredictable *ex ante* but predictable *ex post*, consistent with our simple theoretical model and imperfect information on the part of the private sector.

We then begin our empirical reassessment of the transmission of monetary policy to financial markets and the macroeconomy. In Section 4, we revisit high-frequency empirical estimates of the effects of monetary policy announcements on financial markets, as in Kuttner (2001) and Gürkaynak et al. (2005), using our expanded set of orthogonalized monetary policy surprises. In line with previous estimates, we find very strong effects of monetary policy surprises on Treasury yields and the stock market. A comparison of the estimates using conventional vs. orthogonalized monetary policy surprises shows that the two have very similar effects on asset prices, in line with the prediction of our theoretical model. The implication for empirical research is that standard event studies using conventional high-frequency monetary policy surprises can reliably estimate the financial market effects of monetary policy announcements.

In Section 5, we turn to high-frequency identification of the effects of monetary policy on macroeconomic variables in a structural VAR or local projections framework, as in Gertler and Karadi (2015), Ramey (2016), Miranda-Agrippino and Ricco (2021), and Plagborg-Møller and Wolf (2021). Our expanded set of monetary policy surprises greatly improves the first-stage F-statistic for our high-frequency instrument, solving one of the main difficulties faced by those earlier studies. Our orthogonalized monetary policy surprises produce estimates of monetary policy's effects that do not suffer from price or activity puzzles, and are up to four times larger than when conventional, unadjusted monetary policy surprises are used. Thus, we find substantial evidence that the econometric endogeneity of conventional moentary policy surprises used by previous authors leads to a significant bias that attenuates or even reverses the sign of their estimates. We collect lessons learned from revisiting previous empirical work and present new "best practice" estimates of the dynamic macroeconomic effects of monetary policy shocks using our orthogonalized monetary policy surprises.

We also revisit the role of the Fed's internal "Greenbook" forecasts for explaining the endogeneity of monetary policy surprises. Miranda-Agrippino and Ricco (2021) documented that Greenbook forecasts (and forecast revisions) have predictive power for monetary policy surprises, and that removing this correlation changes SVAR estimates that use these surprises as instruments for policy shocks. We show that there is nothing particularly special about the Greenbook forecasts in these results: Both in predictions of monetary policy surprises and in SVARs that use adjusted monetary policy surprises as instruments, the use of Greenbook and Blue Chip forecasts produces almost identical results. Since Blue Chip forecasts are publicly observable, our findings challenge the view that the Fed has significant private information, consistent with the findings in Bauer and Swanson (2021) that both types of forecasts are equally (in)accurate. Hence, they call into doubt the presence of strong Fed information effects and support our interpretation in terms of a "Fed response to news" channel.

In Section 6, we conclude and discuss the implications of our results for monetary policy and central bank communication in practice. For example, we address the question of whether policymakers should be concerned about information effects or other effects that might attenuate or counteract the intended effects of montary policy announcements. We also discuss what our new estimates imply about the effectiveness of policy communication in speeches by the Fed chair vs. official communication by the FOMC itself. Finally, we lay out some ideas that hold promise for future research.

Related Literature

Our work is closely related to three main strands of the literature. First, several recent studies have documented that high-frequency monetary policy surprises around FOMC announcements are in fact significantly predictable *ex post* with information that was publicly available prior to the FOMC announcement. For example, Cieslak (2018) shows predictability using the lagged federal funds rate and employment growth; Miranda-Agrippino (2017) and Miranda-Agrippino and Ricco (2021) use broad-based macroeconomic factors from a dynamic factor model; Bauer and Swanson (2021) use major macroeconomic data release surprises—such as for nonfarm payrolls, unemployment, GDP, and inflation—and changes in financial markets, such as the S&P500, yield curve slope, and commodity prices; Karnaukh (2020) uses the most recent Blue Chip GDP forecast revisions; Bauer and Chernov (2021) use option-implied skewness of Treasury yields; and Sastry (2021) uses the consumer sentiment release, recent S&P500 stock returns, and the most recent Blue Chip GDP forecast. Relative to these previous studies, we extend the predictability findings to additional predictors and an expanded sample. We also present new evidence that Blue Chip forecasts have predictive power for monetary policy surprises that is just as strong as the predictive power of the Fed's Greenbook forecasts documented by Miranda-Agrippino and Ricco (2021).

The above studies have also proposed a number of possible explanations for the predictability evidence they document. For example, Karnaukh (2020) argues that bond markets were slow to incorporate the information in the Blue Chip forecasts, although this raises the question why competition for profits by market participants wouldn't drive the sluggish response away. Miranda-Agrippino (2017) argues that there are substantial, predictable risk premia on short-term interest rate securities; however, Piazzesi and Swanson (2008) and Schmeling et al. (2021) estimate that the risk premia on such short-term securities is small, while Cieslak (2018) argues that those risk premia would need to be implausibly large to explain the observed predictability in the data and that a risk premium interpretation is inconsistent with a variety of other financial market evidence. Miranda-Agrippino and Ricco (2021) argue that the predictability is evidence of a "Fed information effect", according to which the Fed's monetary policy surprises reveal to the markets information about the Fed's forecast for the economy.[3] However, we show in this paper that Blue Chip forecasts have equally strong predictive power for those policy surprises, indicating that the Fed is unlikely to have significantly private information, and that Fed information effects may not be an important source of that predictability. Moreover, Bauer and Swanson (2021) show that the Fed's Greenbook forecasts are no more accurate than Blue Chip forecasts, that Blue Chip forecasters do not revise their forecasts in response to FOMC announcements in a way consistent with the Fed information effect, and that previous authors' results that supported a Fed Information Effect can be explained by major macroeconomic data releases and financial market changes that were omitted from those previous studies.[4] Instead, in this paper and in Bauer and Swanson (2021), we argue that the predictability of monetary policy surprises is due to financial markets not having full information about the Fed's monetary policy rule and underestimating *ex ante* how responsive the Fed would be to economic data; this interpreation of the evidence is also very similar to Cieslak (2018) and Schmeling et al. (2021). Note, however, that our analysis in the present paper does not hinge on this particular interpretation, since we investigate the practical consequences of the predictability of monetary policy surprises, no matter what the source of that predictability is.

The second strand of literature related to the present paper uses high-frequency monetary policy surprises to estimate the effects of monetary policy on asset prices. Kuttner (2001) uses daily changes in the current-month or next-month federal funds futures rate around an FOMC announcement to measure the surprises component of the announcement and the effects of changes in the federal funds rate on short- and longer-term Treasury yields, while Bernanke and Kuttner (2005) estimate the effects of those changes on the stock market. Gürkaynak et al. (2005) extend Kuttner's analysis by focusing on intradaily changes in financial markets around FOMC announcements and by looking at interest rate futures with

[3]See Romer and Romer (2000), Campbell et al. (2012), Nakamura and Steinsson (2018), and Bauer and Swanson (2021) for extensive discussions and evidence for and against the Fed information effect.

[4]Using an alternative, more model-based approach, Sastry (2021) similary concludes that there is little or no evidence of a Fed information effect in the data.

several months to maturity, allowing them to separately estimate the effects of changes in the federal funds rate from changes in FOMC forward guidance about future interest rates on bond yields and stock prices. Brand, Buncic and Turunen (2010) extend the Gürkaynak et al. analysis to the euro area, and D'Amico and Farka (2011) consider a more detailed and updated analysis of the stock market. Swanson (2021) extends the Gürkaynak et al. analysis to separately identify the effects of the Fed's asset purchases as well as forward guidance and federal funds rate changes, and Altavilla et al. (2019) apply the analysis in Swanson to the euro area. We revisit this type of analysis in Section 4, re-estimating the effects of monetary policy surprises on asset prices both with and without corrections for the predictability discussed above.

The third strand of literature related to our study uses high-frequency monetary policy surprises to help estimate and identify the effects of monetary policy on macroeconomic variables in a structural VAR or local projections framework. Early examples are Cochrane and Piazzesi (2002), Faust et al. (2003), and Faust, Swanson and Wright (2004). Stock and Watson (2012, 2018) discuss how to use high-frequency monetary policy surprises as an external instrument to identify the effects of monetary policy in a VAR, and Gertler and Karadi (2015) and Ramey (2016) follow this approach to obtain estimates that are now regarded as benchmarks. In the present paper, we reassess the VAR and local projections analysis in these studies in light of our expanded set of monetary policy surprises and our corrections for the predictability of those surprises discussed above.

2 A Simple Model with Incomplete Information

To gain intuition and guide our empirical work below, we present a simple theoretical model of incomplete information and private sector learning about the Fed's monetary policy rule. Readers who are interested only in our empirical results can skip this section and proceed directly to the beginning of our empirical analysis in Section 3.

The basic idea is that monetary policy surprises can arise from a discrepancy between the true and perceived responsiveness of the Fed to the state of the economy. For example, if the Fed is more responsive to the output gap than the public expects, then a high output gap will lead to a positive monetary policy surprise. If the private sector's underestimate persists for several periods, as will typically be the case in a model of learning, then the monetary policy surprises will end up being correlated with the output gap *ex post* even though they were unpredictable by the private sector *ex ante*.

2.1 The Simple Model

In the interest of clarity, we make the model as simple as possible, following along the lines of the model in Bauer and Swanson (2021), but extended in two ways: First, we explicitly consider the case where the parameters of the Fed's monetary policy rule may change over time; and second, we allow for changes in the interest rate to feed back directly to the economy.

For simplicity, the state of the economy in the model is captured by a scalar variable x_t. For concreteness, x_t is taken to be procyclical (e.g., the output gap). We assume that x_t follows a simple backward-looking linear process,

$$x_t = \rho x_{t-1} - \theta i_{t-1} + \eta_t, \tag{1}$$

where time t is discrete, $|\rho| < 1$ and $\theta \geq 0$ are parameters, i_t denotes the interest rate, and η_t is an exogenous $i.i.d.$ Gaussian process with mean zero and variance σ^2_η. In contrast to Bauer and Swanson (2021), we allow $\theta \neq 0$ in (1), which complicates the model but explicitly allows the interest rate i_t to affect future values of x_t. Intuitively, equation (1) is a simple, backward-looking IS curve, with the negative sign on θ corresponding to the standard intuition that higher interest rates reduce future economic activity.

Each period t is divided into two subperiods, with x_t realized in the first subperiod and i_t set by the Federal Reserve in the second subperiod. The Fed sets i_t according to the monetary policy rule

$$i_t = \alpha_t x_t + \varepsilon_t, \tag{2}$$

where α_t denotes the Fed's responsiveness to x_t, and ε_t is an exogenous $i.i.d.$ Gaussian process with mean zero and variance σ^2_ε. In contrast to Bauer and Swanson (2021), we explicitly allow the parameter α_t in (2) to be time-varying; for simplicity, we assume that it follows a random walk,

$$\alpha_t = \alpha_{t-1} + u_t, \tag{3}$$

where u_t is an exogenous $i.i.d.$ Gaussian process with mean zero and variance σ^2_u.

We assume that the Fed has full information and observes all variables and parameters of the model perfectly. The private sector knows the parameters ρ, θ, σ^2_η, σ^2_ε, and σ^2_u, and observes x_t and i_t each period, but does not observe α_t (or ε_t or u_t), and thus must form beliefs about α_t based on the history of the observed x_t and i_t. We assume that the private sector's belief formation is fully Bayesian and thus rational. We let $\mathcal{H}_t \equiv \{i_t, x_t, i_{t-1}, x_{t-1}, \ldots\}$ denote the history of variables observed by the private sector up to time t. At the beginning of period t, before x_t and i_t are realized, we assume that the private sector's prior beliefs about α_t are Gaussian with mean $a_t = E[\alpha_t|\mathcal{H}_{t-1}]$ and variance $\sigma_t^2 = \text{Var}[\alpha_t|\mathcal{H}_{t-1}]$.

Once the private sector observes x_t, it expects the interest rate to be $E[i_t|x_t, \mathcal{H}_{t-1}] = a_t x_t$. The Fed's actual interest rate decision in the second subperiod then leads to the monetary policy surprise

$$\begin{aligned} mps_t &\equiv i_t - E[i_t|x_t, \mathcal{H}_{t-1}] \\ &= (\alpha_t - a_t)x_t + \varepsilon_t. \end{aligned} \tag{4}$$

Equation (4) illustrates that monetary policy surprises can be due either to exogenous policy shocks ε_t or to imperfect information about the Fed's monetary policy rule, $\alpha_t \neq a_t$.

After observing i_t, the private sector updates its beliefs about α_t optimally using Bayesian updating (i.e., Kalman filtering):

$$a_{t+1} = E[\alpha_t|\mathcal{H}_t] = a_t + k_t mps_t, \tag{5}$$

where the Kalman gain parameter k_t is given by

$$k_t = \frac{\omega_t}{x_t}, \tag{6}$$

$$\omega_t = \frac{x_t^2\sigma_t^2}{x_t^2\sigma_t^2 + \sigma_\varepsilon^2}\,, \tag{7}$$

and

$$\sigma_{t+1}^2 = \sigma_t^2(1 - \omega_t) + \sigma_u^2. \tag{8}$$

The direction of the parameter update naturally depends upon the signs of both x_t and mps_t: The private sector will raise its belief about α_t for a hawkish surprise ($mps_t > 0$) during an expansion ($x_t > 0$), as well as for a dovish surprise ($mps_t < 0$) during a recession ($x_t < 0$).

The model in Bauer and Swanson (2021) assumed constant $\alpha_t = \alpha$, i.e., $\sigma_u^2 = 0$, for simplicity. In that case, the belief variance $\sigma_{t+1}^2 = \sigma_t^2(1 - \omega_t)$ tends to zero as $t \longrightarrow \infty$, so the private sector would gradually learn the true value of α over time. In the more general case here, the private sector can never fully learn the Fed's policy rule.

Since the updating in equations (4)–(5) is optimal, the monetary policy surprise mps_t is unpredictable *ex ante*, based on any information that is available to the private sector as of time t. This is evident from equation (4), which implies that $E[mps_t|x_t, \mathcal{H}_{t-1}] = 0$. Nevertheless, the monetary policy surprises mps_t can be correlated with x_t *ex post* if $\alpha_t > a_t$ for several periods in a row. From equation (4), $\text{Cov}(mps_t, x_t) = (\alpha_t - a_t)\text{Var}(x_t)$, which is positive if $\alpha_t > a_t$ on average over a given sample.[5] If the private sector is underestimating the Fed's responsiveness to the economy x_t, then the monetary policy surprise mps_t will be *ex post* positively correlated with a procyclical business cycle indicator such as x_t. The presence of *ex post* predictability in financial markets, despite a lack of *ex ante* predictability, is a common implication of models of imperfect information and learning by investors; for other examples, see Lewellen and Shanken (2002) and Johannes, Lochstoer and Mou (2016).

Our empirical analysis in Section 3 in fact finds a significant procyclical correlation between monetary policy surprises and macroeconomic and financial variables. Our model suggests that a straightforward explanation of this correlation is that financial markets simply underestimated how responsive the Fed would be to the economy over our sample, i.e., that $\alpha_t > a_t$ over our sample on average.

One way we could have $\alpha_t > a_t$ over our sample is if the Fed became more responsive to the economy, so that α_t increased over time. In fact, several pieces of evidence presented below are consistent with such a pattern. If α_t increases, then a logical consequence of Bayesian learning is that the private sector's beliefs a_t will tend to lag behind, and thus on average $a_t < \alpha_t$. The reason is that signals about α_t are downweighted in the update of the parameter belief, since $\omega_t \in [0, 1]$. To see this more clearly, rewrite the updating rule (5) as:

$$a_{t+1} = (1 - \omega_t)a_t + \omega_t \alpha_t + \frac{\omega_t}{x_t}\varepsilon_t. \tag{9}$$

For example, suppose that at the end of period $t = 1$, the private sector's beliefs are correct, so that $a_2 = \alpha_1$, and then the Fed becomes more responsive, so that $\alpha_2 - \alpha_1 = u_2 > 0$. Assume for simplicity that there is no policy shock, so $\varepsilon_2 = 0$. After the interest rate $i_2 = \alpha_2 x_2$ is observed, the private sector's belief update is $a_3 - a_2 = \omega_2(\alpha_2 - a_2) = \omega_2 u_2$, which is smaller than the actual parameter change, u_2. This example illustrates a general pattern: If the Fed becomes more responsive over time, then the perceived responsiveness parameter will tend to be smaller than the true parameter.

There are a number of plausible reasons to think that private-sector learning about the Fed's monetary policy rule would be quite slow in practice, with the result that changes in α_t would cause a persistently large discrepancy $\alpha_t - a_t$. First, learning about a persistent component (α_t) from a noisy time series (i_t) is difficult and happens only gradually, with long-lasting biases in beliefs; see Farmer, Nakamura and Steinsson (2021) for a recent discussion. Second, the private sector in reality faces a multidimensional learning problem: Realistic policy rules are of course multivariate, requiring the public to learn about several

[5] While mps_t would also be correlated with x_t if, on average, $\alpha_t < a_t$, the resulting negative correlation would be at odds with the procyclical correlations we document in Section 3, below.

parameters at once as well as the latent state variable, which greatly slows down the learning process (Johannes et al., 2016). Third, the private sector must form beliefs about which macroeconomic and financial variables enter the Fed's monetary policy rule, i.e., about its functional form. Fourth, the Fed's monetary policy rule could contain nonlinearities—which we have also abstracted from here—so that, in practice, the Fed responds most aggressively to the economy when the economic data is most extreme. These extreme events occur only very rarely, so it is extraordinarily difficult for the private sector to learn the Fed's true responsiveness to the economy during these rare episodes.

2.2 Empirical Support for the Model

Empirically, there is substantial evidence that the Fed's monetary policy has in fact become more responsive to the economy over the past few decades. First, a number of studies have investigated shifts in the parameters of the Fed's monetary policy rule, going back to the seminal work of Clarida, Gali and Gertler (2000), who documented a substantial increase in the Fed's responsiveness to inflation and output when Paul Volcker became Fed Chairman in 1979. Empirical monetary policy rules with explicitly time-varying parameters also generally suggest a tendency for the Fed's responsiveness to inflation and real activity to have increased since the 1980s (Cogley and Sargent, 2005; Primiceri, 2005; Boivin, 2006; Kim and Nelson, 2006; Bianchi, Lettau and Ludvigson, 2021). In Figure 1, we report results from estimating a simple time-varying moentary policy rule for the Fed, obtained using recursive, exponentially-weighted least squares estimates as described in Appendix A. There is a clear upward trend in the Fed's response coefficients to both inflation and output over the past 30 years.

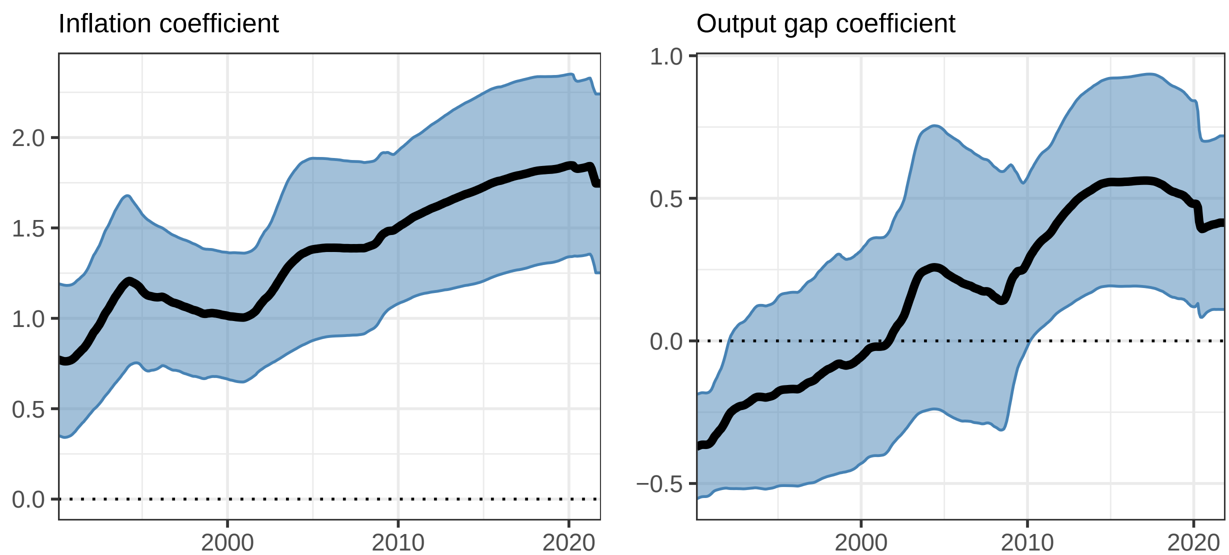
These empirical estimates are also supported by numerous speeches by Federal Reserve officials. For example:

- In 2001, Chairman Greenspan noted that "The Federal Reserve has seen the need to respond more aggressively than had been our wont in earlier decades" (Wall Street Journal, 2001).

- In 2008, Chairman Bernanke stated that "By way of historical comparison, this policy response stands out as exceptionally rapid and proactive" (Bernanke, 2008).

- In 2012, Vice Chair Yellen introduced an "optimal control" approach to monetary policy. Under this approach, which Yellen characterized as consistent with the current strategy of the FOMC, monetary policy responds more strongly to unemployment than policy rules that had characterized past Fed behavior (Yellen, 2012).

Figure 1: Recursive Least Squares Estimates of Fed Monetary Policy Rule Parameters



Exponentially-weighted recursive least squares estimates of the Federal Reserve's monetary policy rule parameters using expanding windows beginning in 1976 and ending between 1990 and 2021, with shaded two-standard-error bands based on Newey and West (1987) with 12 lags. Regressions are estimated at monthly frequency, inflation is measured using the one-year change in the log core PCE price index, and the output gap is the Congressional Budget Office estimate. See text and Appendix A for details.

- Both Chairs Bernanke and Yellen have emphasized and elaborated on a "balanced approach" to monetary policy (e.g., Bernanke, 2013; Yellen, 2017), which puts more weight on resource utilization than historical policy rules. The Fed makes this explicit in its Monetary Policy Report to Congress, which regularly compares policy rules: the coefficient on the unemployment gap in the "balanced-approach rule" is two, whereas this coefficient in the classic Taylor (1993) rule is one.[6]

It's also reasonable to think that the Fed's view of optimal monetary policy has become more responsive to the economy over time. Many prominent theoretical and empricial studies of monetary policy over the past 30 years have increasingly supported the the view that more systematic and proactive monetary policy leads to better macroeconomic outcomes (e.g. Taylor, 1999; Clarida et al., 2000; Stock and Watson, 2002; Woodford, 2009).[7]

Finally, empirical evidence from surveys provides direct support for the view that the private sector has typically underestimated the responsiveness of the Fed to the economy. In

[6] See, for example, the July 2021 Monetary Policy Report, available at https://www.federalreserve.gov/monetarypolicy/2021-07-mpr-part2.htm (accessed December 2, 2021).

[7] Changes in the Fed's preferences over economic outcomes or in the biases of its own own forecasts could also have caused monetary policy to become more responsive to the economy. For example, Lakdawala (2016) documents changes in the Fed's preferences, while Capistrán (2008) found that the Fed underpredicted inflation before Volcker and then overpredicted inflation, which would be consistent with a shifting asymmetric loss function.

particular, Cieslak (2018) and Schmeling et al. (2021) show that survey forecasts systematically underpredicted changes in the federal funds rate over our sample, particularly during easing episodes.[8]

2.3 Implications of the Model

The simple model of incomplete information and learning outlined above has a number of implications for our empirical analysis. First, as discussed above, equation (4) shows that as a result of imperfect public information about the policy rule, monetary policy surprises can be correlated with information that is publicly available prior to the FOMC announcements. This is true even if the surprises are unpredictable *ex ante* because financial markets are perfectly rational and risk premia on short-term securities are small or zero.

Second, the model suggests that the effects of monetary policy surprises on asset prices can be estimated using standard high-frequency regressions. The reason is that revisions to interest rate expectations—the only asset prices in this model—are affected by monetary policy announcements *only through* mps_t, and not separately by ε_t. To show this, we introduce new notation for the change in private-sector expectations in response to the monetary policy announcement in period t, $\Delta E_t(z) = E[z|\mathcal{H}_t] - E[z|\mathcal{H}_{t-1}, x_t]$ for expectations about a generic variable z. Bayesian updating and the fact that α_t is a martingale imply that changes in beliefs about all future rule coefficients are simply

$$\Delta E_t(\alpha_{t+n}) = k_t mps_t, \quad \text{for all } n \geq 0. \tag{10}$$

Changes in expectations of future interest rates are

$$\begin{aligned} \Delta E_t(i_{t+n}) &= \Delta E_t(\alpha_{t+n} x_{t+n}) \\ &\approx \Delta E_t(\alpha_{t+n}) E(x_{t+n}|\mathcal{H}_{t-1}, x_t) + \Delta E_t(x_{t+n}) E(\alpha_{t+n}|\mathcal{H}_{t-1}, x_t), \end{aligned} \tag{11}$$

where the first equality follows from the policy rule (2) and the fact that the policy shock ε_t is unpredictable, and the second line is a first-order approximation that simplifies the argument in the presence of an endogenous output gap ($\theta \neq 0$). In the simpler case with an exogenous output gap ($\theta = 0$), as in the model of Bauer and Swanson (2021), revisions to rate expectations are exactly equal to the first term in (11), which from (10) depends only

[8] See also the Online Appendix to Bauer and Swanson (2021), which provides related evidence on the predictability of fed funds rate survey forecast errors.

on mps_t and not on ε_t:

$$\Delta E_t(i_{t+n}) = \Delta E_t(\alpha_{t+n}) E(x_{t+n}|\mathcal{H}_{t-1}, x_t) = \rho^n \omega_t mps_t. \tag{12}$$

In the more general case, we need to account for revisions to output gap expectations, which from (1) and recursive substitution are

$$\Delta E_t(x_{t+n}) = -\theta \sum_{j=0}^{n-1} \rho^{n-j-1} \Delta E_t(i_{t+j}). \tag{13}$$

From induction on equations (11) and (13), with initial condition $\Delta E_t(i_t) = mps_t$, it is evident that the revisions $\Delta E_t(x_{t+1})$, $\Delta E_t(i_{t+1})$, $\Delta E_t(x_{t+2})$, $\Delta E_t(i_{t+2})$, and so forth, all depend only on mps_t and not separately on ε_t. That is, up to first order, a monetary policy announcement at time t changes private-sector expectations of future interest rates i_{t+n} by an amount that is a function of the surprise mps_t, with no separate role for ε_t. Accordingly, the effects of a monetary policy shock ε_t manifest themselves entirely through mps_t.

As a result, an econometrician can use high-frequency data on monetary policy surprises mps_t to estimate the effects of those surprises on the yield curve (or other asset prices) using high-frequency regressions of the form

$$\Delta E_t(i_{t+n}) = b_0 + b_1\, mps_t + e_t, \tag{14}$$

and those estimates will also be representative of the effects of an exogenous change in monetary policy ε_t. Although the high-frequency monetary policy surprises mps_t may be correlated with x_t, our model predicts that there is no omitted variable issue: Once we condition on mps_t, there is no separate role for x_t or ε_t. Thus, mps_t can still be used, without adjustment, to estimate the effects of an exogenous change in monetary policy ε_t on asset prices in a narrow window of time around an FOMC announcement. This implies that the high-frequency empirical estimates in Kuttner (2001), Gürkaynak et al. (2005), Bernanke and Kuttner (2005), and others should reliably estimate the effects of an exogenous change in monetary policy (ε_t) on the yield curve, the stock market, and other asset prices. We check this prediction of our model in Section 4, below.

A third implication of our model is that it may be problematic to use monetary policy surprises for estimation of the dynamic effects of monetary policy on macroeconomic variables in a structural VAR or local projections framework. To be a valid external instrument for a monetary policy shock, mps_t must be exogenous with respect to the other structural shocks and the lagged variables of the VAR (Stock and Watson, 2018). However, according to our model, mps_t can be correlated with x_t *ex post*, and the evidence in Section 3, below, confirms that mps_t is strongly correlated with various macroeconomic and financial variables in practice. Therefore, it is likely that the econometric exogeneity condition is violated and mps_t is not a valid instrument for the monetary policy shock.

In Bauer and Swanson (2021), we recommend orthogonalizing mps_t with respect to the macroeconomic and financial variables that are observed before the FOMC announcement to remove this correlation. According to our model, such a procedure would (i) isolate the component of mps_t that is due to the monetary policy shock ε_t; (ii) leave estimates of the effects of monetary policy on asset prices largely unchanged;[9] and (iii) increase the likelihood that the resulting series is a valid instrument for monetary policy shocks in a VAR. In Sections 4 and 5, below, we implement this correction and assess to what extent it affects empirical estimates typical of those in the literature.

3 Monetary Policy Surprises and Predictability

In this section, we present new evidence for the predictability of high-frequency monetary policy surprises around FOMC announcements, extending the results of previous studies, such as Cieslak (2018), Miranda-Agrippino and Ricco (2021), and Bauer and Swanson (2021).[10] We expand on earlier work in three main ways: First, we use a new, more extensive dataset of high-frequency monetary policy surprises from Swanson and Jayawickrema (2021). Second, we document predictive power for additional macroeconomic and financial variables, which we show to be robust across different sample periods and measures of monetary policy surprises. Third, we assess the information content in macroeconomic forecasts for subsequent monetary policy surprises, and find that the Blue Chip survey consensus and the Fed's Greenbook forecasts both contain the same amount of information. We interpret these results through the lens of our model and argue that they support the view that predictability arises from imperfect information in the private sector about the Fed's monetary policy rule.

[9] For high-frequency asset price regressions such as (14), orthogonalizing the monetary policy surprises mps_t and isolating the component due to ε_t is not necessary and may actually reduce the efficiency of the regression estimates. The reason is that, according to our model, yield changes are related to the full monetary policy surprise mps_t and not just the exogenous component ε_t.

[10] Throughout our paper, we use the term "monetary policy surprises" to denote high-frequency interest rate changes around FOMC announcements. Given the predictability of these changes, it may seem odd to speak of "surprises." However, this is standard terminology in the literature, so we stick with it. In addition, our simple model in Section 2 is consistent with the view that these surprises are unpredictable *ex ante* and that the predictability is due to imperfect information on the part of the private sector, which leads to correlation between the economy and the monetary policy surprises *ex post*.

3.1 Monetary Policy Surprises around FOMC Announcements

The Swanson and Jayawickrema (2021) dataset covers the period from 1988 to 2019, which begins earlier and ends later than the studies cited above and includes 322 FOMC announcements and 880 speeches by the Fed Chair. For comparability to previous work, we focus first on FOMC announcements.

From 1994 onward, FOMC announcement dates and times are relatively easy to collect, since each announcement was communicated clearly to the markets through a press release.[11] Prior to 1994, the FOMC typically did not issue such press releases (except after a discount rate change), and market participants had to infer whether there had been a change in the federal funds rate from the size and type of open market operation conducted by the Fed each morning. In this case, the term "FOMC announcement" corresponds to the date and time of the corresponding open market operation.[12] Swanson and Jayawickrema (2021) measure intradaily interest rate changes over a 30-minute window starting 10 minutes before each FOMC announcement and ending 20 minutes afterward, using intradaily data from Tick Data.

To construct high-frequency monetary policy surprises, some authors use the change in the current-month federal funds futures contract (e.g., Kuttner, 2001), some use the change in a farther-ahead federal funds futures contract (e.g., Gertler and Karadi, 2015), and others use a range of federal funds and Eurodollar futures contracts (e.g., Gürkaynak et al., 2005; Nakamura and Steinsson, 2018).[13] In this paper, we follow the last approach and use the first four quarterly Eurodollar futures contracts, ED1–ED4.[14] Rather than focus on two dimensions of monetary policy, as in Gürkaynak et al. (2005), we follow Nakamura and Steinsson (2018) and take just the first principal component of the changes in ED1–ED4 around FOMC announcements, which we rescale so that a one-unit change in the principal component corresponds to a 1 percentage point change in the ED4 rate. Gürkaynak et al. (2005) showed that FOMC announcements cause surprises both about the current federal

[11]From 1994 to May 1999, the absence of such a press release at 2:15pm following an FOMC meeting indicated to the markets that there was no change in the federal funds rate target. Beginning in May 1999, the FOMC began issuing explicit press releases in those cases as well. See Swanson (2006).

[12]Note that in the early years of the sample, 1988–90, changes in the federal funds rate were more frequent and there were several cases where the FOMC's decision was not immediately obvious to markets after just one open market operation. In those cases, there can effectively be two or three announcements in a row, corresponding to the consecutive days of open market operations which gradually clarified the Fed's position to the markets. See Swanson and Jayawickrema (2021) for details.

[13]Some authors have also used other measures—see Gürkaynak, Sack and Swanson (2007a) for some examples.

[14]Federal funds futures are also often included in the construction of monetary policy surprsies but are not available in Tick Data until 2010. Gürkaynak et al. (2007a) show that Eurodollar futures are the best predictor of future values of the federal funds rate at horizons beyond 6 months, and are virtually as good as federal funds futures at horizons less than 6 months.

funds rate target and the expected path of the federal funds rate for the next several months, i.e., their "target" and "path" factors. Because the first principal component is essentially equal to a weighted average of the target and path factors, it parsimoniously captures some of the main features of both types of monetary policy surprises.

3.2 Predictability with Macroeconomic and Financial Data

The literature cited earlier has documented several variables that predict upcoming monetary policy surprises. For our analysis here, we focus on macroeconomic and financial variables that were previously found by Bauer and Swanson (2021) and Bauer and Chernov (2021) to be good predictors, but we also explored a number of other variables. In all cases, we make sure that the relevant data was available to financial markets prior to the FOMC announcement itself. Our goal was to choose a parsimonious and robust set of predictors which also have an intuitive relationship to the Fed's monetary policy rule, consistent with our simple model from Section 2, above. We ultimately settled on the following six predictors:

- *Nonfarm payrolls surprise*: the surprise component of the most recent nonfarm payrolls release prior to the FOMC announcement, measured as the difference between the released value of the statistic minus the median expectation for that release from the Money Market Services survey.[15]

- *Employment growth:* the log change in nonfarm payroll employment from one year earlier to the most recent release before the FOMC announcement, as used in Cieslak (2018).

- *S&P 500*: the log change in the S&P500 stock price index from three months (65 trading days) before the FOMC announcement to the day before the FOMC announcement.

- *Yield curve slope*: the change in the slope of the yield curve from three months before the FOMC announcement to the day before the FOMC announcement, measured as the second principal component of one- to ten-year zero-coupon Treasury yields from Gürkaynak, Sack and Wright (2007b).

- *Commodity prices*: the log change in the Bloomberg Commodity Spot Price index (BCOMSP) from three months before the FOMC announcement to the day before the FOMC announcement.

[15] Prior to each major macroeconomic data release, Money Market Services conducted a survey of financial market participants to determine the market expectation for the release. The survey was continued by Action Economics and is now owned by Haver Analytics. See Bauer and Swanson (2021) for additional details.

- *Treasury skewness*: the implied skewness of the ten-year Treasury yield, measured using options on 10-year Treasury note futures with expirations in 1–3 months, averaged over the preceding month, from Bauer and Chernov (2021).

With these predictors, we estimate regressions of the form:

$$mps_t = \alpha + \beta' X_{t-} + \varepsilon_t \tag{15}$$

where t indexes FOMC announcements in our sample, mps_t denotes a measure of the monetary policy surprise, X_{t-} contains the six predictors described above (which are known prior to the announcement t, indicated by the time subscript $t-$), and ε_t is a regression residual.

The results from four different versions of regression (15) are reported in Table 1. The first column considers our baseline measure of the monetary policy surprise, described above, over our full sample of 322 FOMC announcements from 1988 to 2019. The R^2 is about 16 percent, most predictors are statistically significant, and the signs of the estimated coefficients are intuitive and consistent with the model in Section 2, with strong nonfarm payroll employment, a strong stock market, and high commodity prices predicting a hawkish monetary policy surprise. Similary, when the yield curve becomes more upward-sloping (i.e., when short-term interest rates fall relative to long-term rates, as they do during monetary easing cycles), or when implied skewness on the 10-year Treasury yield is negative (suggesting markets are most concerned about a decrease in interest rates), the Fed is likely to follow with an easing surprise.

The other three columns of Table 1 report results for alternative estimation samples and monetary policy surprises. The second column repeats regression (15) with the same data but begins the sample in 1994, when the FOMC started explicitly announcing its monetary policy decisions. The results over this sample are very similar to the first column, with an R^2 that is even a bit higher. The third column reports results for a sample period that stops in June 2007, before the financial crisis and zero lower bound period, again with similar estimates and a higher R^2. The last column shows results for a different measure of the monetary policy surprise, specifically, the change in the three-month-ahead federal funds futures contract, FF4, as used by Gertler and Karadi (2015).[16] We estimate this regression over the largest sample for which we have FF4 data, 1990:1–2019:6 (obtained from

[16] Ramey (2016) and Miranda-Agrippino and Ricco (2021) also use FF4 as their primary measure of the monetary policy surprise, for comparability to Gertler and Karadi (2015). Gertler and Karadi also take a 30-day moving average of the high-frequency monetary policy surprises to create their high-frequency external instrument; we do not do that here because, as Ramey (2016) points out, the 30-day moving average induces extra serial correlation and predictability in those surprises that is not present in the underlying high-frequency changes in FF4 itself.

Table 1: Predictive Regressions Using Macroeconomic and Financial Data

	(1)	(2)	(3)	(4)
Nonfarm payrolls	0.094	0.113	0.082	0.155
	(2.442)	(1.977)	(1.806)	(3.696)
Empl. growth (12m)	0.005	0.004	0.005	0.003
	(2.108)	(1.404)	(1.184)	(1.512)
Δ log S&P 500 (3m)	0.084	0.112	0.154	0.020
	(1.433)	(1.578)	(1.931)	(0.351)
Δ Slope (3m)	-0.010	-0.010	-0.011	-0.017
	(-1.406)	(-1.153)	(-1.049)	(-2.041)
Δ log Comm. price (3m)	0.120	0.093	0.225	0.103
	(2.392)	(1.461)	(3.527)	(1.946)
Treasury skewness	0.032	0.035	0.050	0.023
	(3.006)	(2.917)	(2.109)	(2.137)
R^2	0.161	0.173	0.192	0.163
Sample	1988:1–2019:12	1994:1–2019:12	1988:1–2007:6	1990:1–2019:6
N	322	218	216	259
Policy surprise	*mps*	*mps*	*mps*	FF4

Coefficient estimates β from predictive regressions $mps_t = \alpha + \beta' X_{t-} + \varepsilon_t$, where t indexes FOMC announcements. Columns (1)–(3) use our baseline monetary policy surprise measure *mps* described in the text, while column (4) uses the change in FF4 (also used in Gertler and Karadi, 2015). Predictors X are observed prior to the FOMC announcement: the surprise component of the most recent nonfarm payrolls release, employment growth over the last year, the log change in the S&P500 from 3 months before to the day before the FOMC announcement, the change in the yield curve slope over the same period, the log change in a commodity price index over the same period, and the option-implied skewness of the 10-year Treasury yield from Bauer and Chernov (2021). Heteroskedasticity-consistent t-statistics in parentheses. See text for details.

an extension of the Gürkaynak et al. (2005) dataset used in Bauer and Swanson (2021)). Again, the results in this column are very similar to the first three columns.

Overall, the results in Table 1 confirm the substantial predictability of high-frequency monetary policy surprises found by previous authors, for a variety of different monetary policy surprise measures and samples.

3.3 Predictability with Macroeconomic Forecast Data

In an influential recent paper, Miranda-Agrippino and Ricco (2021) (MAR) showed that the Fed's internal "Greenbook" forecasts contain substantial information that is correlated with the high-frequency monetary policy surprise around the subsequent FOMC announcement. The interpretation given by MAR is based on a Fed information effect, discussed above, whereby the monetary policy surprise reveals to the private sector information about the Fed's internal macroeconomic forecast. However, our predictability evidence in Table 1, based on publicly available information, raises the question whether one might obtain similar results if in the MAR regressions the internal Greenbook forecasts were replaced with publicly observable forecasts from the Blue Chip survey of professional forecasters. This would then suggest a very different interpretation of the MAR monetary policy surprise predictability findings.

To investigate this question, we repeat the monetary policy surprise predictability regressions in MAR, who followed Romer and Romer (2004) closely. We use exactly the same predictors as Miranda-Agrippino and Ricco: forecasts for real GDP growth and GDP deflator inflation for the previous quarter to three quarters ahead; the unemployment rate forecast for the current quarter; and forecast revisions for all three macro series for the previous quarter to two quarters ahead. As an alternative to the Fed's Greenbook forecasts, we also consider the publicly available Blue Chip consensus forecasts and forecast revisions for the exact same macro variables and forecast horizons.[17]

The results are reported in Table 2. The top panel reports results analogous to those in MAR's Table 1, using the Fed's internal Greenbook forecasts, while the bottom panel repeats the analysis using the publicy available Blue Chip forecasts instead. Each column corresponds to a different sample period, along the lines of Table 1, albeit ending in 2015 rather than 2019 because the Fed only releases its Greenbook forecast data with a five-year lag. For simplicity and brevity, in each column we report only the regression R^2 and p-value for the robust Wald test that all 23 coefficients in each regression are equal to zero.

The results in the top panel of Table 2 confirm those of Miranda-Agrippino and Ricco (2021): There is strong evidence that the Fed's internal Greenbook forecasts are correlated with the subsequent monetary policy surprises. However, the results in the bottom panel of Table 2 show that this predictability is essentially identical when we use the publicly available Blue Chip forecasts instead. Thus, the Greenbook and Blue Chip forecasts seem to contain

[17] The Blue Chip consensus forecasts are from the Blue Chip Economic Indicators survey and correspond to the arithmetic mean of the individual forecasts. The Blue Chip Economic Indicators forecasts, which we use in this analysis, are usually released on the tenth day of the month; we take the tenth day of the month as the date that the forecasts are publicly available. In recent years, the Blue Chip consensus forecast data does not include obersvations for the previous quarter when the macroeconomic data has already been released. In those cases, we add real-time data from ALFRED, see https://alfred.stlouisfed.org/. The Greenbook forecasts are publicly released with a five-year lag and are obtained from the database maintained by the Philadelphia Fed, at https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/philadelphia-data-set.

Table 2: Predictive Regressions Using Macroeconomic Forecasts

	(1)	(2)	(3)	(4)
Greenbook forecasts				
R^2	0.158	0.225	0.183	0.153
adjusted R^2	0.085	0.114	0.085	0.059
p-value	0.0003	0.0002	0.0010	0.0225
Blue Chip forecasts				
R^2	0.144	0.217	0.179	0.168
adjusted R^2	0.070	0.105	0.080	0.076
p-value	0.0058	0.0000	0.0004	0.0040
Sample	1988:1–2015:12	1994:1–2015:12	1988:1–2007:6	1990:1–2015:12
N	289	185	216	231
Policy surprise	*mps*	*mps*	*mps*	FF4

Predictive regressions for monetary policy surprises using macroeconomic forecasts and their revisions. The regressors are forecasts and forecast revisions for the same variables and horizons as in Miranda-Agrippino and Ricco (2021) (see text), using the Fed's own Greenbook forecasts in the top panel, and the consensus forecast in the Blue Chip Economic Indicators survey in the bottom panel. We use the most recent forecasts before each FOMC announcement. Columns (1)–(3) use our baseline monetary policy surprise measure *mps* described in the text, while column (4) uses the change in FF4 (also used in Gertler and Karadi, 2015). We report p-values for robust Wald tests (using White covariance estimates) of joint significance of all predictors.

very similar information for upcoming FOMC announcement surprises. This observation is also consistent with Bauer and Swanson (2021), who showed that Greenbook and Blue Chip forecasts are about equally accurate predictors of future macroeconomic data.

The implication of these findings is that the predictive power of Greenbook forecasts for policy surprises that was documented by MAR does not appear to be due to a Fed information effect. Instead, they just seem to be a reflection of the empirical pattern that we have documented above and in Bauer and Swanson (2021): monetary policy surprises are systematically correlated with macroeconomic and financial data that are publicly available prior to the monetary policy announcement.

3.4 Interpretation of the Predictability Evidence

How should we think about the predictability evidence documented above? First, note that these high-frequency interest rate changes should be unpredictable if (a) bond risk premia are zero or constant, and (b) investor beliefs satisfy the FIRE (Full Information Rational

Expectations) hypothesis.[18] We discuss deviations from each of these two assumptions in turn.

The first possible explanation for the predictability results in Table 1 is that risk premia on the underlying interest rate securities are substantial and time-varying. Indeed, Miranda-Agrippino (2017) makes exactly this arugment. Through the lens of our model in Section 2, this implies that mps_t in equation (4) should include an additional risk premium term that is time-varying and correlated with x_t. One problem with this explanation is that risk premia for these short-maturity interest rate futures seem to be relatively small (Piazzesi and Swanson, 2008; Schmeling et al., 2021). Cieslak (2018) argues that these risk premia would have to be implausibly large to explain the observed correlation in the data and that a risk premium interpretation is inconsistent with a variety of other financial market evidence.[19] Thus, we view this explanation as relatively implausible, although we cannot rule it out entirely.

Instead of arguing that risk premia on short-term interest rates are large, our preferred explanation is based on moderate deviations from the strong assumption of FIRE. Much empirical work in macroeconomics has documented that expectations—of households, firms, or investors—do not satisfy the FIRE assumption.[20] Directly relevant for our setting here, Cieslak (2018) shows that the forecast errors for the federal funds rate in the Blue Chip survey of professional forecasters are strongly predictable. The online appendix of Bauer and Swanson (2021) updates and extends this evidence, showing that close to one-fourth of the variation in federal funds rate survey forecast errors is predictable with information observed before the survey responses were collected.[21] Under the FIRE assumption, forecast errors should be unpredictable using information that is publicly observable at the time the forecasts are made. Thus, this body of evidence strongly supports the view that public expectations of the Fed's policy rate do not satisfy the FIRE assumption.[22]

A simple and plausible deviation from FIRE that can explain the predictability results in Table 1 is that the private sector has incomplete information about the Fed's monetary

[18]One way of seeing this is to note that high-frequency interest rate changes are essentially identical to negative excess returns on the underlying security, since over the very short holding period there is no material change in maturity or risk-free return. Excess returns are unpredictable when conditions (a) and (b) are satisifed. Schmeling et al. (2021) provide a recent discussion.

[19]As discussed below, Cieslak (2018) also shows that the forecast errors for the federal funds rate in the Blue Chip survey of professional forecasters are also strongly predictable with the same variables that predict the market's forecast errors, implying that risk premia cannot be the whole story.

[20]Prominent examples are Greenwood and Shleifer (2014) and Coibion and Gorodnichenko (2015).

[21]Bauer and Chernov (2021) show related evidence, using conditional Treasury skewness and the shape of the yield curve as predictors for funds rate forecast errors.

[22]Another possible explanation of our predictability results is the heterogeneous use of common information, as argued by Sastry (2021).

policy reaction function, as in our model of Section 2. Specifically, if financial markets underestimated the Fed's responsiveness to the economy, then that could explain the procyclical correlation of macroeconomic and financial variables with monetary policy surprises documented in Table 1. For further arguments in support of this explanation, see Cieslak (2018), Schmeling et al. (2021), and Bauer and Swanson (2021).

An alternative explanation of the *ex post* predictability of monetary policy surprises relies on information effects. As the learning model in Miranda-Agrippino and Ricco (2021) shows, if the Fed's announcements reveal information that the private sector uses to update its beliefs about the state of the economy, then high-frequency monetary policy surprises can be correlated with past macroeconomic data. However, the evidence above and in Bauer and Swanson (2021) suggests that the Fed does not seem to possess an information advantage concerning the state of the economy and the future economic outlook. Thus, it seems unlikely that the Fed's monetary policy announcements reveal significant new information about the economy to the private sector.

Overall, our view is that the evidence most strongly supports our story of imperfect information about the Fed's monetary policy rule. However, the exact reason for the predictability of the monetary policy surprises is not particularly important for the rest of our paper. What matters is that those high-frequency monetary policy surprises are correlated with macroeconomic and financial variables pre-dating the announcement, which has important implications for estimating the transmission of monetary policy to financial markets and the macroeconomy using these surprises. This is what we turn to next.

4 Monetary Policy Effects on Asset Prices

In this section, we estimate the effects of monetary policy announcements on asset prices. Relative to previous studies we make two contributions: First, we use a novel measure of monetary policy surprises that is *orthogonal* to macroeconomic and financial data observed before the announcement, and compare the estimates to those obtained for a conventional measure of the monetary policy surprise. Second, we consider not only policy announcements made by the FOMC but also those communicated in post-FOMC press conferences, speeches, and testimony by the Federal Reserve Chair.

4.1 The Event Study Approach

Monetary policy influences inflation and real activity through its effects on financial conditions. Changes in the current target and future expectations for the federal funds rate affect interest rates all along the yield curve, stock prices, corporate bond yields, and exchange ratesa, among other assets. A large empirical literature in monetary economics estimates the transmission of monetary policy to financial markets. Starting with the landmark studies by Cook and Hahn (1989) and Kuttner (2001), event studies have been the method of choice for such empirical analysis, due to their promise to sharply identify the causal effects of monetary policy actions on interest rates and other asset prices.[23]

These event study regressions are usually of the form

$$y_t = \alpha + \beta mps_t + \varepsilon_t, \tag{16}$$

where t indexes monetary policy announcements, y_t is an asset return or interest/exchange rate change, mps_t is a measure of the policy surprise, and both y_t and mps_t are measured over tight windows around the announcement. The idea is that the monetary policy surprise mps_t captures a monetary policy shock and we can estimate the effects of this shock on financial markets using regression (16). But accurate estimation of such causal effects on asset prices requires four crucial assumptions.

The first assumption is that there is no reverse causation, i.e., that changes in asset prices do not affect the monetary policy action (Cook and Hahn, 1989). With intradaily data and the usual 30-minute announcement windows, this assumption is very plausible: The policy decision is made, and the FOMC statement formulated, up to several hours in advance of the actual announcement via the release of the statement. It is therefore hard to argue that the FOMC decision could react in some way to asset price changes in a sufficiently narrow window of time around the announcement.[24]

The second assumption is that there are no omitted variables that are correlated with mps_t and independently affect y_t. News released during the event window on day t will generally affect y_t, but is unlikely to be correlated with the (predetermined) policy action mps_t, for the same reason as above.[25] However, information *prior to the FOMC announcement* may predict both mps_t and y_t, which would call this assumption into question. Previous event studies have generally not considered this possibility, based on the premise that high-

[23]Event studies have been used to study the effects of both conventional monetary policy (e.g. Bernanke and Kuttner, 2005; Gürkaynak et al., 2005; Hanson and Stein, 2015; Nakamura and Steinsson, 2018) and unconventional monetary policy such as forward guidance and large-scale asset purchases (e.g. Gürkaynak et al., 2005; Gagnon et al., 2011; Swanson, 2011; Bauer and Rudebusch, 2014; Bauer and Neely, 2014; Swanson, 2021). Work on unconventional monetary policy is surveyed by Kuttner (2018).

[24]This assumption is possibly more problematic with daily data. However, Cook and Hahn (1989) argue that it is likely to be satisfied even with daily data, and even before the FOMC released policy statements at predeterminted times (i.e., even before 1994).

[25]In addition, our narrow intraday announcement windows keeps the amount of other news about the economy that is released during these times to a minimum.

frequency asset price changes are unpredictable. By contrast, our simple model in Section 2 predicted that mps_t may well be correlated with macroeconomic and financial variables observed before t, and our evidence in Section 3 confirmed this. Importantly, our model also predicted that the effects on y_t would be completely captured by the monetary policy surprise, and that once we condition on mps_t there is no separate role for monetary policy shocks (ε_t in the model) or macroeconomic and financial data (x_t). Thus, according to our model, OLS estimates of β in equation (16) would not suffer from omitted variable bias.

Third, the surprise mps_t must be truly unanticipated.[26] If the regressor contains a component that is anticipated by financial market participants, and if asset prices do not respond to this anticipated component, then this will tend to make the estimated coefficient small and insignificant due to the presence of classical measurement error. Cook and Hahn (1989) regressed yield changes on the target rate change around FOMC decisions, but the target changes are partly anticipated by financial markets. The important contribution of Kuttner (2001) was to separate the unexpected from the expected component of the target rate change using federal funds futures, which allowed him to uncover strong and highly significant effects on bond yields. Many researchers have followed this approach since. The predictability of mps_t, documented in Section 3, challenges the assumption that we have completely isolated the unexpected component of the policy surprise, and it raises the possibility of measurement error. However, estimates of the asset price response will only be affected if financial markets react differently to the predicted component of the policy surprise than to the orthogonal component. Again, our model in Section 2 predicts that all components of the policy surprise should lead to the same asset price reaction, so that there is no measurement error in the classical sense, and no bias of the OLS estimate of β in equation (16).

The fourth and last assumption is that the surprise should not contain any information effects (Romer and Romer, 2000; Campbell et al., 2012; Nakamura and Steinsson, 2018). Such effects would be present if the central bank's monetary policy decision reveals private information about the economic outlook that directly affects macroeconomic expectations, in addition to the actual monetary policy shock. For some asests, such as stocks, information effects would typically have an effect opposite to that of a monetary policy shock. Thus, their presence could in principle lead to estimates of β that are smaller or even of the opposite sign than if mps_t only captured a monetary policy shock.[27] However, Bauer and Swanson (2021) found that the responses of macroeconomic surveys, stock prices, and exchange rates

[26] See also Kuttner (2018) for a discussion of this assumption in the context of LSAP event studies.

[27] An example would be a more positive assessment of the current economic outlook by the central bank than by the public, and a hawkish policy surprise, $mps_t > 0$, as a result. Such an information effect might raise forecasts for output, inflation, and dividends, whereas a contractionary policy shock would lower them.

show little evidence of information effects.

4.2 Conventional and Orthogonalized Monetary Policy Surprises

We update and extend previous results in the literature with an event study that uses our new data set of 322 FOMC announcements from 1988 to 2019, described in Section 3, above. We estimate the event-study regression in equation (16) using two alternative measures of the policy surprise mps_t. First, as a natural starting point, we use a conventional, unadjusted high-frequency monetary policy surprise measure described in Section 3: the first principal component of high-frequency changes in the Eurodollar futures rates ED1 to ED4. This measure is essentially equal to a weighted average of the target and path factors of Gürkaynak et al. (2005) and therefore captures news about both the current federal funds rate target and future policy path.

Our second measure of the monetary policy surprise addresses the predictability issues raised in Section 3, above. Specifically, we construct an orthogonal measure of the monetary policy surprise by taking the residuals from the regression (15), that is,

$$mps_t^{\perp} = mps_t - \hat{\alpha} - \hat{\beta}' X_{t-}, \tag{17}$$

where X_{t-} and $\hat{\beta}$ correspond to the predictors and estimated regression coefficients in the first column of Table 1. The orthogonal surprise $mps_t^{\perp}$ is, by construction, uncollrelated with those macroeconomic and financial data observed before the FOMC announcement, and thus is more likely to satisfy the crucial event-study assumptions noted above. In the remainder of this section, we compare the effects of mps_t and $mps_t^{\perp}$ on asset prices, and in Section 5 we compare the effects of the two different monetary policy surprise measures on macroeconomic variables in an SVAR or local projections framework.

4.3 Asset Prices and FOMC Announcements

We estimate the effects of monetary policy surprises on Treasury yields and stock prices using high-frequency event-study regressions of the form (16). The Treasury yield responses are measured using 30-minute changes in Treasury futures prices around each FOMC announcement, while the stock market response is measured using S&P 500 futures price changes over the same 30-minute windows.[28]

[28] These 30-minute windows are the same as for the monetary policy surprise. The data source is Tick Data. In all cases we use the current-quarter futures contract, which has the highest liquidity. Data for the two-year T-Note contract begins in January 1991, while the five-year T-Note contract begin in July 1988, so for these two Treasury yields some FOMC announcements are missing from our regressions. Changes

Table 3: Asset Price Responses to Monetary Policy Surprises

	FOMC		Chair speeches	
	mps_t	$mps_t^{\perp}$	mps_t	$mps_t^{\perp}$
Two-year yield	0.73	0.74	0.73	0.72
t-stat.	(18.6)	(16.7)	(23.4)	(22.0)
R^2	0.784	0.689	0.856	0.827
Five-year yield	0.63	0.64	0.66	0.66
t-stat.	(14.4)	(13.8)	(16.5)	(15.8)
R^2	0.626	0.550	0.737	0.714
Ten-year yield	0.41	0.41	0.49	0.49
t-stat.	(9.5)	(9.9)	(13.9)	(13.2)
R^2	0.435	0.363	0.651	0.627
30-year yield	0.25	0.25	0.39	0.38
t-stat.	(6.3)	(6.7)	(10.5)	(10.1)
R^2	0.206	0.173	0.479	0.455
S&P500	-5.39	-5.50	-1.59	-1.56
t-stat.	(-7.7)	(-6.6)	(-2.5)	(-2.5)
R^2	0.304	0.266	0.027	0.025
Observations	322	322	295	295

Estimated coefficients β and regression R^2 from high-frequency event-study regressions $y_t = \alpha + \beta mps_t + \varepsilon_t$, where t indexes FOMC announcements or Fed Chair speeches, y_t denotes the change in the two-, five-, ten-, or 30-year Treasury yield or log S&P 500 price index in a narrow window of time around each announcement, and the regressor mps_t is either the unadjusted high-frequency monetary policy surprise measure mps_t, or $mps_t^{\perp}$, the residual from regressing mps_t on the predictors in Table 1. Heteroskedasticity-consistent t-statistics in parentheses. Sample: 1988:1 to 2019:12. See text for details.

The results for the unadjusted monetary policy surprises *mps* are reported in the first column of Table 3. All of the Treasury yields and stock prices respond very strongly to monetary policy surprises, with t-statistics of six or more. The Treasury yield responses decline with maturity, but even for the 30-year yield there is still a 25 basis point (bp) increase per 100 bp monetary policy surprise, a t-statistic greater than six and an R^2 over 20 percent.[29] The same surprise leads to a 5.4 percent drop in the S&P 500, with a t-statistic

in futures prices are converted to changes in yields using the duration of the notional underlying security obtained from Bloomberg. For the S&P500, we use the S&P500 futures changes up to August 1997 and switch to the e-mini S&P500 futures changes from September 1997 onward, due to the e-mini futures having higher liquidity and longer trading hours. For additional details, see Swanson and Jayawickrema (2021).

[29] Recall from Section 3 that the monetary policy surprise is normalized to move the ED4 futures rate one-for-one.

close to eight. These large and highly statistically significant estimates are similar to those documented by previous authors, such as Kuttner (2001), Bernanke and Kuttner (2005), Gürkaynak et al. (2005), Hanson and Stein (2015), and Swanson (2021), among others.

Analogous results for our orthogonalized monetary policy surprise measure, $mps_t^{\perp}$, are reported in the second column of Table 3, and they are very similar to the first column. The point estimates are almost identical, the t-statistics are very similar, and the regression R^2 are similar albeit a little lower in the second column. Additional, unreported estimates of an alternative regression specification that includes mps_t together with the macroeconomic and financial variables from Table 1 yielded similar coefficient estimates on mps_t as in the first column of Table 3, and coefficients on the additional variables that were statistically insignificant.

These estimates suggest that the predictability of monetary policy surprises does not cause any noticeable problems for standard high-frequency event-study regressions estimating the effects of monetary policy surprises on financial markets. Neither omitted variable bias nor classical measurement error appears to be present in these regressions, in line with the predictions of our model in Section 2. The economic and financial news variables are correlated with mps_t, but once we account for the effects of mps_t, there are no independent effects of these other variables on asset prices. In addition, the component of mps_t correlated with news variables predating t apparently leads to a similar asset price response as the orthogonal component of mps_t.

The key takeaway is that conventional monetary policy surprises can be used to estimate the effects of monetary policy on financial markets, even though these policy surprises are partly predictable. This empirical conclusion is consistent with a simple model in which the predictability of monetary policy surprises arises as a consequence of the private sector's imperfect information about the Fed's monetary policy rule.

4.4 Monetary Policy Surprises around Fed Chair Speeches

News about monetary policy is not just released through FOMC announcements but also through other communication by FOMC members and the Board of Governors. Speeches by the Fed Chair are particularly important given the influence of the Chair on the Committee's decisions. Leveraging the work of Swanson and Jayawickrema (2021), we construct measures of the monetary policy surprise around post-FOMC press conferences, speeches, and Congressional testimony by the Federal Reserve Chair and investigate their effects on asset prices. (For brevity, we refer to these types of communication by the Fed Chair as "speeches".) Over our sample period, 1988–2019, there are 880 such speeches by the Fed

Chair (compared to 322 FOMC announcements), but many of those speeches are on topics unrelated to monetary policy.[30] To identify those speeches that did contain significant news about monetary policy, we did the following: First, we included all 40 post-FOMC press conferences and all 126 semiannual monetary policy report testimonies by the Fed Chair to Congress, since these press conferences and testimonies always discuss U.S. monetary policy at length.[31] Second, we included all 22 speeches by the Fed Chair at the Fed's annual Jackson Hole symposium for central bank leaders, since these speeches also typically discuss U.S. monetary policy in detail and are closely followed by the markets. Third, we identified all of the remaining speeches by the Fed Chair that led to a substantial (3bp or more) reaction in the two-quarter-ahead Eurodollar futures contract (ED3); for each of these additional speeches, we checked whether it contained news about monetary policy, or whether the market was moved by news unrelated to the speech, by reading the market commentary in *The Wall Street Journal* or *New York Times* that afternoon or the following morning.[32] This resulted in an additional 107 speeches by the Fed Chair that contained significant news about monetary policy.

All together, the above criteria leave us with 295 Fed Chair speeches that contained significant news about monetary policy. For each of these 295 speeches, we have the exact date and time of the speech and high-frequency asset price changes around that speech from Swanson and Jayawickrema (2021).[33]

The last two columns of Table 3 report the estimated effects of Fed Chair speeches on financial markets. Two-year and five-year Treasury yields respond almost identically to Fed Chair speeches as they do to FOMC announcements, while ten- and 30-year Treasury yields respond even more strongly. The R^2 for Fed Chair speech effects are also even higher than those for FOMC announcements. Together, these observations confirm the general point in Swanson and Jayawickrema (2021) that speeches by the Fed Chair are even more important

[30]For example, the Fed Chair has often been called on by Congress to testify about bank regulation, fiscal policy, Treasury debt policy, Social Security, the GSEs, the exchange rate, and other economic issues of national significance.

[31]Although the monetary policy report testimonies are semiannual, they are given to each house of Congress, with extensive question and answer sessions each day. This results in a total of four of these testimonies per year.

[32]While this methodology necessarily involves some degree of personal judgement, most of the time it is quite clear from the market commentary whether the Chair's speech was interpreted as containing news about the likely path of monetary policy.

[33]Because speeches, testimony, and press conferences take time, often an hour or more, Swanson and Jayawickrema (2021) do not use 30-minute windows for them, but instead use wider intradaily windows that are tailored to the length of the speech or testimiony, typically about 90 minutes for a speech or press conference and 210 minutes for testimony. In addition, if there is a macroeconomic data release that occurs during one of these windows, they adjust the window start and end times to exclude the effects of the macro data release. See Swanson and Jayawickrema (2021) for details.

for the Treasury market than FOMC announcements themselves.

By contrast, the response of the stock market is substantially weaker, with an R^2 that is much lower. The modest stock market response to Chair speeches is somewhat puzzling in light of the fact that monetary policy typically has pronounced effects on the stock market (Bernanke and Kuttner, 2005; Gürkaynak et al., 2005). One possible explanation is based on information effects: Speeches by the Fed Chair could potentially have larger information effects than FOMC announcements, given the extensive conversations the Chair is having with the public or Congress about the Fed's outlook for monetary policy and the U.S. economy. For example, many of the Chair's speeches are semiannual monetary policy reports to Congress, which are three hours long and include extensive question-and-answer sessions about many aspects of the U.S. economy as well as monetary policy. As argued in Nakamura and Steinsson (2018), Cieslak and Schrimpf (2019) and Jarocinski and Karadi (2020), information effects could mute the negative stock market response to changes in the expected policy path, or even reverse its sign. Another explanation is that other news besides the Chair's speech could have moved interest rates and stock prices during the event window. Our announcement windows for Chair speeches are necessarily longer than for FOMC announcements (75 minutes for regular speeches and press conferences and 210 minutes for testimony vs. 30 minutes for FOMC announcements) and sometimes occur in the mornings, when economic data are released.[34] Any news about employment or output would tend to move interest rates and stock prices in the same direction, in contrast to news about monetary policy (Andersen et al., 2007), explaining why the stock market response is less negative.[35] A third possible explanation is that the stock market is more sensitive to actual federal funds rate changes than to forward guidance, as found by Gürkaynak et al. (2005). The Chair's speeches do not change the current federal funds rate and thus can be thought of as pure forward guidance. Of course, all of these mechanisms could be at work, and without further evidence we cannot distinguish between them.

For monetary policy surprises around Fed Chair speeches, we also estimate predictive regressions using macroeconomic and financial data that predate the speeches. The predictability is generally quite a bit lower than for FOMC announcements, with R^2 in the

[34] As discussed above, we minimized this contamination as much as possible by excluding macroeconomic data releases from our Chair speech event windows and by reading *The Wall Street Journal* and *New York Times* market commentary to determine whether the Chair's speech was the main news moving markets, but there could always be some remaining effects of macroeconomic news in these windows.

[35] A strong correlation of yield changes with the policy surprise could still be observed because interest rate changes across maturities are generally very highly correlated, and the "policy surprise" is just a measure of changes in short-term interest rates. (In fact, the correlation of yield changes across maturities is even stronger for other types of news than for monetary policy news, as the latter is inherently multi-dimensional (Bauer, 2015).) The muted stock market response could be explained by the fact that the bond-stock correlation depends on the types of news.

single digits. As shown in the last column of Table 3, using the orthogonalized monetary policy surprise $mps_t^{\perp}$ in asset price regressions has little effect on the high-frequency estimates relative to using the unadjusted mps_t itself.

5 Monetary Policy Effects on the Macroeconomy

Many recent studies use high-frequency changes in interest rates around FOMC announcements as an instrument to help estimate the effects of monetary policy on macroeconomic variables such as output and inflation; for a survey, see Ramey (2016). Our results in Section 3, however, imply that these high-frequency monetary policy surprises are correlated with those economic variables, violating the standard exogeneity condition that is required for the instrument to be valid. Our orthogonalization procedure discussed above corrects the monetary policy surprises for this correlation and should alleviate the problem.

We now investigate to what extent the high-frequency identification of the effects of monetary policy shocks in structural VARs (SVARs) and local projections are affected by this correlation and our proposed correction. We begin, in Section 5.1, by laying out the basic Proxy-SVAR method and revisiting the analysis in Gertler and Karadi (2015), which has become a canonical benchmark specification for monetary policy VARs. In Section 5.2 we estimate local projections similar to those in Ramey (2016), and in Section 5.3 we consider the alternative estimation method of Plagborg-Møller and Wolf (2021) that uses a recursive SVAR with the monetary policy instrument ordered first. In Section 5.4 we revisit some of the analysis in Miranda-Agrippino and Ricco (2021) and show that similar SVAR results are obtained when either Blue Chip consensus forecasts or Greenbook forecasts are used to orthogonalize the policy surprises. Finally, in Section 5.5, we summarize lessons learned and present new "best practice" estimates of the macroeconomic effects of monetary policy shocks.

5.1 Revisiting Gertler and Karadi (2015)

5.1.1 Baseline VAR Specification

As in Gertler and Karadi (2015), we begin by estimating a reduced-form VAR with four macroeconomic variables as our baseline specification: the log of industrial production, the log of the consumer price index, the Gilchrist and Zakrajšek (2012) excess bond premium, and the two-year Treasury yield. All variables are monthly. Industrial production and the CPI are taken from the FRED database at the Federal Reserve Bank of St. Louis. We include the GZ excess bond premium (available from the Federal Reserve Board's website) for comparability to Gertler and Karadi and because Caldara and Herbst (2019) found it to be important for the estimation of monetary policy VARs. The two-year Treasury yield is from Gürkaynak et al. (2007b) database on the Federal Reserve Board's website. As discussed in Swanson and Williams (2014) and Gertler and Karadi (2015), the two-year Treasury yield was essentially unconstrained during the 2009–15 zero lower bound period in the U.S., making it a better measure of the stance of monetary policy than a shorter-term interest rate like the federal funds rate. Note that Gertler and Karadi used the one-year Treasury yield rather than the two-year yield, but only because they were unable to get a sufficiently large F-statistic for their first-stage instrumental variables regression; as shown below, we do not have this problem, which makes use of the two-year Treasury yield feasible for our analysis.[36]

We stack these four variables into a vector Y_t and estimate the reduced-form VAR

$$Y_t = \alpha + B(L)Y_{t-1} + u_t, \tag{18}$$

where $B(L)$ denotes a matrix polynomial in the lag operator, u_t is a 4×1 vector of regression residuals that are serially uncorrelated, and $\mathrm{Var}(u_t) = \Omega$, which is not necessarily a diagonal matrix. We follow Gertler and Karadi (2015), Ramey (2016), and many others and use a specification with 12 monthly lags. We estimate regression (18) using standard ordinary least squares over the sample from January 1973 to February 2020. The GZ excess bond premium data begin in 1973, preventing us from beginning the sample earlier, and we end the sample in February 2020 to avoid the dramatic swings in industrial production that begin with onset of the Covid-19 pandemic in the U.S. We also consider and discuss alternative sample periods, below, since this was a main point discussed by Ramey (2016).

We assume that the economy is driven by a set of serially uncorrelated structural shocks, ε_t, as discussed in Ramey (2016), with $\mathrm{Var}(\varepsilon_t) = I$. It is standard in the literature to assume that ε_t has the same length as u_t, although we do not impose that restriction and allow ε_t to be in principle a vector of any size, so that the economy could be driven by any number of structural shocks. Since the dynamics of the economy are determined by $B(L)$ in (18), the effects of different structural shocks ε_t on Y_t are completely determined by differences in their impact effects on Y_t in period t, which are given by their effects on u_t.

[36] Gertler and Karadi (2015) also used the month-average Treasury yield in their analysis while we use the end-of-month values. The end-of-month value corresponds more naturally to our high-frequency monetary policy surprise instrument; because Gertler and Karadi use the month-average Tresaury yield, they also take a 30-day moving average of their high-frequency monetary policy surprise instrument. This 30-day moving average creates extra serial correlation and predictability in their instrument, which leads to concerns about the instrument's validity, as discussed by Ramey (2016). Nevertheless, our results below are all very similar whether we use the 1- or two-year Treasury yield or the end-of-month or month-average yield in our analysis.

We assume that this relationship is linear,

$$u_t = S\varepsilon_t, \tag{19}$$

where S is a matrix of appropriate dimensions, as is standard in the literature.[37]

We assume that one of these structural shocks is a "monetary policy shock", and we order that shock first in ε_t and denote it by ε_t^{mp}. The idea of a structural monetary policy shock is that sometimes the Fed is faced with a decision that is a "close call" between two options and must pick one option or the other; the difference in effects between these two choices is the outcome of a structural monetary policy shock. Given our choice of high-frequency instrument—the first principal component of the first four eurodollar futures contracts, ED1–ED4—this shock should be thought of as a change in the outlook for the path of short-term interest rates over the next four quarters. Intuitively, this includes changes in the current federal funds rate as well as some degree of "forward guidance" about the near-term path of future values of the federal fund rate.

The first column of S thus describes the impact effect of the structural monetary policy shock ε_t^{mp} on u_t and Y_t, since that shock is ordered first in ε_t. The variances of u_t and ε_t imply that

$$SS' = \Omega. \tag{20}$$

The identification problem is that there are infintiely many potential matrices S that satisfy (20) so that S cannot be uniquely determined by the data (even with infinitely many observations of Y_t). The econometrician must bring additional information to bear on the problem—either theoretical or empirical—in order to estimate S and the dynamic effects of a structural shock on Y_t. The identification problem in monetary policy VARs is simplified somewhat by the fact that estimation of the effects of monetary policy shocks does not require identification of the entire matrix S, but only of its first column, which we denote by s_1.

5.1.2 High-Frequency Identification

To identify the impact effect s_1 of a structural monetary policy shock ε_t^{mp}, we use the high-frequency identification approach of Gertler and Karadi (2015), described in detail in Stock and Watson (2012, 2018).

Let z_t denote our set of high-frequency monetary policy surprises, converted to a monthly series by summing over all of the high-frequency surprises *mps* within each month.

[37]The literature typically assumes that S is a square matrix, but we do not impose that restriction and allow it to potentially have a large number of columns, corresponding to the length of ε_t.

In order for z_t to be a valid instrument for ε_t^{mp}, it must satisfy an instrument *relevance* condition,

$$E[z_t \varepsilon_t^{mp}] \neq 0, \tag{21}$$

and an instrument *exogeneity* condition,

$$E[z_t \varepsilon_t^{-mp}] = 0, \tag{22}$$

where ε_t^{-mp} denotes any element of ε_t other than the first.[38]

The appeal of high-frequency monetary policy surprises is that they very plausibly satisfy conditions (21)–(22). For instrument relevance, the variable ε_t^{mp} is the total quantity of exogenous news about monetary policy in month t; it is clear that our monetary policy surprises around FOMC announcements (and Fed Chair speeches) represent a very important part of this news, implying $E[z_t \varepsilon_t^{mp}] > 0$.[39] For instrument exogeneity, high-frequency monetary policy surprises capture interest rate changes in very narrow windows of time around FOMC announcements (and Fed Chair speeches); by restricting attention to such narrow windows of time, it is essentially impossible for any other structural shock ε_t^{-mp} to move financial markets significantly at the same time, so these other shocks should be uncorrelated with z_t, implying (22).[40] Stock and Watson (2012, 2018) refer to z_t as an *external instrument* because it comes from information outisde of the VAR—in particular, from high-frequency financial market data.

To obtain estimates of the impact effects s_1, we follow Stock and Watson (2012) and Gertler and Karadi (2015). For concreteness, order the two-year Treasury yield last in Y_t, and denote the corresponding reduced-form residual by u_t^{2y}. We regress the vector u_t on u_t^{2y} via two-stage least squares, using z_t as the instrument.[41] Because $u_t = S\varepsilon_t$, it is straightforward to show that (21)–(22) imply this regression produces an unbiased and consistent estimate of the desired column s_1, with the last element normalized to unity. (In our empirical results

[38] Local projections estimation of impulse response functions, which we also consider below, requires an additional *lead-lag exogeneity* condition, $E[z_t \varepsilon_{t+j}] = 0 \ \forall j \neq 0$ (Stock and Watson, 2018). In an SVAR framework, equations (18)–(19) and the serial independence of the ε_t make this condition unnecessary.

[39] Note that $z_t \neq \varepsilon_t^{mp}$ in general because the latter also includes information about monetary policy not released in FOMC announcements or Chair speeches, such as speeches by other FOMC members, FOMC meeting minutes releases, etc.

[40] For lead-lag exogeneity, discussed in footnote 38, previous studies have typically assumed that monetary policy surprises are uncorrelated with all information that predates the FOMC announcement; thus, it is natural to view the lead-lag exogeneity condition as being satisfied for $j < 0$, while the case $j > 0$ holds due to the standard VAR assumption that the shocks ε_{t+j} are exogenous.

[41] Note that empirically, the sample for the two-stage least squares regression to determine s_1 does not have to be the same as was used to estimate $B(L)$ in the reduced-form VAR, as discussed by Stock and Watson (2012, 2018). In our dataset, high-frequency measures of *mps* are only available from 1988:1–2019:12, while we estimate the reduced-form VAR over the longer sample 1973:1–2020:2.

below, we rescale the estimated s_1 so that the last element is normalized to 25 basis points rather than one percent.)

However, the monetary policy surprise predictability that we document in Section 3, above, violates the exogeneity condition (22) and thus raises serious questions about the validity of z_t as an instrument. In particular, (22) is violated if z_t is correlated with macroeconomic news that occurs within the month, and all of the financial market predictors in Table 1 are very plausibly correlated with shocks to output, inflation, and the excess bond premium.[42] Thus, the structural VARs estimated by previous authors using high-frequency identification typically have an endogeneity problem that biases their estimates in the attenuation direction. For example, as shown in Table 1, news about higher output or inflation reflected in the stock market or commodity prices tends to predict a higher value of z_t; thus, the estimated effects of a monetary policy tightening are contaminated by the fact that tighter monetary policy is correlated with news about higher output and inflation, biasing the estimated effects of a monetary policy tightening on real activity and inflation in the positive direction (attenuating or even reversing the sign of the estimated effects).[43]

To eliminate this endogeneity problem, we project out the correlation of z_t with the macroeconomic and financial predictors from Section 3, as suggested by Bauer and Swanson (2021) and implemented in Section 4, above. We construct a monthly orthgonalized monetary policy instrument $z_t^\perp$ by summing the high-frequency orthogonalized announcement surprises $mps_t^\perp$ each month. This instrument is more likely to satisfy the exogeneity condition (22), leading to estimates of the effects of monetary policy on the economy that are free from the bias. Moreover, $z_t^\perp$ should still satisfy the relevance condition (21), because most of the variation in mps was not predictable by macroeconomic and financial variables and represents information about the future path of monetary policy.

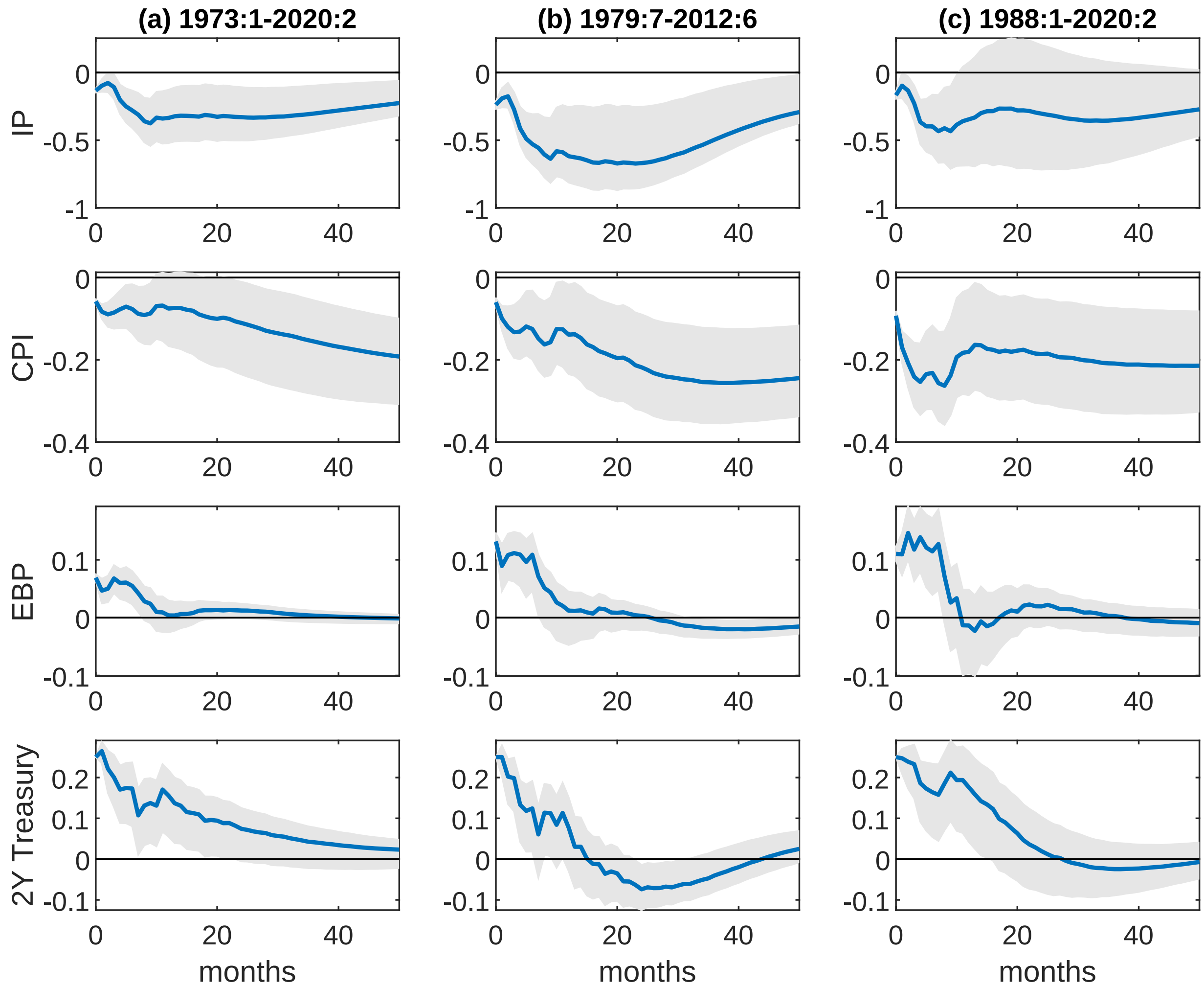
5.1.3 Results Based on FOMC Announcements

Figure 2 reports impulse response functions to a 25bp monetary policy shock in our baseline structural VAR, described above, using the unadjusted high-frequency monetary policy surprise instrument, z_t. This specification corresponds very closely to that in Gertler and Karadi (2015), Ramey (2016), and others. Column (a) reports the results for our full sam-

[42] The nonfarm payrolls surprise in Table 1 is also plausibly correlated with ε_t^{-mp}. Even though the released data describes month $t-1$, the surprise is realized in month t, and a VAR which recognized this information structure would classify the surprise as an information shock in month t. In addition, the lead-lag exogeneity condition in footnote 38 is violated if z_t is correlated with macroeconomic or monetary policy shocks from previous months, which is the case for all of the macroeconomic and financial market predictors in Table 1.

[43] Note that this endogeneity bias could create the illusion of a "Fed information effect" (Romer and Romer, 2000; Campbell et al., 2012; Nakamura and Steinsson, 2018) even if there is no such information effect in the data, a point emphasized by Bauer and Swanson (2021).

Figure 2: Structural VAR with External Instrument, Different Sample Periods



Structural VAR impulse response functions to a 25bp monetary policy shock, identified using the unadjusted high-frequency *mps* measure around FOMC announcements for three different sample periods: (a) full sample, 1973:1–2020:2; (b) Gertler and Karadi's sample, 1979:7–2012:6; and (c) 1988:1–2020:2, since our high-frequency *mps* data begin in 1988. Shaded regions report bootstrapped 90% standard-error bands. See text for details.

ple, January 1973 to February 2020, while columns (b)–(c) report results for two different subsamples. The scale of the IRFs are normalized so that the two-year Treasury yield increases by 25 basis points (bp) on impact. The solid blue lines report the estimated impulse response functions, while the shaded gray regions report 90% standard-error bands around those point estimates, computed using 10,000 bootstrap replications.[44]

The results in column (a) of Figure 2 are very similar to those in Gertler and Karadi

[44]We compute these standard error bands using the wild bootstrap procedure of Mertens and Ravn (2013) and Gertler and Karadi (2015). This method accounts for the uncertainty both in the estimated impact effect vector s_1 and in the reduced-form VAR coefficient matrices $B(L)$.

(2015), which is not surprising given the very similar specification and data, although we have used the two-year Treaury yield instead of the one-year yield, a longer sample (1973:1–2020:2), and a slightly different measure of the high-frequency monetary policy surprise with several more years of data (1988:1–2019:12). The two-year Treasury yield increases 25bp on impact, by construction, and then decline gradually back toward steady state. The excess bond premium increases about 5bp on impact, remains at about that level for several months, and then declines back toward steady state. Industrial production drops slightly on impact and then declines more significantly afterward, with a trough response of about -0.35 percent after about 1 year. The CPI drops slightly on impact, by about 0.05 percent, and then declines gradually a bit more over the next several years.

Column (b) of Figure 2 repats the anaysis in column (a), but for Gertler and Karadi's sample, July 1979 to June 2012. The standard error bands in column (b) are somewhat larger, due to the smaller sample size, but the impulse response functions are otherwise similar. Output, inflation, and the excess bond premium respond by somewhat more on impact for this sample, but have very similar shapes and are within the range of sampling variability.

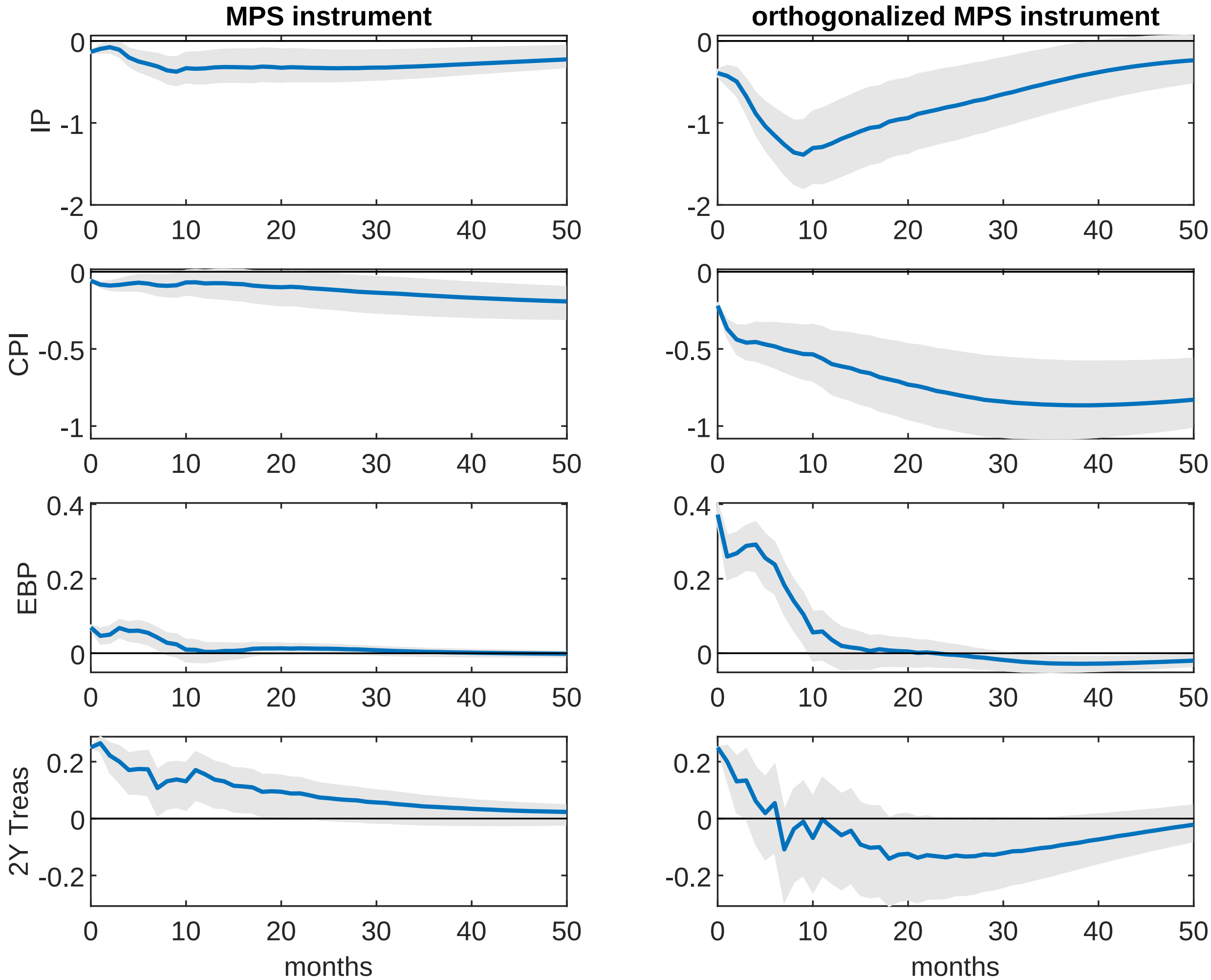
Column (c) of Figure 2 repeats the analysis once more, for the sample beginning in 1988, when our high-frequency *mps* data are first observed. Although Ramey (2016) suggests that samples beginning after the mid-1980s may not have enough variation in monetary policy to produce good estimates of its effects, we find no evidence of such a problem here: our results in column (c) are very similar to those in the first two columns, albeit with larger standard errors than in column (a), due to the shorter sample.

The impulse response functions in Figure 2 are also robust to standard variations in our baseline specification, such as using the one-year Treasury yield instead of the two-year yield or including the unemployment rate as an additional variable. We do not report those results here in the interest of space, but Appendix Figure B.1 provides them for four variations of our baseline specification that match those used by previous authors, and they are all very similar to those in Figure 2.[45]

We now turn to one of the main research questions of this paper: How much difference does orthogonalizing the high-frequency surprises make for estimating the effects of monetary policy on the economy? Figure 3 provides an answer to this question, with the left column

[45]Where these specification changes make the most difference is in the first-stage F-statistics for the two-stage least squares regression. In general, the specification chosen by Gertler and Karadi (2015) (headline CPI, month-average one-year Treasury yield, no unemployment in the VAR) helps to maximize the first-stage F-statistic. This is a problem that we generally don't have to worry about, because our dataset includes Chair speeches as well as FOMC announcements, substantially increasing our first-stage F-statistics and helping to avoid a weak instrument problem.

Figure 3: Structural VAR with External Instruments



Structural VAR impulse response functions to a 25bp monetary policy shock, identified in the left column using the unadjusted high-frequency *mps* measure around FOMC announcements, and in the right column using high-frequency change in *mps* around FOMC announcements orthogonalized with respect to economic news available prior to the announcement. Sample: 1973:1–2020:2. Shaded regions report bootstrapped 90% standard-error bands. See text for details.

repeating the baseline results for our full sample from Figure 2(a), and the right column reporting results for the same specification and sample but using the orthogonalized monetary policy surprise instrument, $z_t^{\perp}$.

The first point to note in Figure 3 is that the persistence of the two-year Treasury yield response is much lower in the right-hand column, returning back to steady state in less than one year rather than four years. This is intuitive if we think of economic data as being persistent, so that the Fed's response to that data—which we have projected out in the right column—leads to an upwardly biased estimate of interest rate persistence in the left column.

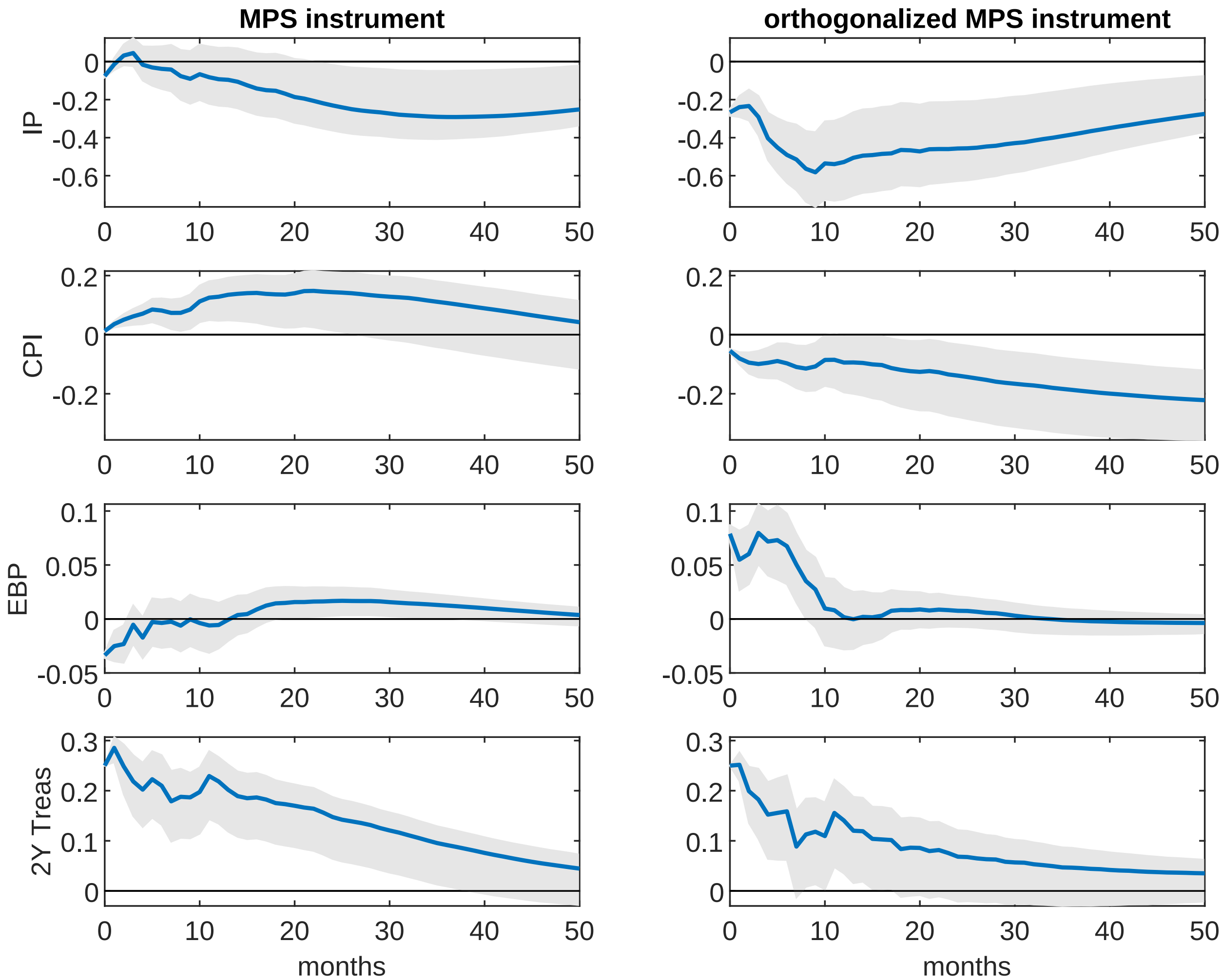
The second key point to take away from Figure 3 is that the responses of output, inflation, and the excess bond premium in the right column are all larger than in the left column, by a factor of about four. For example, industrial production has a trough response of about -1.4 percent in the right column vs. -0.35 percent in the left column. These stronger impulse responses are intuitive if we think of the right column as being free of the bias that is likely contaminating the estimates shown in the left column. For example, standard macroeconomic models such as Christiano et al. (2005) imply that positive news about output or inflation causes the Fed to raise interest rates while also causing output and/or inflation to increase; this is exactly opposite to the standard effects of monetary policy and leads to an upward bias in the top two panels of the left column.[46] In the right column, the monetary policy instrument is orthogonalized with respect to this news, eliminating the bias.

It's also interesting to note that, in the right column of Figure 3, the responses of output and the policy instrument have very different persistences, with a relatively transitory effect on the two-year yield and a long-lasting effect on industrial production. This endogenous persistence of output can be explained with medium-scale DSGE models that feature, for example, consumption habits, staggered wage contracts, and variable capital utilization (e.g., Christiano et al., 2005).

Finally, a potential concern with high-frequency identification is that the instrument may be weak, with relatively little relevance. Stock and Watson (2012) propose a rule of thumb according to which the instrument is weak if the first-stage F-statistic in the two-stage least squares regression is less than 10. In our SVAR results above, the first-stage F-statistic for z_t is 7.69 in the left column and only 2.44 for $z_t^{\perp}$ in the right column. Thus, the orthogonalization procedure does reduce the relevance of our instrument, to the point where weakness of the instrument may be a serious concern. Even for our unadjusted instrument z_t, the Stock and Watson rule of thumb suggests weakness—indeed, it was precisely this problem that led Gertler and Karadi (2015) to modify their specification to use the month-average one-year Treasury yield rather than the end-of-month two-year Treasury yield we have used here. Instead of modifying our baseline specification, as Gertler and Karadi did, we propose increasing the power of our high-frequency instrument by bringing to bear additional data on high-frequency interest rate responses to speeches by the Fed Chair, which Swanson and Jayawickrema (2021) showed have been an even more important source of information about monetary policy than FOMC announcements themselves.

[46] Similarly, good economic news about output or the excess bond premium typically causes the Fed to raise interest rates and the excess bond premium to fall; this is again opposite to the standard effects of monetary policy on the excess bond premium and leads to a downward bias of the EBP response in the left column as well.

Figure 4: Structural VAR with External Instruments, Including Chair Speeches



Structural VAR impulse response functions to a 25bp monetary policy shock, identified in the left column using raw high-frequency *mps* measure around FOMC announcements and speeches by the Fed Chair, and in the right column using high-frequency *mps* around FOMC announcements and Fed Chair speeches orthogonalized with respect to economic news available prior to the announcement. Sample: 1973:1–2020:2. Shaded regions report bootstrapped 90% standard-error bands. See text for details.

5.1.4 Results Based on FOMC Announcements and Chair Speeches

In Figure 4, we repeat the structural VAR estimation and identificaton from Figure 3, but this time including speeches by the Fed Chair as well as FOMC announcements in our high-frequency measure of monetary policy surprises. As before, we sum up all of the high-frequency monetary policy surprises in a given month to arrive at a monthly instrumental variable, z_t. The power of the instrument z_t is greatly increased by this addition, with the first-stage F-statistic in the two-stage least squares regression rising from 7.69 in the previous section to 15.83 here. For the orthogonalized instrument $z_t^{\perp}$, the first-stage F-

statistic increases from 2.44 to 10.23.

Comparing the left column of Figure 4 to Figure 3, the two-year Treasury yield response is almost identical. The response of industrial production is also similar, albeit with a slight output puzzle for about two months shortly after the shock's impact. The CPI in the left column of Figure 4 displays a true price puzzle, responding positively for more than four years after the shock, and the excess bond premium response also displays a puzzle, dropping on impact and remaining at zero or below for about a year.

Thus, several of the impulse responses in the left-hand column of Figure 3 exhibit puzzling behavior. One possible explanation for this is that speeches by the Fed Chair convey more information about the economy and financial markets—either through a "Fed information effect" or a "Fed response to news" channel—than do FOMC announcements. Many speeches by the Fed Chair, especially the semiannual monetary policy reports to Congress, do in fact discuss the U.S. economy and the Fed's response to the economy at length, so this explanation is plausible. Thus, the endogeneity problem for the unadjusted high-frequency *mps* instrument may be even larger in Figure 4 than it was in Figure 3.

The right column of Figure 4 eliminates this endogeneity by using the orthogonalized monetary policy surprise instrument $z_t^\perp$ rather than the unadjusted z_t. Orthogonalization has substantial effects on the estimated impulse responses. First, all of the output, price, and excess bond premium puzzles are eliminated once we switch to the orthogonalized instrument. Second, the two-year Treasury yield response is somewhat less persistent in the right column than in the left, consistent with our finding in Figure 3. Third, the impulse response functions in the right-hand column of Figure 4 are very similar to those in Figure 3 in shape and timing, although they are a bit smaller. Thus, despite the low first-stage F-statistics using just FOMC announcements, the estimated effects of monetary policy are robust and very similar when we extend the instrument set to include speeches by the Fed Chair. Overall, the differences between the columns are similar to those in Figure 3 and are consistent with the orthogonalized monetary policy instrument being purged of endogenous Fed responses to economic data.

5.1.5 Summary

To summarize, there are three main points to take away from our reassessment of the high-frequency SVAR estimates in Gertler and Karadi (2015). First, we have consistently found that estimates using unadjusted monetary policy surprises as an external instrument are biased, leading to attenuated or "puzzling" dynamic responses. That is, estimates of the effects of monetary policy on output or inflation using unadjusted monetary policy surprises generally produce estimates that are either too small or even go in the opposite direction from what standard economic theory would predict. Using our adjusted, orthogonalized monetary policy surprise instrument consistently produced better results. This is not too surprising, given that our corrected monetary policy surprises should be largely free of the econometric endogeneity problems that we documented for the unadjusted surprises.

Second, using Fed Chair speeches as well as FOMC announcements to measure the monetary policy surprise each month also helps to produce more reliable estimates. This is most evident comparing our local projections estimates in Figure 5 to Figure C.1, below, but we have also found this to be the case more generally as well. This finding is also not too surprising, since the larger set of monetary policy announcement events roughly doubles the explanatory power of the external instrument and leads to first-stage instrumental variables F-statistics that are much higher than those using FOMC announcements alone.

Third, the results are generally robust to variations in sample period and specification, as in Figures 2 and B.1, especially when using our orthogonalized monetary policy surprise measure. This robustness to using a later sample period is an important point when comparing our SVAR results to those using local projections, below.

5.2 Revisiting Ramey's (2016) Local Projections Estimates

An alternative approach to structural VARs is to estimate the dynamic effects of a monetary policy shock via Jordà (2005) local projections. The idea is to directly regress future values of macroeconomic variables on the identified monetary policy shock, with controls for lags and other relevant macroeconomic variables. When the monetary policy shock is unobserved but we have an external instrument, like our high-frequency monetary policy surprise measures z_t and $z_t^{\perp}$, we can perform the local projections regressions on the two-year Treasury yield using these instruments. This procedure, known as LP-IV, is performed by Ramey (2016) and discussed in detail in Stock and Watson (2018). In this section, we revisit Ramey's local projections estimates to assess the importance of monetary policy surprise predictability for those results.

We match our LP-IV specification to our VAR as closely as possible by using the same variables and the same number of lags (12 months). Although Ramey (2016) used only three monthly lags for her LP-IV specification, we found that using so few lags led to substantial differences relative to using a larger number more consistent with a VAR (see also the discussion in Ramey, 2022). Thus, our LP-IV regressions have the form

$$Y_{t+h} = \alpha^{(h)} + A^{(h)}(L)Y_{t-1} + \theta^{(h)}Y_t^{2y} + \eta_t^{(h)}, \tag{23}$$

where Y includes the same variables as in our VAR, $h \geq 0$ indexes the horizon of the impulse response function, the regression (23) is estimated separately for each horizon h, $\alpha^{(h)}$ is a constant, $A^{(h)}(L)$ is a matrix polynomial of degree 11 (allowing for 12 lags), $\theta^{(h)}$ is the coefficient of interest, Y^{2y} denotes the two-year Treasury yield, and $\eta_t^{(h)}$ is the regression residual. Equation (23) is estimated via two-stage least squares using either the unadjusted z_t or orthogonalized $z_t^{\perp}$ as the instrument for Y_t^{2y}. Our sample period for the estimation runs from 1988:1–2020:2, since our high-frequency *mps* data begin in 1988. Standard errors are computed using Newey and West (1987) with h lags.

The results from this procedure are generally more poorly estimated than for our SVAR specifications above: they have large standard errors, suffer from month-to-month volatility, and also show large differences when speeches by the Fed Chair are excluded vs. included in the monetary policy surprise instrument. Figure 5 reports results for the latter case, when Fed Chair speeches are included in the monetary policy surprise measure. (The corresponding results when Fed Chair speeches are excluded from the instrument have even larger standard errors and are reported in Appendix Figure C.1.)[47]

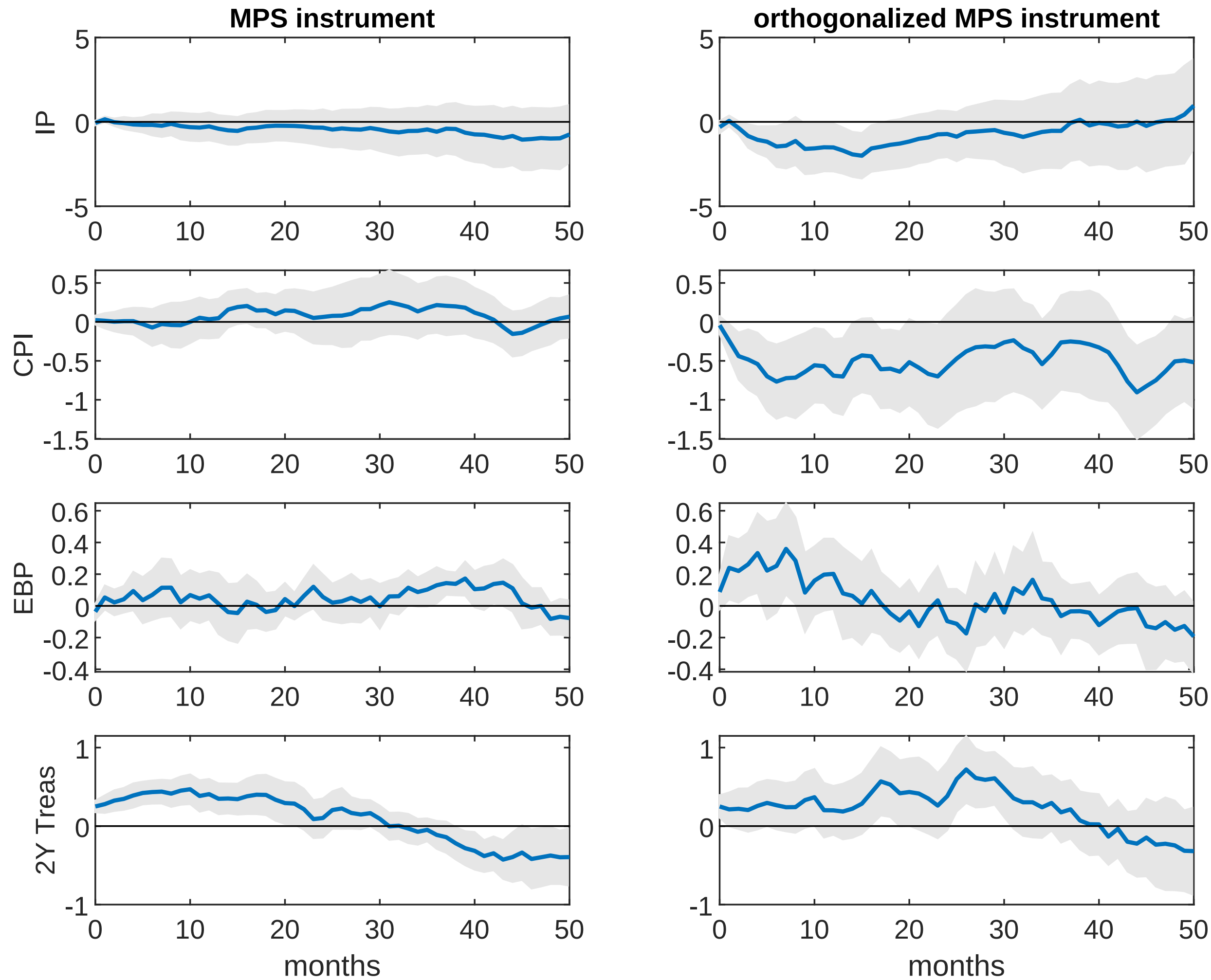
While the impulse responses in Figure 5 are imprecisely estimated and somewhat more erratic, they are otherwise qualitatively consistent with those for SVARs shown in Figures 3–4. Comparing the left and right columns of Figure 5, the estimates in the right column produce stronger responses of output, inflation, and the excess bond premium to the monetary policy shock, and eliminate the slight output puzzle, price puzzle, and EBP puzzle that are present in the left column. Thus, as in Figures 3–4, using the unadjusted high-frequency *mps* instrument seems to produce results that are biased, with attenuated or puzzling responses, and that bias is largely eliminated when we use the *mps* measure that has been orthogonalized with respect to macroeconomic and financial news.

We conclude from this exercise that the estimated impulse responses to a montary policy shock using LP-IV are generally similar to those from a structural VAR, but substantially less precisely estimated. This conclusion contrasts somewhat with Ramey (2016), who found more substantial differences between LP-IV and SVAR impulse responses, but we found those differences to be primarily due to the shorter, 3-month lag length Ramey used for her LP-IV specification.[48] Our main point, however, is that conventional, unadjusted high-frequency surprises are a poor choice of instruments for monetary policy shocks in local projections, which agrees with Ramey's conclusions, and we have shown how one

[47]Recall that the first-stage F-statistics for the instrumental variable when we include Fed Chair speeches are much higher (15.83 and 10.23) than when the Chair's speeches are excluded (7.69 and 2.44), so it's not too surprising that the estimates in Figure 5 are more precisely estimated than in Figure C.1.

[48]See also Ramey (2022). Ramey also suggested part of the difference between her LP-IV and SVAR results was due to the later sample period for the former, but our results in Figure 2 suggest that the different sample period is not a major issue.

Figure 5: Local Projections



Local Projections impulse reponse functions to a 25bp monetary policy shock, identified in the left column using unadjusted high-frequency *mps* measure around FOMC announcements and speeches by the Fed Chair, and in the right column using high-frequency *mps* measure around FOMC announcements and Fed Chair speeches orthogonalized with respect to economic news available prior to the announcement. Sample period: 1988:1–2020:2. Shaded regions report 90% standard-error bands. See text for details.

can construct instruments that are more relevant and more likely to be exogenous.

5.3 Revisiting Plagborg-Møller and Wolf (2021)

Plagborg-Møller and Wolf (2021) (PMW) recommend an alternative procedure for estimating impulse response functions using an external instrument, which they call the "internal instrument" approach. Instead of estimating a standard SVAR or LP-IV regression, they recommend including the instrument in the VAR, ordering it first, and using a recursive (Cholesky) ordering to estimate its effects. Intuitively, this allows the other variables in the

VAR to respond to the instrument on impact, while the dynamics are asymptotoically the same (in population, and for infinite lag length) as a conventional VAR or LP-IV estimation.

Here we revisit the estimates of PMW using our new instrument series, based on monetary policy surprises around both FOMC announcements and Chair speeches. Because our high-frequency surprise data runs from 1988:1–2019:12 and is included in the VAR, the sample for the estimation is 1988:1–2019:12. As in our other SVARs and LP-IV regressions, we include 12 monthly lags in the VAR and normalize the monetary policy shock to have an impact effect of 25bp on the two-year Treasury yield.

The results are shown in Figure 6. Overall, they are quite similar to our proxy-SVAR results in Figure 4, but they are less precisely estimated due to the shorter sample and larger number of parameters (since the coefficients on the lags of z_t must be estimated). As we know from our estimates across different subsamples in Figure 2, starting the estimation in 1988 instead of 1973 does not substantially affect the point estimates, but it does noticeably reduce the precision. Comparing the left and right columns of Figure 6, we see again that orthogonalizing the monetary policy surprises substantially increases the size of the estimated effects and removes any price puzzle types of responses in the left column.

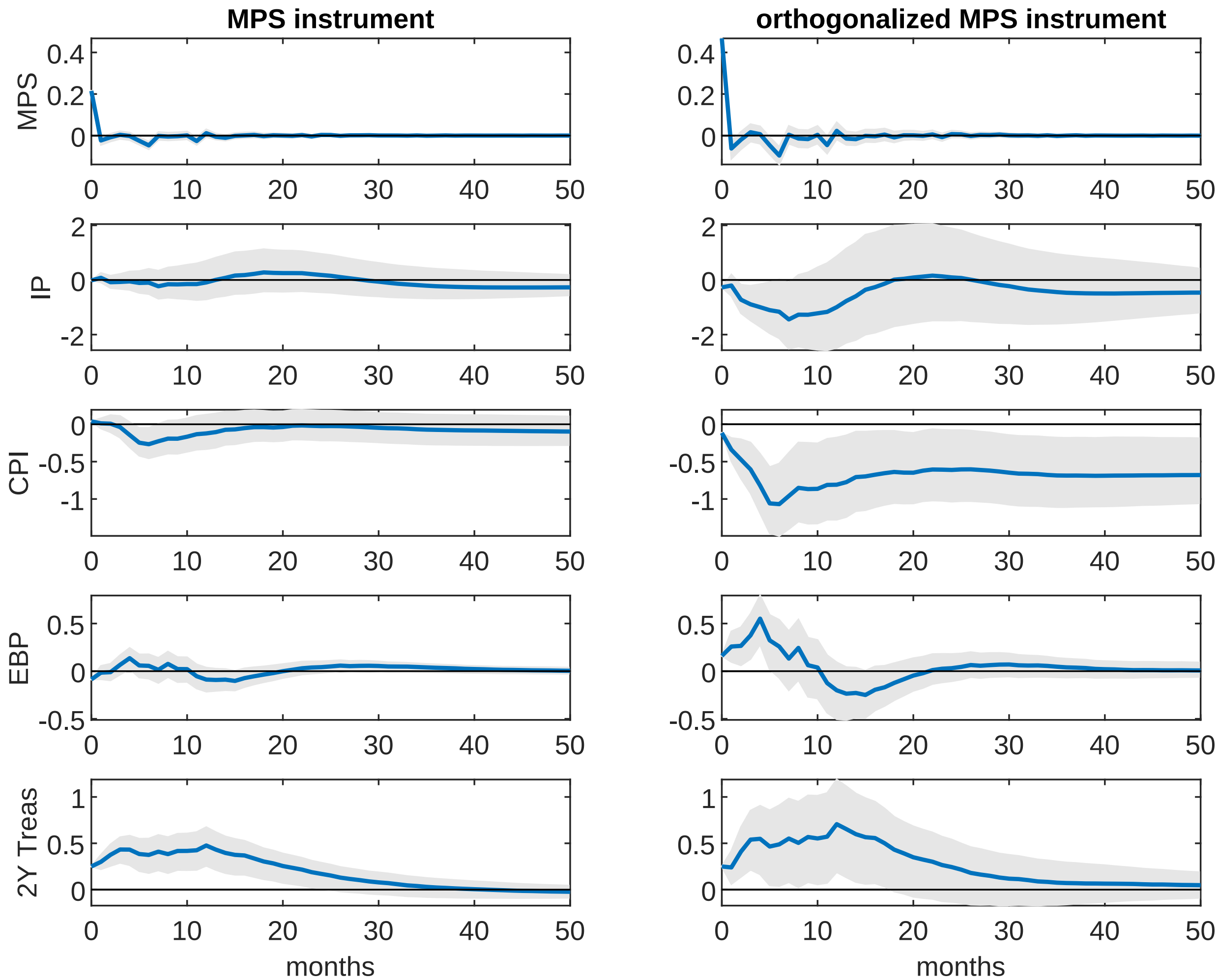
Figure 6 is also interesting because including the instrument in the VAR automatically orthogonalizes it with respect to lags of all the variables in the VAR. Despite this, the unadjusted *mps* instrument in the left-hand column does a relatively poor job of estimating the effects of monetary policy on the economy, with estimates that are similar to the left column of Figure 4. By contrast, our orthogonalization with respect to the predictors in Table 1 seems to do a much better job of removing the econometric endogeneity. Apparently the endogeneity that is present in the *mps* variable is not well captured by the lags of the variables in the VAR.

As was the case with our previous SVARs in Figure 3–4, the VAR structure here seems to improve the quality of our estimates, relative to unrestricted local projections. However, restricting the sample to begin in 1988, when our high-frequency data become available, reduces the precision of the estimated dynamics in Figure 6. Based on these findings, an SVAR specification with identification using external instruments, as in Section 5.1, seems preferable to a recursive SVAR with an internal instrument.

5.4 Revisiting Miranda-Agrippino and Ricco (2021)

We now turn to the SVAR analysis of Miranda-Agrippino and Ricco (2021) (MAR), who orthogonalized monetary policy surprises with respect to the Fed's internal "Greenbook" forecasts and demonstrated that this leads to substantially different impulse responses to

Figure 6: Recursive Structural VAR with Internal Instrument



Structural VAR impulse response functions to a 25bp monetary policy shock, identified in the left column using raw high-frequency *mps* measure around FOMC announcements and speeches by the Fed Chair, and in the right column using high-frequency *mps* around FOMC announcements and Fed Chair speeches orthogonalized with respect to economic news available prior to the announcement. Instrument is ordered first in a recursive SVAR, following the methodology of Plagborg-Møller and Wolf (2021). Sample: 1988:1–2019:12. Shaded regions report bootstrapped 90% standard-error bands. See text for details.

monetary policy shocks when using the resulting series for high-frequency identification.[49] They interpreted these results as supporting a strong role for a Fed information effect (Romer and Romer, 2000; Campbell et al., 2012; Nakamura and Steinsson, 2018), given the apparent importance of the Fed's own private forecasts. However, the results in Section 3.3 showed that the Blue Chip survey forecasts, which are publicly available on a monthly basis, have very similar predictive power for monetary policy surprises as the Fed's own Greenbook

[49] Relatedly, Lakdawala (2019) orthogonalizes monetary policy surprises with respect to the difference between Greenbook and Blue Chip forecasts.

forecasts, which the public does not see until five years after the FOMC meeting. This raises the question whether orthogonalizing monetary policy surprises with respect to public Blue Chip forecasts—in line with our general approach of orthogonalizing monetary policy surprises with respect to publicly available information—yields results similar to those of MAR. If so, this would raise further doubts about the Fed information effect.

Before going into the details of this analysis, it is helpful to compare, at a high level, the approach of MAR to the one we propose in this paper. Overall, MAR suggest a very similar correction to monetary policy surprises as we do. However, they recommend the use of a different set of predictors and base their approach on a different motivation. Since they document predictability of monetary policy surprises based on the information in Greenbook forecasts, they argue that this predictabtiliy is caused by a Fed information effect. They therefore recommend orthogonalizing the policy surprises with respect to the Greenbook forecasts. Our prescription is based on a different premise, and it is also practically simpler in that the data for the orthogonalization is publicly available in real time.

Most of the analysis of MAR closely follows the specification of Gertler and Karadi (2015). The key is a comparison of the impulse responses obtained using the Gertler-Karadi monetary policy surprise instrument, FF4GK, to the results obtained using a new monetary policy instrument, MPI, which MAR construct according to the following three-step approach:

1. Regress the high-frequency announcement surprises FF4 on Greenbook forecasts and forecast revisions for real GDP growth, inflation and unemployment (for details see Section 3.3 or MAR's Table 1) and calculate the residuals.

2. Aggregate the announcement-frequency residual series to a monthly time series, with zeros for months without monetary policy announcements.

3. Regress these monthly values onto 12 lags and again calculate the residual.[50]

As a result, the MAR monthly instrument series MPI is orthogonal to the Fed's own macroeconomic forecasts and does not exhibit any serial correlation.

We construct an alternative instrument series, MPINEW_BC, using the exact same three-step approach, but with the Blue Chip consensus forecasts instead of the Greenbook forecasts in the first step. We use exactly the same policy surprise, sample period, variables, methods, and forecast horizons as MAR. For each FOMC announcement, we regress FF4 on the most recent available Blue Chip forecasts and revisions, as in Section 3.3. The resulting

[50] Only observations with a non-zero dependent variable are used in the regression. That is, zeros in the monthly time series are not affected by this step.

Figure 7: Greenbook vs. Blue Chip Forecasts in Miranda-Agrippino & Ricco SVARs

Structural VAR impulse response functions to a 100bp monetary policy shock identified using three different external instrument series: the unadjusted Gertler-Karadi instrument (FF4GK), the Miranda-Agrippino and Ricco instrument orthogonalized to Greenbook forecasts (MPI), and a new instrument we construct ortogonalized to Blue Chip rather than Greenbook forecasts (MPINEW_BC). Specification, sample period, and estimation method are exactly as in Figure 3 of Miranda-Agrippino and Ricco (2021). Shaded areas are 95% credibility bands based on the simulated posterior distribution.

monthly instrument series is therefore orthogonal to publicly available forecasts, but does not take into account any private information that the Fed may possess, which might be contained in the Greenbook forecasts.

Figure 7 is analogous to Figure 3 in MAR and shows the responses of industrial production, the unemployment rate, the CPI, and the one-year Treasury yield to a 100bp monetary policy shock. (Thus, the monetary policy shock in Figure 7 is four times larger than in Figures 2–6, for comparability to MAR.) The three different lines correspond to the three different external instruments used to identify the monetary policy shock. The lines for FF4GK and MPI exactly replicate the responses shown in MAR's Figure 3.[51] One of their main points was that the response of IP and unemployment are very different for MPI than for the FF4GK instrument. In particular, using MPI they don't find an output or unemployment puzzle, with strong and significantly negative responses of IP and positive responses of the unemployment rate to a monetary policy tightening.

The third line in Figure 7, labeled MPINEW_BC, shows the same impulse responses but using our new external instrument for identification. Strikingly, the response of IP to a monetary policy shock is at least as negative, and in fact even more negative, as when using MPI. Similarly, the response of the unemployment is at least as positive for our instrument as for MAR's instrument.

[51] We are grateful for excellent replication code that the authors made available via the journal's website, see https://www.openicpsr.org/openicpsr/project/116841/version/V1/view.

The results of this exercise suggest that there is nothing special in the Greenbook forecasts, and that the publicly available Blue Chip forecasts contain very similar information about upcoming monetary policy surprises. Thus, there appears to be little to no role for a Fed information effect in explaining the different macroeconomic responses to a policy shock documented by MAR. Instead, their results may well be driven by the "Fed response to news" channel of Bauer and Swanson (2021). What is clear is that their results are due to the correlation between monetary policy surprises and publicly available macroeconomic and financial news predating the FOMC announcement that we emphasize in this paper.

The main point of MAR, however, is that one should not use unadjusted high-frequency surprises as instruments for monetary policy shocks. Our analysis very much supports this conclusion, and we similarly propose to orthogonalize the observed high-frequency surprises to construct better instruments. However, we emphasize that one can use publicly available data to do so, and that there is no need to rely on Greenbook forecasts that are made public only after a lag of five years. While our preferred explanation of the endogeneity of conventional monetary policy surprises differs from that of MAR, since it does not rely on information effects, this is not crucial for the main points we make in this paper.[52]

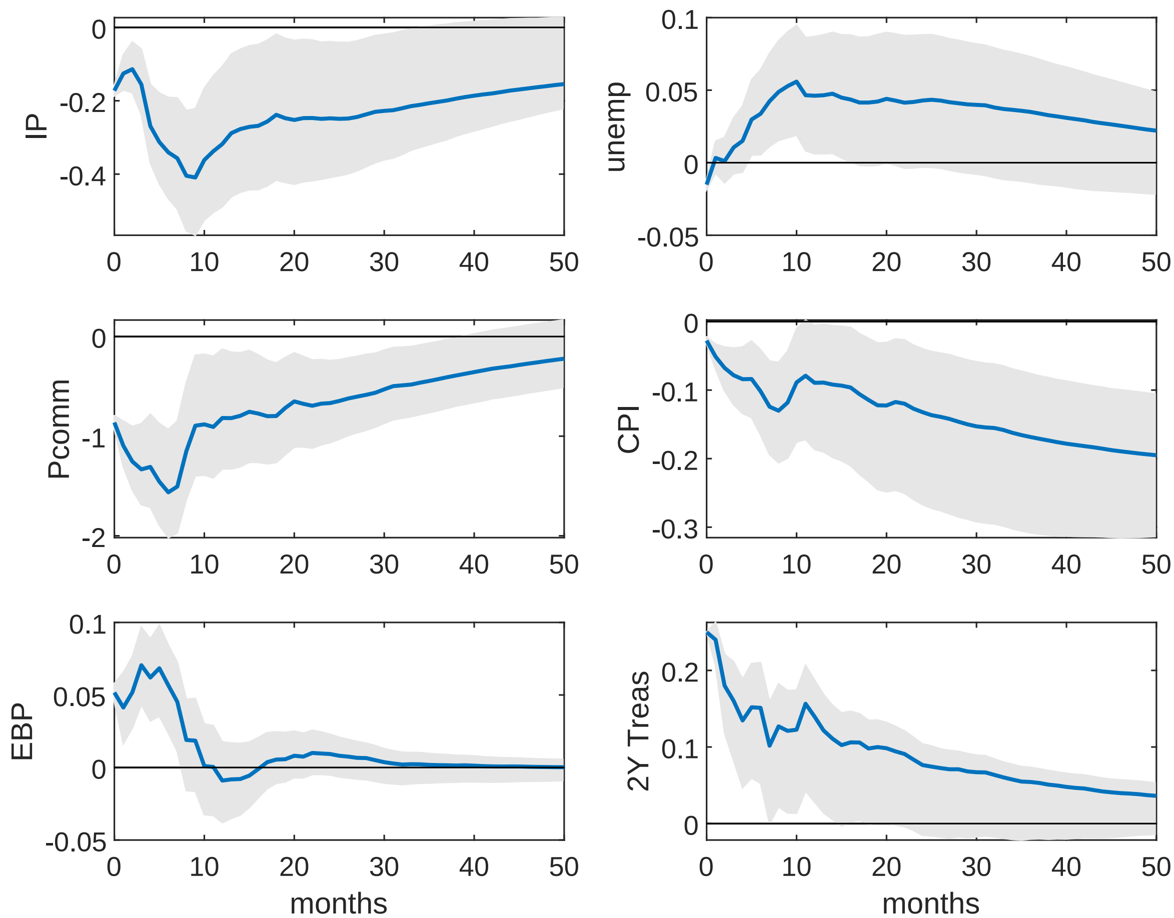
5.5 Best Practice Estimates of Monetary Policy's Effects

We close our empirical analysis of the effects of monetary policy on the macroeconomy with a summary of what we have found to produce the most reliable estimates, and a final set of estimates that incorporate these lessons learned:

- High-frequency monetary policy surprises need to be orthogonalized with respect to macroeconomic and financial data observed before the policy announcements, in order to avoid estimation bias and create instruments that are more likely to be exogenous.
- Including additional monetary policy announcements, such as speeches by the Chair, improves the relevance of the instruments and the precision of the estimates.
- Estimates from SVAR models tend to be more precise and less erratic than those based on local projections, but the two are qualitatively similar.
- Using a longer sample period for estimation of the reduced-form VAR helps improve the precision of the estimates and leads to qualitatively similar results.

[52] Our analysis Our investigation of the MAR monetary policy instruments and results yielded some additional insights about different high-frequency surprises that are somewhat tangential to our main points; see Appendix D.

Figure 8: Best Practice Estimates of Structural VAR



Structural VAR impulse response functions to a 25bp monetary policy shock, identified using high-frequency *mps* measure around FOMC announcements and speeches by the Fed Chair orthogonalized with respect to economic news available prior to the announcement. Sample: 1973:1–2020:2. Shaded regions report bootstrapped 90% standard-error bands. See text for details.

- Including the instrument series in a recursive SVAR does not fix the endogeneity problem and still requires an orthogonalization of the monetary policy surprises with respect to macroeconomic and financial data.

- Including additional variables in the VAR, such as the unemployment rate or commodity prices, makes relatively little difference for the other impulse responses (see, e.g., Figure B.1). Nevertheless, the effect of monetary policy on these other variables may be interesting for their own sakes, and hence worth including.

Taking these lessons to heart, we report a benchmark set of impulse response functions in Figure 8. These are computed using a structural VAR with external instruments, as in Section 5.1. We combine FOMC announcements and Fed Chair speeches to construct the monthly monetary policy surprise instrument, and we use the orthogonalized instrument series $z_t^{\perp}$. We estimate the reduced-form VAR over the full available sample period from 1973:1 to 2020:2, and we use the instrument series from 1988:1 to 2019:12 to estimate the impact effects of the structural monetary policy shock on the variables of the VAR. Finally, we include the unemployment rate and an index of commodity prices in the VAR becaues the responses of these variables are often of interest and have been included by many previous authors, even though all of our other impulse response functions are very similar if unemployment and commodity prices are excluded.[53]

As in our previous estimates, we normalize the monetary policy shock in Figure 8 to increase the two-year Treasury yield 25bp on impact. After the initial jump, we estimate that the two-year yield gradually returns to steady state over the next several years (although only the first four years are plotted in Figure 8, as in our previous figures). In response to this shock, we estimate that the excess bond premium jumps 5bp in the impact month, while commodity prices fall almost 1 percent. The excess bond premium rises a bit further over the next six months before returning to steady state after about a year, while commodity prices fall further for the first eight months before gradually returning to steady state over the next four to five years.

Industrial production falls almost 0.2 percent in the impact month and declines further over the next nine months before turning around and gradually returning to steady state over the next several years. The unemployment rate is essentially unchanged on impact, rises slightly over the next ten months by about 0.05 percentage points, and then very slowly returns back toward steady state over the next several years. Finally, the CPI response is the most sluggish, dropping 0.05 percent in the impact month and then gradually decreasing about 0.2 percent over the next five years before very slowly starting to head back toward steady state.

It's interesting to compare the large and rapid response of commodity prices in Figure 8 to the sluggish response of the CPI. This difference is consistent with standard medium-scale New Keynesian DSGE models that imply inflation inertia, such as Christiano et al. (2005). If we replace the CPI in the VAR with the core CPI, the core CPI response is even more sluggish.

Overall, the results in Figure 8 are consistent with those we presented earlier and consis-

[53]Since Sims (1992), commodity price series have often been included in VARs to avoid a price puzzle. We emphasize that even without commodity prices, our VAR estimates do not exhibit a price puzzle, as long as orthogonalized monetary policy surprises are used as instruments for monetary policy shocks (see, for example, Figures 3 and 4). The Bloomberg spot commodity price index is not available back to 1973, so we use the log of the Commodity Research Burea's monthly index of commodity prices, downloaded from Bloomberg.

tent with standard macroeconomic models. Our hope is that these may serve as a guideline and benchmark for future estimates.

6 Conclusion

This paper investigates the use of high-frequency monetary policy surprises to estimate the effects of monetary policy on financial markets and the real economy. This investigation is necessitated by the emerging consensus in the literature that high-frequency monetary policy surprises are significantly correlated with macroeconomic and financial data that predate the monetary policy announcements. An additional motivation is the concern that these surprises may have become less relevant over time as measures of monetary policy shocks (Ramey, 2016).

We first confirmed and extended previous evidence on the predictability of high-frequency monetary policy surprises. We also presented substantial evidence—and a simple theoretical model—that suggest that this predictability can be attributed to the "Fed response to news" channel of Bauer and Swanson (2021), according to which financial markets simply underestimated how responsive the Fed would be to the economy. Our explanation is a plausible alternative to a "Fed information effect," according to which the Fed's monetary policy announcements reveal information about the state of the economy that the private sector did not previously have.

When measuring the effects of monetary policy on financial markets, we found that standard ordinary least squares regressions using high-frequency data and unadjusted monetary policy surprises produced reliable estimates. This observation follows both from our simple theoretical model and from regressions comparing the effects of unadjusted high-frequency monetary policy surprises and monetary policy surprises that have been orthogonalized with respect to major macroeconomic and financial news that predates the monetary policy announcement.

However, when estimating the effects of monetary policy on macroeconomic variables using a structural VAR or local projections, we found that unadjusted monetary policy surprises led to estimates that are biased. The bias arises because the macroeconomic data in the VAR are correlated with the monetary policy surprise, so that, e.g., a monetary policy tightening is correlated with positive innovations to output and inflation, which attenuates or even reverses the estimated effects of the tightening. In this case, using our orthogonalized high-frequency monetary policy surprises provides us with an instrument for monetary policy that is exogenous with respect to the other variables in the VAR and produces impulse response functions that are substantially stronger and devoid of opposite-signed "puzzles" such as the "price puzzle".

An additional difficulty of working with high-frequency monetary policy surprises in a VAR or local projections framework, especially for our orthogonalized monetary policy surprises, is that they can have low explanatory power for monthly changes in monetary policy. In other words, even though our orthogonalized monetary policy surprise measure is an *exogenous* instrument, it may not be very *relevant,* a concern that has also been expressed by Ramey (2016). We addressed this concern by bringing to bear additional monetary policy surprise data in the form of speeches, press conferences, and Congressional testimony by the Federal Reserve Chair. Using this larger set of monetary policy surprises avoids potential weak instrument problems while still confirming the general pattern of the effects of monetary policy on the economy.

Our results also have important implications for central bank communication and the conduct of monetary policy. First, our evidence here, as well as in Bauer and Swanson (2021), finds little or no evidence that FOMC announcements have a substantial "Fed information effect" component. Although the minutes of recent FOMC meetings reveal that some participants worried about the potential for counterproductive information effects,[54] our results indicate that policymakers have little need to fear that information effects might attenuate the effects of their announcements, except possibly in exceptional circumstances (which our results cannot rule out).

Second, our estimates of the effects of monetary policy on financial markets confirms previous estimates in the literature, despite the increasing evidence that those monetary policy surprises are correlated with economic and financial data that predates the FOMC announcements.

Third, our estimates of the macroeconomic effects of monetary policy are stronger than many previous high-frequency-based estimates, because our orthogonalization of the high-frequency monetary policy surprises removes an estimation bias that was present in those studies. Thus, like Romer and Romer (2004) and Coibion (2012), we estimate relatively large effects of monetary policy on real activity and inflation.

Going forward, our results suggest several avenues for future research. The predictability—or rather, *ex post* correlation—of high-frequency monetary policy surprises with macroeconomic and financial data certainly deserves further investigation, extending the analysis to other central banks, additional predictors, and decompositions os monetary policy surprises into changes in risk premia and short-rate expectations. Explicitly incorporating empiri-

[54]For example, in the minutes of the FOMC meeting on March 15, 2020, participants were concerned that a strong monetary easing surprise "ran the risk of sending an overly negative signal about the economic outlook." See https://www.federalreserve.gov/monetarypolicy/fomcminutes20200315.htm.

cal monetary policy rules into this analysis also would be valuable in order to learn more about the exact sources of this predictability. Regarding information effects, our empirical evidence here and in Bauer and Swanson (2021) suggest that they are unlikely to be strong *on average*, but it does not rule out that some exceptional FOMC announcements convey information about the economic outlook. Further research is needed to understand when this channel may be relevant for individual announcements, and recent work by Cieslak and Pang (2021) using comovement of asset prices is an important step in this direction. Regarding the macroeconomic effects of monetary policy, our analysis has focused on policy surprises that shift the current target rate and expected policy path, but did not consider the effects of balance sheet policies such as quantitative easing. Based on the lessons in this paper, methods for high-frequency identification may be combined with unconventional monetary policy surprises, such as those measured by Swanson (2021), to yield new insights in this area.

Appendix

A Recursively Estimated Monetary Policy Rule

We estimate the following monetary policy rule

$$i_t = r_t^* + \pi_t^* + \beta_t(\pi_t - \pi_t^*) + \gamma_t(y_t - y_t^*) + u_t,$$

according to which the Fed reacts to year-over-year core PCE inflation, π_t, and the output gap, $y_t - y_t^*$. The dependent variable, i_t, is the two-year Treasury yield, which we use instead of the federal funds rate to somewhat alleviate the effects of the zero lower bound. All data series are from FRED, including the CBO's estimates of potential GDP (y_t^*). Our data is monthly from June 1976 to July 2021, and we linearly interpolate the quarterly output gap series.[55] We estimate the response coefficients β_t and γ_t, as well as the combined intercept $r_t^* + (1 - \beta_t)\pi_t^*$, using exponentially-weighted least squares and an expanding estimation window.[56] The forgetting factor is set to $\nu = 0.005$, which implies an effective sample size of 200 months. That is, estimation at time t uses data from the beginning of the sample to time t, and the weights for data at $t-j$ are proportional to $(1-\nu)^j$. We begin our estimation in January 1990 and estimate the parameters for each month until July 2021. We obtain Newey-West standard errors using 12 lags to construct 95% confidence intervals.

Figure 1 plots the estimated response parameters $\hat{\beta}_t$ and $\hat{\gamma}_t$ and confidence confidence intervals. An upward trend is clearly present in both estimated series. The inflation coefficient starts out slightly below one but increases quickly, satisfying the "Taylor principle" ($\beta_t > 1$) for most of the sample, and reaches its peak of about 1.8 near the end of the sample. The output gap coefficient is close to zero and statistically insignificant for most of the first twenty years of our sample period, and increases towards a peak around 0.6 in 2017, before declining somewhat towards the end of the sample. In both series, the estimates over the last decade are substantially higher than the earlier estimates. In sum, this evidence supports the view that the Fed has become more responsive to economic conditions, including both inflation and real activity.

B Structural VAR Robustness

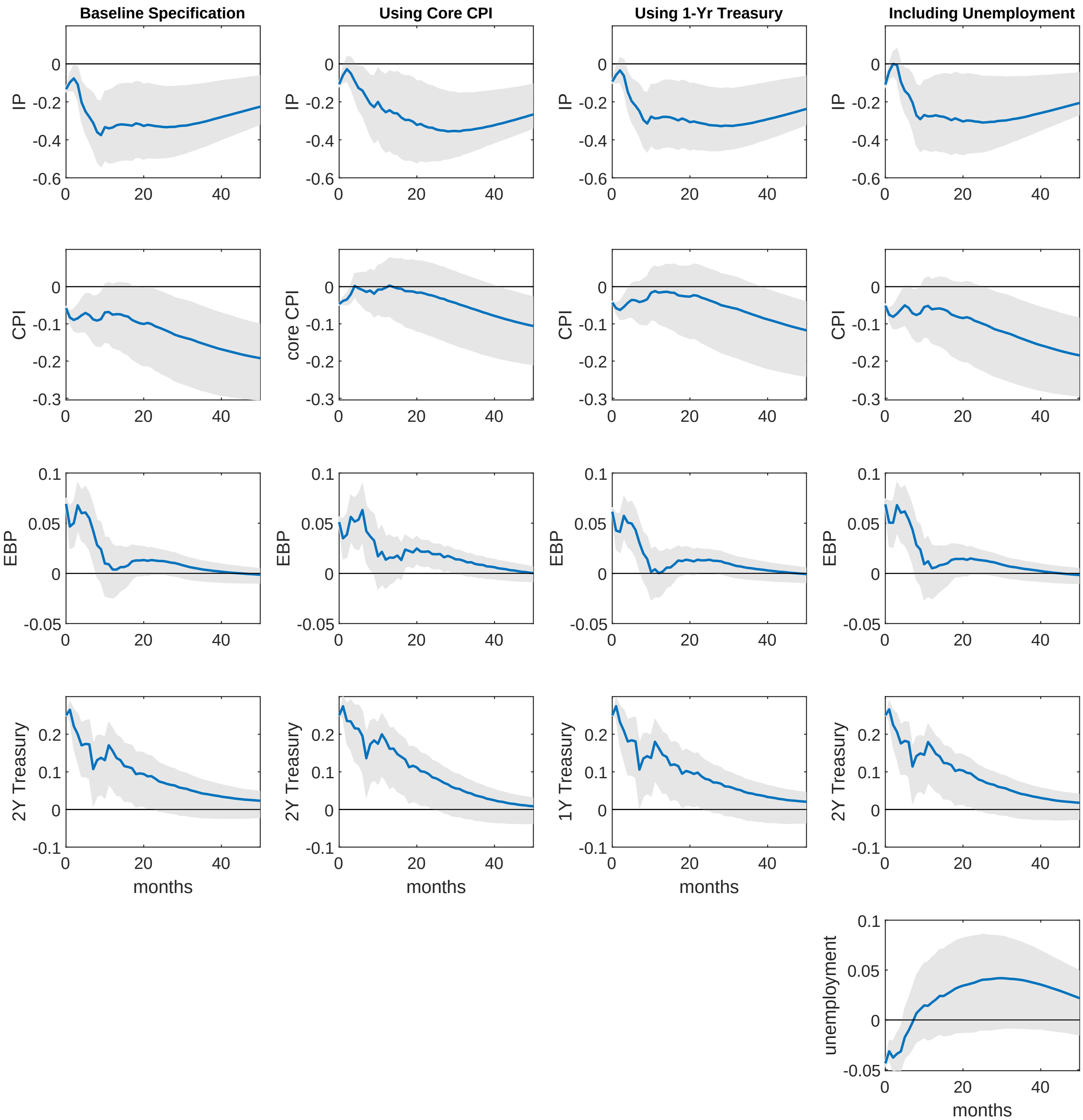
This section demonstrates the robustness of the results from our baseline structural VAR specification presented in the main text.

In Figure B.1, we present results from four variations on our baseline specification. The first column of the figure repeats the results from our baseline specification, over our full sample, 1973:1–2020:2, and using the unadjusted monetary policy surprise measure *mps* around FOMC announcements as our high-frequency instrument, since that corresponds

[55] We use the fully revised output gap series due to the difficulties in constructing a long and consistent real-time output gap series. While revisions to the output gap may affect estimated policy rules (Orphanides, 2001), they are unlikely to affect our overall result.

[56] Exponentially-weighted least squares is equivalent to constant-gain recursive least squares.

Figure B.1: Structural VAR Impulse Responses for Four Specification Variations, Using Unadjusted Monetary Policy Surprises around FOMC Announcements



Structural VAR impulse reponses to a 25bp monetary policy shock, identified using the unadjusted high-frequency *mps* measure around FOMC announcements, for four different specifications. The baseline specification includes the log of Industrial Production, log of the CPI, Gilchrist and Zakrajšek (2012) excess bond premium, and the two-year Treasury yield. Sample: 1973:1–2020:2. Shaded regions report bootstrapped 90% standard-error bands. See text for details.

most closely to the instrument that has been used by previous authors. The results in the first column of Figure B.1 thus are the same as in column (a) of Figure 2 and the left-hand column of Figure 3. In the second column of Figure B.1, we repeat the analysis using the core CPI instead of the headline CPI; in the third column, we repeat the analysis using the one-year Treasury yield instead of the two-year Treasury yield; and in the fourth column, we repeat the analysis including the unemployment rate as a fifth variable in the specification, as is sometimes done in the literature (e.g., Ramey, 2016).

As can be seen in Figure B.1, the impulse response functions are very similar across all of these specifications. The different specifications also generally yield differences in the first-stage F-statistics for the regression of the reduced-form residual u_t^{2y} on the high-frequency monetary policy instrument, z_t. In the first column, the first-stage F-statistic is 7.69, in the second column 7.38, in the third column 13.58, and in the fourth column 7.73. Note that the higher first-stage F-statistic in the third column was exactly why Gertler and Karadi (2015) used that specification as their baseline. Nevertheless, Gertler and Karadi found that their estimated SVAR results were very similar using the two-year Treasury yield instead of the one-year yield, which we likewise find in Figure B.1.

C Local Projections

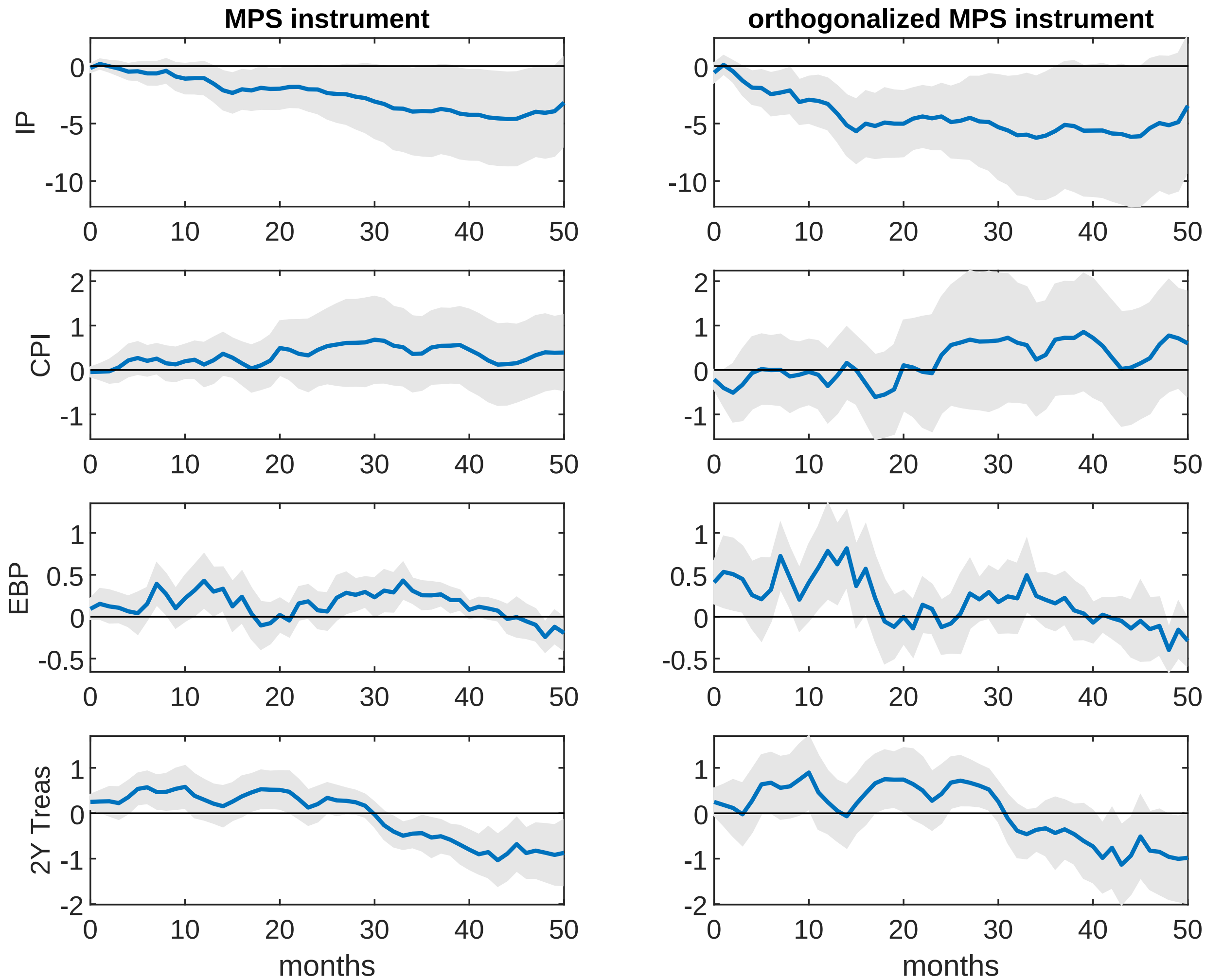
Figure C.1 reports estimated impulse response functions using the LP-IV specification (23) with the high-frequency monetary policy instrument around FOMC announcements each month as the external instrument (excluding speeches by the Fed Chair). The impulse response functions in Figure C.1 are larger than in Figures 3–6, but the standard errors are also much larger, so we would not reject these other estimates. Ramey (2016) suggests that the later sample period may be partly responsible for the difference between the LP-IV and VAR results, but our results in Figure 2 suggest that the different sample period is not a major issue. The impulse response functions for industrial production in particular in Figure C.1 are very large, especially for the orthogonalized *mps* instrument, although the standard errors are correspondingly large. It is likely that part of the problem here is that the orthogonalized surprises $z_t^{\perp}$ are a weak instrument—recall that the first-stage F-statistic for this instument is only 2.44. Overall, the results in Figure C.1 are very imprecise and should be treated very cautiously.

D Miranda-Agrippino and Ricco (2021)

We noticed two issues in our reassessment of the results in Miranda-Agrippino and Ricco (2021) that are only tangentially related to our main points, but which are helpful for interpreting the results in their paper and in ours.

First, it is important to consider the properties of the unadjusted monetary policy surprises. As also noted by Ramey (2016), the Gertler-Karadi version of FF4, which is a 30-day moving average of the underlying high-frequency FF4 surprises, introduces serial correlation into the resulting series FF4GK. As a result, using FF4 or FF4GK leads to quite different results. In particular, impulse responses obtained using FF4 are more similar to

Figure C.1: Local Projections Impulse Responses, Identified Using Raw vs. Orthogonalized Monetary Policy Surprises around FOMC Announcements

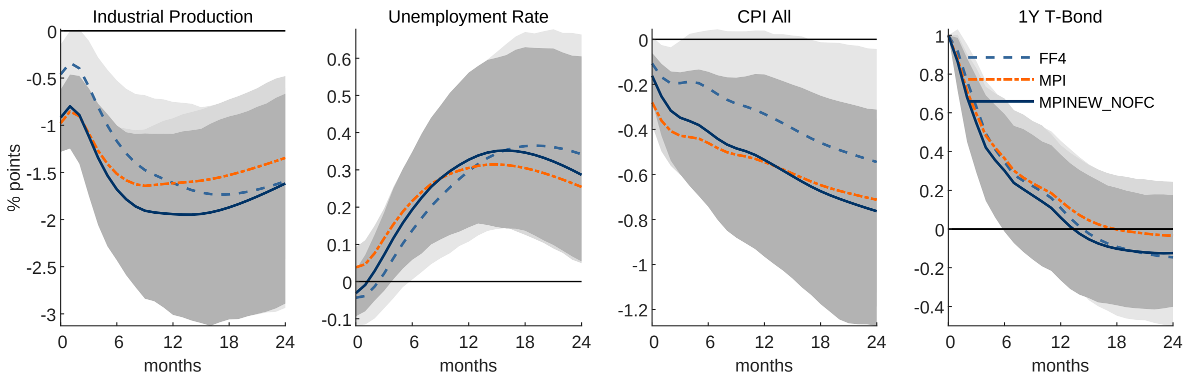


Local Projections impulse reponse functions to a 25bp monetary policy shock, identified in the left column using the unadjusted high-frequency *mps* measure around FOMC announcements, and in the right column using high-frequency change in *mps* around FOMC announcements orthogonalized with respect to economic news available prior to the announcement. Sample: 1988:1–2020:2. Shaded regions report 90% standard-error bands. See text for details.

those obtained using MPI in Figure 7. Figure D.1 shows that results for FF4 are more similar to results for MPI than the results for FF4GK are. That is, the orthogonalization of high-frequency surprises with respect to macro forecasts and the removal of serial correlation actually makes a smaller difference for the SVAR results than it initially appeared. By contrast, our results in Sections 5.1–5.3 showed that simple orthogonalization of the surprises with respect to macroeconomic and financial data makes a very substantial difference for the resulting impulse responses.

Second, we have also found that an instrument series that does not use any information in macroeconomic forecasts, but only removes serial correlation, leads to results not too

Figure D.1: Additional results for Miranda-Agrippino & Ricco



Structural VAR impulse reponse functions to a monetary policy shock identified with three different external instrument series: raw FF4 series, Miranda-Agrippino and Ricco instruments using Greenbook forecasts (MPI), and a new instrument series that does not orthogonalize FF4 with respect to macroeconomic forecasts, and only removes serial correlation (MPINEW_NOFC). Specification, sample period, and estimation method are exactly as in Figure 3 of Miranda-Agrippino and Ricco (2021). Shaded areas are 95% credibility bands based on the simulated posterior distribution.

different from those obtained using MPI or MPINEW_BC. This is evident in Figure D.1, which shows results for an instrument series MPINEW_NOFC which is obtained in exactly the same way as MPI except for the fact that we did not orthogonalize the surprises with respect to Greenbook forcasts. The similarity of the IRFs for MPI and for MPINEW_NOFC suggests that orthogonalizing with respect to macro forecasts has a very modest impact on the resulting estimates.

Overall, it appears that most of the differences in the impulse responses shown in Figure 7—between those for FF4GK on the one hand, and those for MPI and MPINEW_BC on the other hand—appear to be due to the serial correlation in the FF4GK series.

References

Altavilla, Carlo, Luca Brugnolini, Refet Gürkaynak, Roberto Motto, and Guiseppe Ragusa (2019) "Measuring Euro Area Monetary Policy," *Journal of Monetary Economics*, 108, 162–179.

Andersen, Torben G, Tim Bollerslev, Francis X Diebold, and Clara Vega (2007) "Real-Time Price Discovery in Global Stock, Bond and Foreign Exchange Markets," *Journal of international Economics*, 73 (2), 251–277.

Bauer, Michael D. (2015) "Nominal Interest Rates and the News," *Journal of Money, Credit and Banking*, 47 (2-3), 295–332.

Bauer, Michael D. and Mikhail Chernov (2021) "Interest Rate Skewness and Biased Beliefs," Working Paper w28954, National Bureau of Economic Research.

Bauer, Michael D. and Christopher J. Neely (2014) "International Channels of the Fed's Unconventional Monetary Policy," *Journal of International Money and Finance*, 44, 24–46.

Bauer, Michael D. and Glenn D. Rudebusch (2014) "The Signaling Channel for Federal Reserve Bond Purchases," *International Journal of Central Banking*, 10 (3), 233–289.

Bauer, Michael D. and Eric T. Swanson (2021) "An Alternative Explanation for the 'Fed Information Effect'," Working Paper 2020-06, Federal Reserve Bank of San Francisco.

Bernanke, Ben (2008) "Federal Reserve Policies in the Financial Crisis," https://www.federalreserve.gov/newsevents/speech/bernanke20081201a.htm, remarks at the Greater Austin Chamber of Commerce on December 1.

——— (2013) "Communication and Monetary Policy," https://www.federalreserve.gov/newsevents/speech/bernanke20131119a.htm, remarks at the National Economists Club Annual Dinner, Herbert Stein Memorial Lecture, Washington, D.C., on November 19.

Bernanke, Ben and Kenneth Kuttner (2005) "What Explains the Stock Market's Reaction to Federal Reserve Policy?" *Journal of Finance*, 60 (3), 1221–1257.

Bianchi, Francesco, Martin Lettau, and Sydney C Ludvigson (2021) "Monetary Policy and Asset Valuation," forthcoming in Journal of Finance.

Boivin, Jean (2006) "Has US Monetary Policy Changed? Evidence from Drifting Coefficients and Real-Time Data," *Journal of Money, Credit and Banking*, 38 (5), 1149–1173.

Brand, Claus, Daniel Buncic, and Jarkko Turunen (2010) "The Impact of ECB Monetary Policy Decisions and Communication on the Yield Curve," *Journal of the European Economic Association*, 8 (6), 1266–1298.

Caldara, Dario and Edward Herbst (2019) "Monetary Policy, Real Activity, and Credit Spreads: Evidence from Bayesian Proxy SVARs," *American Economic Journal: Macroeconomics*, 11 (1), 157–192.

Campbell, Jeffrey, Charles Evans, Jonas Fisher, and Alejandro Justiniano (2012) "Macroeconomic Effects of Federal Reserve Forward Guidance," *Brookings Papers on Economic Activity*, 2012, 1–54.

Capistrán, Carlos (2008) "Bias in Federal Reserve inflation forecasts: Is the Federal Reserve irrational or just cautious?" *Journal of Monetary Economics*, 55 (8), 1415–1427.

Christiano, Lawrence, Martin Eichenbaum, and Charles Evans (2005) "Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy," *Journal of Political Economy*, 113 (1), 1–45.

Cieslak, Anna (2018) "Short-Rate Expectations and Unexpected Returns in Treasury Bonds," *Review of Financial Studies*, 31 (9), 3265–3306.

Cieslak, Anna and Hao Pang (2021) "Common shocks in stocks and bonds," *Journal of Financial Economics*, 142 (2), 880–904.

Cieslak, Anna and Andreas Schrimpf (2019) "Non-Monetary News in Central Bank Communication," *Journal of International Economics*, 118, 293–315.

Clarida, Richard, Jordi Gali, and Mark Gertler (2000) "Monetary Policy Rules and Macroeconomic Stability: Evidence and Some Theory," *Quarterly Journal of Economics*, 115 (1), 147–180.

Cochrane, John and Monika Piazzesi (2002) "The Fed and Interest Rates—A High-Frequency Identification," *American Economic Review*, 92 (2), 90–95.

Cogley, Timothy and Thomas J Sargent (2005) "Drifts and Volatilities: Monetary Policies and Outcomes in the Post-WWII US," *Review of Economic Dynamics*, 8 (2), 262–302.

Coibion, Olivier (2012) "Are the effects of monetary policy shocks big or small?" *American Economic Journal: Macroeconomics*, 4 (2), 1–32.

Coibion, Olivier and Yuriy Gorodnichenko (2015) "Information Rigidity and the Expectations Formation Process: A Simple Framework and New Facts," *American Economic Review*, 105 (8), 2644–2678.

Cook, Timothy and Thomas Hahn (1989) "The Effect of Changes in the Federal Funds Rate Target on market Interest Rates in the 1970s," *Journal of Monetary Economics*, 24 (3), 331–351.

D'Amico, Stefania and Mira Farka (2011) "The Fed and the Stock Market: An Identification Based on Intraday Futures Data," *Journal of Business and Economic Statistics*, 29 (1), 126–137.

Farmer, Leland, Emi Nakamura, and Jón Steinsson (2021) "Learning About the Long Run," Working Paper w29495, National Bureau of Economic Research.

Faust, Jon, John Rogers, Eric T. Swanson, and Jonathan Wright (2003) "Identifying the Effects of Monetary Policy Shocks on Exchange Rates Using High Frequency Data," *Journal of the European Economic Association*, 1 (5), 1031–1057.

Faust, Jon, Eric T. Swanson, and Jonathan Wright (2004) "Identifying VARs Based on High Frequency Futures Data," *Journal of Monetary Economics*, 51 (6), 1107–1131.

Gagnon, Joseph, Matthew Raskin, Julie Remache, and Brian Sack (2011) "The Financial Market Effects of the Federal Reserve's Large-Scale Asset Purchases," *International Journal of Central Banking*, 7 (1), 3–43.

Gertler, Mark and Peter Karadi (2015) "Monetary Policy Surprises, Credit Costs, and Economic Activity," *American Economic Journal: Macroeconomics*, 7 (1), 44–76.

Gilchrist, Simon and Egon Zakrajšek (2012) "Credit Spreads and Business Cycle Fluctuations," *American Economic Review*, 102 (4), 1692–1720.

Greenwood, Robin and Andrei Shleifer (2014) "Expectations of Returns and Expected Returns," *Review of Financial Studies*, 27 (3), 714–746.

Gürkaynak, Refet, Brian Sack, and Eric T. Swanson (2005) "Do Actions Speak Louder Than Words? The Response of Asset Prices to Monetary Policy Actions and Statements," *International Journal of Central Banking*, 1 (1), 55–93.

——— (2007a) "Market-Based Measures of Monetary Policy Expectations," *Journal of Business & Economic Statistics*, 25 (2), 201–212.

Gürkaynak, Refet, Brian Sack, and Jonathan Wright (2007b) "The U.S. Treasury Yield Curve: 1961 to the Present," *Journal of Monetary Economics*, 54 (8), 2291–2304.

Hanson, Samuel and Jeremy Stein (2015) "Monetary Policy and Long-Term Real Rates," *Journal of Financial Economics*, 115 (3), 429–448.

Jarocinski, Marek and Peter Karadi (2020) "Deconstructing Monetary Policy Surprises—The Role of Information Shocks," *American Economic Journal: Macroeconomics*, 12, 1–43.

Johannes, Michael, Lars A. Lochstoer, and Yiqun Mou (2016) "Learning about consumption dynamics," *Journal of Finance*, 71 (2), 551–600.

Jordà, Òscar (2005) "Estimation and Inference of Impulse Responses by Local Projections," *American Economic Review*, 95, 161–182.

Karnaukh, Nina (2020) "Growth Forecasts and News about Monetary Policy," Working Paper 2020-27, Fisher College of Business, Ohio State University.

Kim, Chang-Jin and Charles R Nelson (2006) "Estimation of a Forward-Looking Monetary Policy Rule: A Time-Varying Parameter Model Using Ex Post Data," *Journal of Monetary Economics*, 53 (8), 1949–1966.

Kuttner, Kenneth N. (2001) "Monetary Policy Surprises and Interest Rates: Evidence from the Fed Funds Futures Market," *Journal of Monetary Economics*, 47 (3), 523–544.

——— (2018) "Outside the Box: Unconventional Monetary Policy in the Great Recession and Beyond," *Journal of Economic Perspectives*, 32 (4), 121–46.

Lakdawala, Aeimit (2016) "Changes in Federal Reserve Preferences," *Journal of Economic Dynamics and Control*, 70, 124–143.

——— (2019) "Decomposing the Effects of Monetary Policy Using an External Instruments SVAR," *Journal of applied econometrics*, 34 (6), 934–950.

Lewellen, Jonathan and Jay Shanken (2002) "Learning, asset-pricing tests, and market efficiency," *Journal of Finance*, 57 (3), 1113–1145.

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

Miranda-Agrippino, Silvia (2017) "Unsurprising Shocks: Information, Premia, and the Monetary Transmission," Staff Working Paper 626, Bank of England.

Miranda-Agrippino, Silvia and Giovanni Ricco (2021) "The Transmission of Monetary Policy Shocks," *American Economic Journal: Macroeconomics*, 13 (3), 74–107.

Nakamura, Emi and Jón Steinsson (2018) "High-Frequency Identification of Monetary Non-Neutrality: The Information Effect," *Quarterly Journal of Economics*, 133 (3), 1283–1330.

Newey, Whitney and Kenneth West (1987) "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix," *Econometrica*, 55 (3), 703–708.

Orphanides, Athanasios (2001) "Monetary Policy Rules Based on Real-Time Data," *American Economic Review*, 91 (4), 964–985.

Piazzesi, Monika and Eric T. Swanson (2008) "Futures Prices as Risk-Adjusted Forecasts of Monetary Policy," *Journal of Monetary Economics*, 55, 677–691.

Plagborg-Møller, Mikkel and Christian K Wolf (2021) "Local projections and VARs estimate the same impulse responses," *Econometrica*, 89 (2), 955–980.

Primiceri, Giorgio E. (2005) "Time-Varying Structural Vector Autoregressions and Monetary Policy," *Review of Economic Studies*, 72 (3), 821–852.

Ramey, Valerie (2016) "Macroeconomic Shocks and Their Propagation," in Taylor, John B. and Harald Uhlig eds. *Handbook of Macroeconomics, Vol. 2*, Chap. 2, 71–162: North-Holland.

——— (2022) “Postscript to ‘Macroeconomic Shocks and Their Propagation’,” Working Paper, UCSD.

Rigobon, Roberto and Brian Sack (2003) “Measuring the Reaction of Monetary Policy to the Stock Market,” *Quarterly Journal of Economics*, 118 (2), 639–669.

——— (2004) “The Impact of Monetary Policy on Asset Prices,” *Journal of Monetary Economics*, 51 (8), 1553–1575.

Romer, Christina D. and David H. Romer (2000) “Federal Reserve Information and the Behavior of Interest Rates,” *American Economic Review*, 90 (3), 429–457.

——— (2004) “A new measure of monetary shocks: Derivation and implications,” *American Economic Review*, 94 (4), 1055–1084.

Sastry, Karthik (2021) “Disagreement about Monetary Policy,” Working Paper, MIT.

Schmeling, Maik, Andreas Schrimpf, and Sigurd Steffensen (2021) “Monetary Policy Expectation Errors,” Working Paper, SSRN.

Sims, Christopher A (1992) “Interpreting the macroeconomic time series facts: The effects of monetary policy,” *European economic review*, 36 (5), 975–1000.

Stock, James H. and Mark W. Watson (2002) “Has the Business Cycle Changed and Why?” *NBER Macroeconomics Annual*, 17, 159–218.

——— (2012) “Disentangling the Channels of the 2007–09 Recession,” *Brookings Papers on Economic Activity*, Spring, 81–130.

——— (2018) “Identification and Estimation of Dynamic Causal Effects in Macroeconomics Using External Instruments,” *Economic Journal*, 128 (610), 917–948.

Swanson, Eric T. (2006) “Have Increases in Federal Reserve Transparency Improved Private Sector Interest Rate Forecasts?” *Journal of Money, Credit, and Banking*, 38 (3), 791–819.

——— (2011) “Let’s Twist Again: A High-Frequency Event-Study Analysis of Operation Twist and Its Implications for QE2,” *Brookings Papers on Economic Activity*, 151–188.

——— (2021) “Measuring the Effects of Federal Reserve Forward Guidance and Asset Purchases on Financial Markets,” *Journal of Monetary Economics*, 118, 32–53.

Swanson, Eric T. and Vishuddhi Jayawickrema (2021) “Speeches by the Fed Chair Are More Important than FOMC Announcements: An Improved High-Frequency Measure of U.S. Monetary Policy Shocks,” Working Paper, UC Irvine.

Swanson, Eric T. and John C. Williams (2014) “Measuring the Effect of the Zero Lower Bound on Medium- and Longer-Term Interest Rates,” *American Economic Review*, 104 (10), 3154–3185.

Taylor, John B (1993) "Discretion Versus Policy Rules in Practice," in *Carnegie-Rochester Conference Series on Public Policy*, 39, 195–214, Elsevier.

Taylor, John B. (1999) *Monetary Policy Rules*: University of Chicago Press.

Wall Street Journal (2001) "Fed Cuts Interest Rates by Half a Point in Attempt to Spur Second-Half Revival," *WSJ.com*, March 20.

Woodford, Michael (2009) "Convergence in Macroeconomics: Elements of the New Synthesis," *American Economic Journal: Macroeconomics*, 1 (1), 267–79.

Yellen, Janet L. (2012) "Revolution and Evolution in Central Bank Communications," https://www.federalreserve.gov/newsevents/speech/yellen20121113a.htm, remarks at the Haas School of Business, University of California, Berkeley, California on November 13.

——— (2017) "The Economic Outlook and the Conduct of Monetary Policy," https://www.federalreserve.gov/newsevents/speech/yellen20170119a.htm, remarks at the Stanford Institute for Economic Policy Research on Januay 19.

IMFS WORKING PAPER SERIES

Recent Issues

164 / 2021	Thomas Jost Karl-Heinz Tödter	Reducing sovereign debt levels in the post-Covid Eurozone with a simple deficit rule
163 / 2021	Michael D. Bauer Mikhail Chernov	Interest Rate Skewness and Biased Beliefs
162 / 2021	Magnus Reif Mewael F. Tesfaselassie Maik Wolters	Technological Growth and Hours in the Long Run: Theory and Evidence
161 / 2021	Michael Haliassos Thomas Jansson Yigitcan Karabulut	Wealth Inequality: Opportunity or Unfairness?
160 / 2021	Natascha Hinterlang Josef Hollmayr	Classification of Monetary and Fiscal Dominance Regimes using Machine Learning Techniques
159 / 2021	Volker Wieland	The decline in euro area inflation and the choice of policy strategy
158 / 2021	Matthew Agarwala Matt Burke Patrycja Klusak Moritz Kraemer Kamiar Mohaddes	Rising Temperatures, Falling Ratings: The Effect of Climate Change on Sovereign Creditworthiness
157 / 2021	Yvan Lengwiler Athanasios Orphanides	Collateral Framework:Liquidity Premia and Multiple Equilibria
156 / 2021	Gregor Boehl Cars Hommes	Rational vs. Irrational Beliefs in a Complex World
155 / 2021	Michael D. Bauer Eric T. Swanson	The Fed's Response to Economic News Explains the "Fed Information Effect"
154 / 2021	Alexander Meyer-Gohde	On the Accuracy of Linear DSGE Solution Methods and the Consequences for Log-Normal Asset Pricing
153 / 2021	Gregor Boehl Philipp Lieberknecht	The Hockey Stick Phillips Curve and the Zero Lower Bound
152 / 2021	Lazar Milivojevic Balint Tatar	Fixed exchange rate - a friend or foe of labor cost adjustments?
151 / 2021	Thomas Jost Franz Seitz	Designing a European Monetary Fund: What role for the IMF?

150 / 2021	Gerhard Rösl Franz Seitz	Cash and Crises: No surprises by the virus
149 / 2021	Wolfgang Lechthaler Mewael F. Tesfaselassie	Endogenous Growth, Skill Obsolescence and Output Hysteresis in a New Keynesian Model with Unemployment
148 / 2021	Gregor Boehl	Efficient Solution and Computation of Models with Occasionally Binding Constraints
147 / 2021	Brian Fabo Martina Jančoková Elisabeth Kempf Luboš Pástor	Fifty Shades of QE: Conflicts of Interest in Economic Research
146 / 2021	Robert C.M. Beyer Lazar Milivojevic	Dynamics and Synchronization of Global Equilibrium Interest Rates
145 / 2020	Lars P. Feld Volker Wieland	The German Federal Constitutional Court Ruling and the European Central Bank's Strategy
144 / 2020	Mátyás Farkas Balint Tatar	Bayesian Estimation of DSGE Models with Hamiltonian Monte Carlo
143 / 2020	Gregor Boehl Felix Strobel	U.S. Business Cycle Dynamics at the Zero Lower Bound
142 / 2020	Gregor Boehl Gavin Goy Felix Strobel	A Structural Investigation of Quantitative Easing
141 / 2020	Karl-Heinz Tödter	Ein SIRD-Modell zur Infektionsdynamik mit endogener Behandlungskapazität und Lehren für Corona-Statistiken
140 / 2020	Helmut Siekmann Volker Wieland	The Ruling of the Federal Constitutional Court concerning the Public Sector Purchase Program: A Practical Way Forward
139 / 2020	Volker Wieland	Verfahren zum Anleihekaufprogramm der EZB
138 / 2020	Francisco Gomes Michael Haliassos Tarun Ramadorai	Household Finance
137 / 2019	Martin Kliem Alexander Meyer-Gohde	(Un)expected Monetary Policy Shocks and Term Premia
136 / 2019	Luc Arrondel Hector Calvo-Pardo Chryssi Giannitsarou Michael Haliassos	Informative Social Interactions