Has the Information Channel of Monetary Policy Disappeared? Revisiting the Empirical Evidence

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Does the Federal Reserve have an "information advantage" in forecasting macroeconomic variables beyond what is known to private sector forecasters? And are market participants reacting only to monetary policy shocks or also to information on the future state of the economy that the Federal Reserve communicates in its announcements via an "information channel"? This paper investigates the evolution of both the information advantage and information channel over time. Although they appear to be important historically, we find substantially weaker empirical evidence of their presence in the recent years once instabilities are accounted for.

JEL: C11, C14, C22, C52, C53

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The recent literature has found that, in response to unexpected increases in interest rates, survey-based estimates of expected output growth rise while those of inflation decline (Campbell et al., 2012, 2017). This is contrary to the common New Keynesian wisdom that contractionary monetary policy causes a decline in output growth and inflation as well as their expectations. An explanation for this puzzling behavior is the so-called "information channel" of monetary policy. According to the information channel, agents update their beliefs after an unexpected monetary policy action not only because they learn about the current and future path of monetary policy, but also because they learn new information about economic fundamentals. The intuition is that the Federal Reserve communicates not only the future path of monetary policy but also how optimistic it is about the current and future state of the economy: if the Federal Reserve's expectation of future fundamentals is different from the state of the economy perceived by market participants, market participants will update their expectations. In this case, the responses to a monetary policy shock may not be estimated correctly. In fact, if the monetary policy tightening is the endogenous reaction to a future state of the economy that is more positive than markets anticipate, market participants might expect an increase in future output and inflation and update their expectations accordingly.

A sufficient, but not necessary, condition for the information channel is that the central bank has superior knowledge about the state of the economy relative to market participants; that is, it has an "information advantage". When that is the case, it is likely that market participants will update their information about the state of the economy based on the new information contained in central banks' announcements.[1]

[1]Note that this is a sufficient but not necessary condition. The private sector might be updating its expectations on the state of the economy even when the central bank does not have an information advantage. For example, Timmermann (2006) has shown that forecast combination may improve forecast accuracy even if the combination uses noisy or biased forecasts as long as they are not perfectly correlated with the forecasts already included in the pool.

How important is the information channel empirically? Does the Federal Reserve indeed have an information advantage in forecasting macroeconomic variables beyond what is known to private forecasters? And does this matter when estimating the response of the economy to monetary policy shocks?

We revisit the empirical evidence by making an important departure from the previous literature; namely, we allow for instabilities. That is, we allow the information advantage of the Federal Reserve relative to market participants to change over time. As we show, this is an important empirical feature of the data. Furthermore, we also allow the nature of monetary policy shocks to vary over time, depending on whether the information advantage is present in the data. We show that the latter matters when estimating the effects of a monetary policy shock in the economy. When the central bank has an informational advantage, the information channel is at work: the macroeconomic responses are confounded and the researcher may estimate an expansionary response to a contractionary monetary policy shock. On the other hand, when the information advantage disappears, the information channel loses importance: the perils of confoundedness disappear and researchers are able to correctly recover the response in the data.

Once we take instabilities into account, we find substantially weaker evidence for the empirical relevance of the information channel in the most recent period: (i) The Federal Reserve lost its short horizon information advantage regarding the state of the economy relative to market participants; (ii) market surprises are no longer predictable by the Federal Reserve's internal forecasts; and (iii) macroeconomic responses to a monetary policy shock are no longer confounded and private forecasters' responses are less sensitive to monetary policy shocks. Our results are consistent with the hypothesis that the decline in the relevance of the information channel is linked to the improved communication strategies of

Furthermore, Morris and Shin (2002) develop a theoretical model where public information can affect the equilibrium outcomes even if it is noisier than private information.

the Federal Reserve in recent years.

Related literature. Our paper is related to various strands of the literature. First, our paper is related to the large literature estimating the effects of monetary policy shocks – see Christiano, Eichenbaum and Evans (1999, 2005), among others. Traditional Vector Autoregressions (VAR) conventionally estimate a positive, hump-shaped response of output and inflation to an expansionary monetary policy shock measured by an exogenous increase in the Federal Funds Rate (FFR). However, as Campbell et al. (2012) and Nakamura and Steinsson (2018) show, survey expectations of output growth typically rise after an unexpected monetary policy tightening, thus contradicting the predictions of standard economic models.

Melosi (2017) and Nakamura and Steinsson (2018) develop theoretical models to rationalize this "real activity puzzle". In Melosi (2017)'s model, policy actions are publicly observable, but private information about the economy's fundamentals is "dispersed" across market participants and policymakers. Thus, a change in the current policy rate not only affects real interest rates but also provides the public with information on the central bank's view about macroeconomic developments. Melosi (2017) refers to the latter channel as the "signaling channel" of monetary transmission and provides the first econometric analysis of such "signaling effects". He finds that his model can explain the forecast errors observed in the data while perfect information models cannot. Nakamura and Steinsson (2018) suggest a similar explanation based on the information channel of monetary policy. In their model, monetary policy shocks affect not only the real interest rate but also the private sector's belief about the path of the natural rate of interest; this happens because, as the central bank tracks the natural rate of interest, its announcements are likely to contain news about it. They find strong empirical support for both the Federal Reserve (Fed) information channel of monetary policy and the conventional one.

The presence of the information channel and its *evolution over time* is the objective of our paper. Miranda-Agrippino and Ricco (2020) investigate the responses of core macroeconomic aggregates to monetary policy announcements using an identification strategy robust to information frictions. Their instrument is the component of high-frequency market-based monetary surprises at the time of a policy announcement that is orthogonal to both the central bank's own forecasts as well as previous market surprises. In a similar spirit, Jarociński and Karadi (2018) use sign restrictions to separately identify monetary policy and "information shocks" from stock price dynamics. Andrade and Ferroni (2021) investigate the information channel in forward guidance announcements in the euro area and find evidence of information effects.[2]

A series of papers have investigated the empirical importance of the information channel of monetary policy, including Cieslak and Schrimpf (2019), Lunsford (2020), Paul (2020) and Bauer and Swanson (2020). Cieslak and Schrimpf (2019) and Lunsford (2020) classify central banks' announcements according to their characteristics. Cieslak and Schrimpf (2019) distinguish among different types of central bank communication news: news about monetary policy, economic growth and financial risk premia. Their analysis results in a comprehensive database of international monetary policy events classified according to their information content. They show that news about monetary policy prevails in announcements about monetary policy decisions; news about economic growth prevails in press conferences; and the importance of risk premium shocks increases in the unconventional monetary policy period. However, they do not investigate time variation in the effects of monetary policy news. Lunsford (2020) investigates whether the type of forward guidance language used by the Fed can influence information

[2] On the other hand, Bundick and Smith (2019) and Inoue and Rossi (2019) show, using completely different methodologies, that the response of the economy to forward guidance shocks is indeed consistent with standard New Keynesian models' predictions.

effects. He shows that forward guidance shapes the private sector's responses to Federal Open Market Committee (FOMC) monetary policy statements and that forward guidance on the economic outlook has stronger information effects than communication on the policy inclination. Similarly to us, he finds time variation in the transmission of monetary policy shocks. In particular, analyzing the period from February 2000 to May 2006, he finds evidence of a structural break in the magnitude of the Federal Funds Rate surprises in August 2003. He argues that, before this break, FOMC statements only included forward guidance about the economic outlook, while they also included information on the FOMC policy inclinations after the break. He concludes that financial markets, survey forecasters as well as the macroeconomy react differently depending on the type of forward guidance. Our analysis differs from Lunsford (2020) in that we formally evaluate the relative importance of changes in the economic outlook versus pure monetary policy in a larger sample rather than focusing on different forms of forward guidance in a specific sample period. Paul (2020) and Bauer and Swanson (2020) instead focus on alternative explanations for the puzzling response of survey forecasters to monetary policy statements. Paul (2020) finds that the puzzling increase in private forecasters' expectations of output growth to unexpected increases in interest rates is present only when including unscheduled meetings. Bauer and Swanson (2020) find that the puzzling estimates are consistent not only with the central bank's information channel of monetary policy but also with the central bank's response to macroeconomic news. According to the latter, economic news simultaneously causes changes in the Fed's monetary policy as well as in the private sector's forecasts and there is little role for an information effect. Differently from Paul (2020) and Bauer and Swanson (2020), we focus on the interrelation between the information advantage and the information channel of monetary policy and investigate their evolution over time.

Second, there is a large literature that focuses on the evaluation of central banks' forecasts as well as the quality of the Fed's internal forecasts relative to the private sector's. In a seminal contribution, Romer and Romer (2000) showed that the Federal Reserve has an information advantage relative to the private sector when forecasting inflation. On the other hand, both D'Agostino and Whelan (2008) and Rossi and Sekhposyan (2016) find evidence of instabilities in the information advantage. D'Agostino and Whelan (2008) show that the Federal Reserve's superior forecasting performance relative to survey forecasts deteriorated since the early 1990s across medium to long forecast horizons. Our contribution is instead to document that even the central bank's short-horizon forecast advantage disappeared in the most recent period. In addition, while the analysis in D'Agostino and Whelan (2008) is based on ad-hoc sub-samples, we consider general patterns of time variation and let the data uncover the time period when the forecast advantage appears/disappears. Rossi and Sekhposyan (2016) also show that the evidence of central banks' forecast advantage in predicting inflation depends on the time period, and has deteriorated over time. Our paper considers instead a wider range of macroeconomic variables (such as real output growth, unemployment and, especially, interest rates) and links the forecast advantage to the information channel of monetary policy. In relation to this literature, our paper conducts a comprehensive analysis of the information channel of monetary policy, looking at various dimensions considered in the literature beyond forecast evaluation.

Lastly, our work is more distantly related to the literature on forecast rationality, in particular Faust and Wright (2009), Patton and Timmermann (2012), Croushore (2012) and Rossi and Sekhposyan (2016). Faust and Wright (2009), Patton and Timmermann (2012) and Croushore (2012) note that rationality of inflation forecasts depends on the sample period used for forecast evaluation, while Rossi and Sekhposyan (2016) formally investigate the rationality of the central bank as well as the private sector inflation forecasts in the presence of instabilities.

The remainder of the paper proceeds as follows. Section I. presents our analysis of the Federal Reserve's information advantage. Section II. investigates the time-varying information content of high-frequency market-based monetary surprises typically used in the literature to identify monetary policy shocks. Section III. investigates the empirical relevance of the information channel for determining the economy's response to monetary policy while Section IV. investigates the reaction of private forecasters. Section V. concludes.

I. Does the Federal Reserve have an information advantage?

This section revisits the empirical evidence on whether the Federal Reserve has more information than the private sector when forecasting key macroeconomic variables. We establish that, while the Federal Reserve historically had an information advantage when forecasting real GDP growth and inflation, at least at short horizons, this advantage disappeared in the recent period. We also estimate several important change-points in the information advantage that coincide with changes in FOMC communication policy. Finally, we discuss the relationship between the information advantage and relative forecast accuracy (measured by a mean squared error loss function, MSFE) and show that, based on the latter criterion, the Federal Reserve's advantage deteriorated as well.

I.A The evolution of the Federal Reserve's information advantage

To assess whether the Federal Reserve has an information advantage over the private sector in forecasting a macroeconomic variable, x, we consider the following information advantage regression:

$$x_{t+h} - x_{t+h|t}^{BCEI} = \delta + \beta_{GB}\, x_{t+h|t}^{GB} + \beta_{BCEI}\, x_{t+h|t}^{BCEI} + \eta_{t+h} \tag{1}$$

where $x^{GB}_{t+h|t}$ is the Greenbook/Tealbook forecast at horizon h, $x^{BCEI}_{t+h|t}$ is the consensus forecast from the Blue Chip Economic Indicators' (BCEI) survey at horizon h, x_{t+h} denotes the real-time realization of the variable of interest and η_{t+h} is an unforecastable error term. Our goal is to test whether β_{GB} equals zero. In fact, the Fed's forecasts provide additional information above and beyond that in the private sector's forecasts if β_{GB} is different from zero. In other words, a value of β_{GB} different from zero indicates that forecasters would prefer to put weight on both Greenbook/Tealbook forecasts as well as BCEI forecasts if they had a choice.

Because the coefficients in the above regression could be time-varying, we investigate whether β_{GB} is different from zero using tests robust to instabilities. Tests based on the full sample characterize the average out-of-sample performance, which might mask the evolution of the information advantage over time (Rossi, 2006). Instead, we base our analysis on what we label as the "Information-Advantage Fluctuation test" using the general framework in Rossi and Sekhposyan (2016). Specifically, we estimate the information advantage regression in eq. (1) in rolling windows of m forecasts.[3] Let $\beta_{GB,t}$ be the time-varying parameter and let $\widehat{\beta}_{GB,t}$ denote the parameter estimated sequentially in regression (1) for $t = m/2, ..., T - m/2$ using observations centered around time t – that is, the most recent $m/2$ observations as well as the following $m/2$ ones. We then construct a t-statistic at each point in time t:

$$\tau_{GB,t} = \widehat{\beta}_{GB,t} / \sqrt{\widehat{\sigma}^2_{GB}/m} \tag{2}$$

where $\widehat{\sigma}^2_{GB}$ is the Newey and West (1987) HAC estimator of the asymptotic variance of the parameter estimate in the rolling window centered at time t.[4]

[3] Without loss of generality, m is an even integer.

[4] The variance estimate is based on a Newey and West (1987) HAC estimator using a truncation lag equal to $m^{1/4}$. For details on the variance estimator, see Rossi and Sekhposyan (2016). The results presented in this section are robust to using a heteroskedasticity-consistent variance

The Information-Advantage Fluctuation test statistic is:

$$\mathcal{F}_{GB} = max_t \left| \tau_{GB,t} \right|, \tag{3}$$

which we use to test the null hypothesis that $\beta_{GB,t} = 0$ at every point in time t against the alternative that $\beta_{GB,t} \neq 0$ at some point in time t.

Figures 1 and 2 depict $\tau_{GB,t}$ over time. The largest (absolute) value in the sequence of $\tau_{GB,t}$ is the Information-Advantage Fluctuation test statistic, $\mathcal{F}_{GB}$. The (red) dashed horizontal line denotes the corresponding five percent critical value.[5] When $\mathcal{F}_{GB}$ is outside the critical value lines, the test rejects the null hypothesis that $\beta_{GB,t} = 0$ for every t, and we conclude that the central bank had an information advantage at some point in time. Importantly, the critical value properly controls size and guards against sequential testing bias.[6]

The path of $\tau_{GB,t}$ is a local measure of forecast advantage over the rolling window, which we attribute to the center point of the window itself (similarly to usual non-parametric approaches).[7] Since the rolling-window approach involves smoothing, by construction the date is only indicative of when the forecast advantage started/ended; later in this section, we complement our results with Bai and Perron (1998)'s test of multiple discrete breaks. Also, for completeness, we report the coefficient estimates ($\widehat{\beta}_{GB,t}$), which have the same sign as $\tau_{GB,t}$, in the Not-for-Publication Appendix.

estimator instead of the HAC estimator.

[5]The relevant critical value is the t-statistic analog to the Wald test critical values for the survey and model-free forecasts reported in Table II Panel C of Rossi and Sekhposyan (2016).

[6]Note that a rejection does not simply indicate time-variation: the test rejects the hypothesis that the central bank never had an information advantage relative to the survey forecasters. Importantly, the test would also reject if there was no time variation, but the central bank had a constant information advantage. Thus, the path of $\tau_{GB,t}$ contains valuable information on the reason behind the rejection.

[7]Therefore, note that the last year in the figures is 2011 only because that is the center point in the last window we consider: our sample in fact ends in December 2015.

Data. To implement the Information-Advantage Fluctuation test in eq. (1), we require data on the central bank's and private sector's forecasts as well as the corresponding real-time realizations for key macroeconomic variables. In our analysis, we consider forecasts of inflation, GDP growth, unemployment and the interest rate. We also require a strategy to match the forecasts and realizations so that their targets align. As a measure of central bank forecasts, we use the Greenbook/Tealbook forecasts between February 1984 and December 2015, which are prepared by the staff of the Federal Reserve prior to each regular FOMC meeting (eight times per year). These forecasts are based on a maintained assumption about monetary policy and are made available to the public after a five year lag. This lag constrains the end of our sample period. For inflation, we use the forecasts of the annualized, chain-weighted quarter-over-quarter growth in the GDP deflator. For GDP growth, we use the forecasts of the annualized, chain-weighted quarter-over-quarter real GDP growth rate. For the unemployment rate, we use the Greenbook/Tealbook projections for the quarterly average unemployment rate in percentage points. Finally, for the interest rate, we use the projections of the three month Treasury bill rate.

As a measure of private sector forecasts, we use the Blue Chip Economic Indicators (BCEI), which is a monthly commercial survey-based dataset containing consensus (average) forecasts for 16 macroeconomic variables collected from approximately 50 business economists. We consider only forecasts up to four quarters since the series exhibit missing values occurring systematically beyond this horizon. Since the BCEI forecasts are for fixed events, i.e. for selected quarters in reference years, forecasts beyond four quarters are not available for every FOMC round.[8] For inflation, we use the annualized quarter-over-quarter BCEI

[8] For example, for the five-quarter-ahead forecasts of all the variables considered in our analysis, the BCEI forecasts for any FOMC meeting occurring in the last quarter of each year is systematically missing, as survey respondents were only asked to forecast until the last quarter of the next year. This corresponds to two or three meetings out of the eight regular FOMC meetings per year.

consensus forecasts of the GDP deflator price index. For GDP growth, we use the annualized quarter-over-quarter consensus forecasts of real GDP growth and for the unemployment rate the consensus forecasts of the quarterly average of the unemployment rate in percentage points. Finally, for the interest rate we use the forecasts of the quarterly average yield on a three month Treasury bill in percentage points. The forecasts are available for our entire sample from February 1984 - December 2015. At the beginning of the sample, the BCEI survey was conducted over three days, beginning on the first working day of each month, and was subsequently shortened to two days starting in December 2000. The BCEI consensus forecasts are released on the 10th of each month.

To implement the regression in eq. (1), we match the BCEI forecasts to the Greenbook/Tealbook forecasts so that the BCEI forecast is always strictly before the FOMC meeting associated with each Greenbook/Tealbook forecast. This results in the BCEI forecasts sometimes being published before the Greenbook/Tealbook forecasts and sometimes after, but both forecasts are made strictly before the FOMC announcement. Appendix A reports sensitivity analyses using an alternative timing assumption that strictly orders BCEI forecasts before the Greenbook/Tealbook forecasts.

For the realizations, we use real-time data from the Philadelphia Fed's "Real-Time Data Set for Macroeconomists". We use the quarterly first-release values where available and, in a handful of cases, we impute any missing values using second-release values. We use the first-releases because of their timeliness. The Not-for-Publication Appendix shows that our results are robust to using second and third releases for output growth and inflation (interest rates are never revised and revisions to the unemployment rate are negligible). We do not consider final releases since they include ex-post re-definitions and major classification changes that the forecasters would not have known at the time the forecasts were made. For realized inflation, we use the annualized quarter-over-quarter growth rate in the GNP/GDP deflator price index in percentage points; for realized GDP, we use the annualized quarter-over-quarter growth rate in real GNP/GDP in percentage points; for the unemployment rate, we use the quarterly average of the monthly history of (quarterly) vintages provided by the Federal Reserve Bank of Philadelphia. Interest rate data is not revised, thus we use the average quarterly secondary market rate of the three month Treasury bill (TB3MS), which we obtain from the FRED database maintained by the Federal Reserve Bank of St. Louis.

Details on the Greenbook/Tealbook forecasts, the BCEI forecasts, real-time data as well as the data sources are documented in the Not-for-Publication Appendix.

Results. Figures 1 and 2 plot $\tau_{GB,t}$ on the y-axis for the nowcast, the one-quarter-ahead forecast and an average of forecasts from two to four quarters ahead. Recall that the largest absolute value of $\tau_{GB,t}$ is the Fluctuation test statistic, $\mathcal{F}_{GB}$, and the timing reported on the x-axis is the mid-point of the rolling sample used to estimate $\tau_{GB,t}$ over time. The figure also reports the five percent critical value lines for the Information-Advantage Fluctuation test.

First, consider the results for inflation and real GDP growth reported in Figure 1. The figure shows that, for both variables, the Greenbook/Tealbook had an information advantage for the nowcast and one-quarter-ahead forecasts, which deteriorated in the early 2000s. At longer horizons (two-to-four-quarter-ahead quarter ahead), the information advantage is only sporadic and, for most of the sample, Greenbook/Tealbook forecasts do not seem to provide additional information relative to the BCEI consensus forecasts. For unemployment and interest rate forecasts in Figure 2, the information advantage weakened substantially in one- and two-to-four-quarter-ahead forecasts, yet persists throughout the whole sample only for the nowcast.

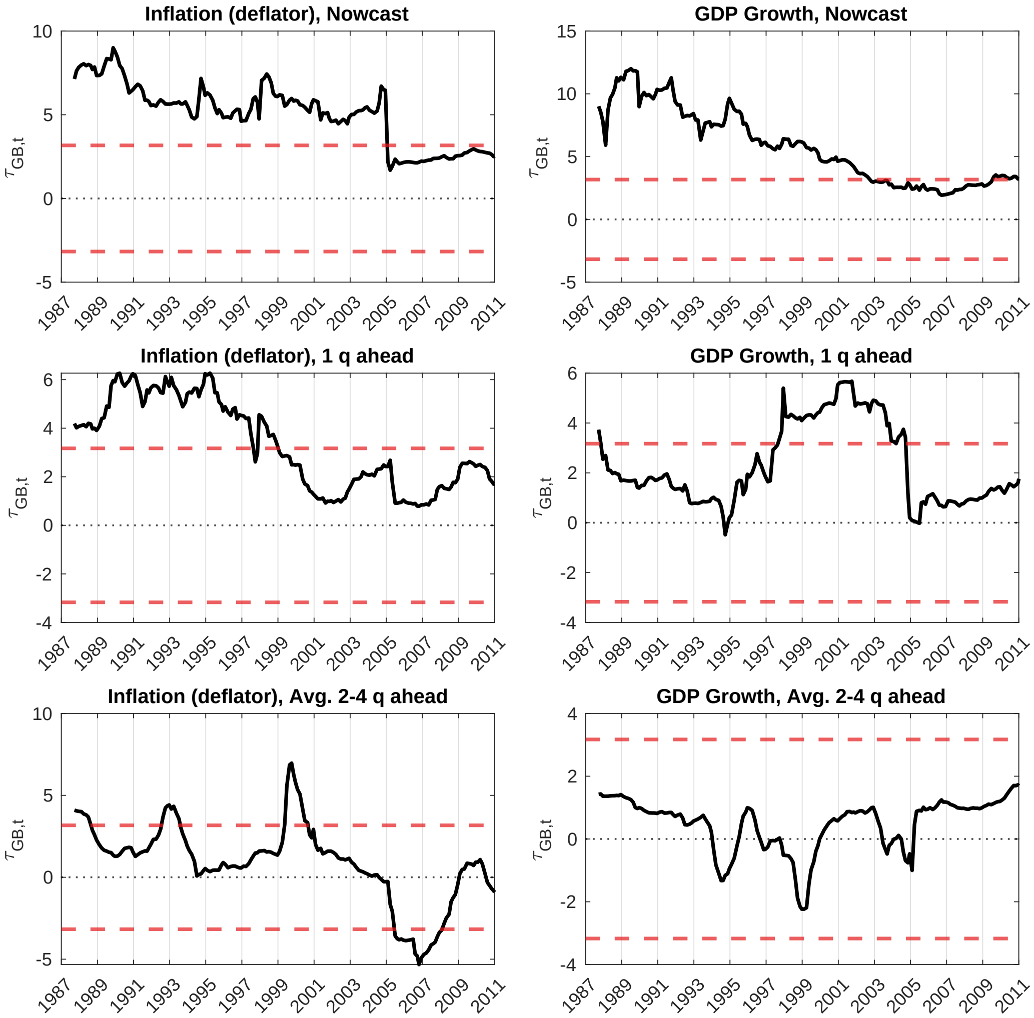

Figure 1: Information advantage fluctuation test: Inflation and GDP growth

Note: The figure shows $\tau_{GB,t}$ from eq. (1) based on $m = 60$ meetings rolling windows using a Newey-West covariance estimator with a truncation lag of $m^{1/4}$. Horizontal axes correspond to mid-window dates. Dashed (red) lines denote 5% critical value lines based on Rossi and Sekhposyan (2016)'s two-sided Fluctuation test.

Remarks. Note that our regressions shed light on whether the central bank has an information advantage relative to survey participants from a historical point of view: finding that the central bank lost its information advantage in

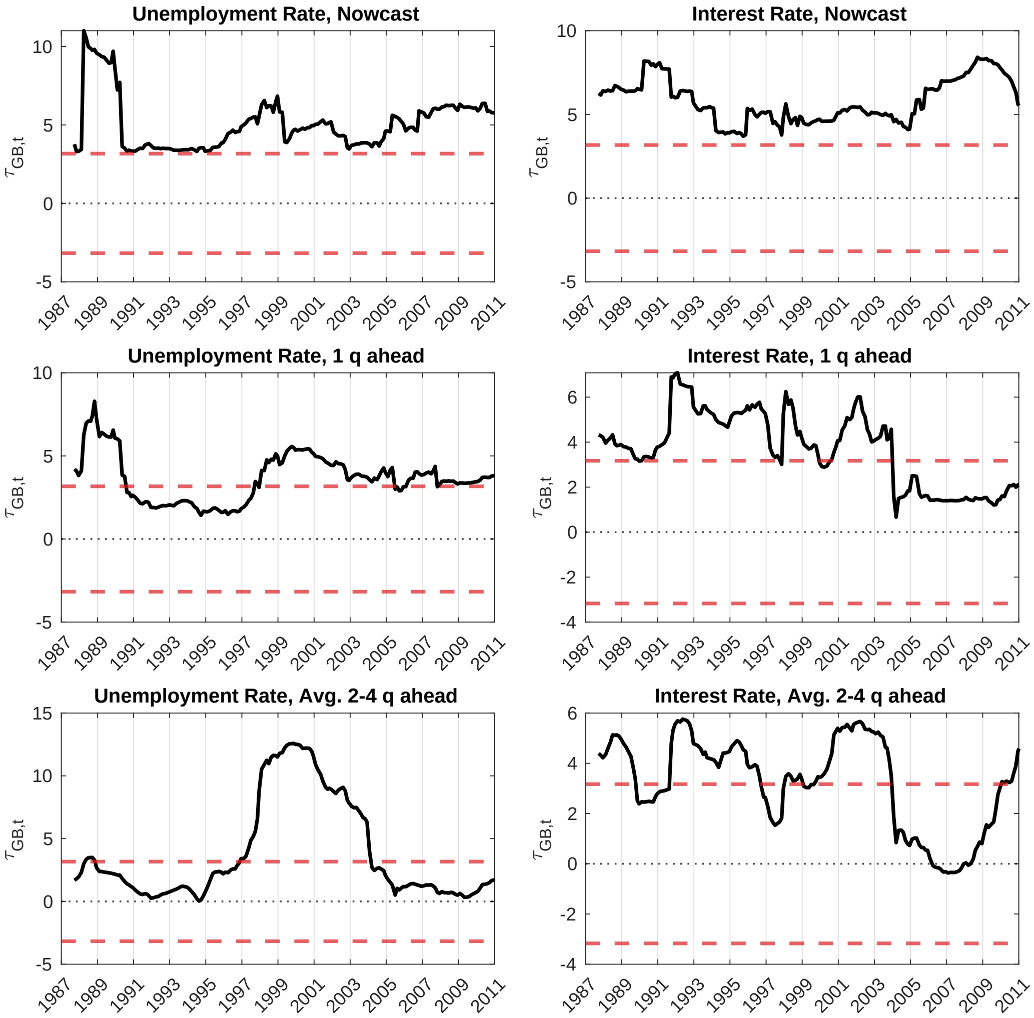

FIGURE 2: INFORMATION ADVANTAGE FLUCTUATION TEST: UNEMPLOYMENT AND INTEREST RATES

Note: The figure shows $\tau_{GB,t}$ from eq. (1) based on $m = 60$ meetings rolling windows using a Newey-West covariance estimator with a truncation lag of $m^{1/4}$. Horizontal axes correspond to mid-window dates. Dashed (red) lines denote 5% critical value lines based on Rossi and Sekhposyan (2016)'s two-sided Fluctuation test.

a given year does not imply that survey participants were aware of it in real time, as Greenbook/Tealbook forecasts become public with a delay of five years. However, the private sector might have been able to gauge the relative accuracy of the Greenbook/Tealbook forecasts in other (informal) ways. For example, Ericsson (2016) shows that FOMC minutes contain useful information which can help infer the staff's Greenbook/Tealbook forecasts of real GDP growth rate years before the public release of these forecasts.

Finally, it is important to note that the Greenbook/Tealbook projections condition on a hypothetical, counterfactual policy path that is not supposed to be a monetary policy forecast. As discussed in Faust and Wright (2008), the conditional nature of the forecasts can be neglected when "the conditioning paths are not too far from the central bank's unconditional expectation for policy and/or that policy feedback is not too large over the relevant horizon". As discussed in Faust and Wright (2008), these assumptions may be reasonable at the very short forecast horizons we focus on. On the other hand, as information on the current interest rate and projections of monetary policy are readily available to private forecasters (e.g. through summaries/analyses/projections published by the FOMC), there is reason to believe that BCEI forecasts might be conditional forecasts as well. Berge, Chang and Sinha (2019) provide a framework to study the conditionality of survey forecasts and analyze both Greenbook/Tealbook and BCEI consensus forecasts. They report that interest rate projections were incorporated efficiently into both central banks' and private sector's forecasts of common macroeconomic variables, leading to the conclusion that both forecasts are conditional.

Robustness. Appendix A investigates the robustness to the relative timing assumptions of Greenbook/Tealbook and BCEI forecasts. Specifically, we report Information-Advantage Fluctuation tests for the case where BCEI forecasts are always published before the corresponding Greenbook/Tealbook forecasts. The Not-for-Publication Appendix reports additional sensitivity analyses to different window sizes as well as the second and third vintages for the real-time realizations (instead of the first release). Our results remain robust to these changes.

I.B Discrete breaks and changes in FOMC communication

The analysis in the previous section establishes that the information advantage of the Federal Reserve weakened in recent years. This section sharpens the evidence by testing for structural breaks and estimating break dates in the information advantage regressions.

While the Information-Advantage Fluctuation test robustly shows that there is little evidence to reject the hypothesis that β_{GB} is zero in recent years, the rolling-window nature of the test makes it difficult to precisely identify the exact point in time in which the departure from zero has taken place. In fact, the non-parametric approach we adopt is designed for smooth changes. When the changes are of a discrete nature, our approach may smooth them out over the rolling windows, thus making it difficult to identify exactly when the change happened. Therefore, we present complementary evidence based on Bai and Perron (1998)'s test, which is designed to identify multiple sharp breaks in parameters.

However, in the context of our analysis, the Bai and Perron (1998) test has several drawbacks. First, it requires that all the parameters change discretely and at the same time. The Fluctuation test, instead, is a non-parametric test that summarizes the time path of the parameter of interest (in this case the coefficient on the Greenbook/Tealbook forecast), while allowing other regression parameters to change (or not) in a data-driven way. Second, and most importantly, while the Bai and Perron (1998) test identifies multiple and discrete change-points, it cannot be used to test the joint hypothesis we are interested in, namely $\beta_{GB,t} = 0$ at every point in time.[9] Therefore, the Information-Advantage Fluctuation and the Bai and Perron (1998) tests complement each other: we report the latter here

[9] For example, in the case that the true β_{GB} coefficient is constant but different from zero, the Fluctuation test will reject, while the Bai and Perron (1998) test will not reject as there is no instability.

to shed additional light on the estimated break dates.

We conduct Bai and Perron (1998)'s test on $\beta_{GB,t}$ in the information advantage regressions in eq. (1).[10] Table 1 reports results for forecasts of inflation, real GDP growth, unemployment and the interest rate for several forecast horizons: the nowcast, one-quarter-ahead and the average over two-, three- and four-quarter-ahead forecasts. For each variable and forecast horizon, consistently with Bai and Perron (1998)'s notation, the table reports the $UDmax$ test statistic as well as the estimated number of breakpoints according to two criteria: the $\sup F(k+1|k)$ (denoted by k_{supF}) and the BIC (denoted by k_{BIC}). In most cases, the two criteria agree on the number of breakpoints, although there are some differences. We follow Bai and Perron (1998)'s recommendation and base our inference on the k_{supF} criterion. The last column in the table reports the estimated break dates, together with their 90 percent confidence intervals.

For inflation, there are broadly three break-points, dating to the early 1990s, 2002/2003, and 2008. For real GDP growth, there are breaks in the early 1990s and late 1990s/early 2000s for the one-quarter and the average of two-to-four-quarter-ahead forecasts. For the nowcast, on the other hand, the break date appears to be in 2010. For the unemployment rate, there are no detected breaks in the nowcast and one-quarter-ahead forecasts, consistently with the Fluctuation test results, while 2007 shows up as a break date at longer horizons. For the interest rate, 2007 is detected as a robust break-point across horizons; however, there are also breaks in 1992 and 2000 at the longer horizons.

As we emphasized earlier, Bai and Perron (1998) test for parameter stability, while the Fluctuation test jointly evaluates parameter stability and whether the

[10] We follow the recommendations in Bai and Perron (2006) and Bai and Perron (2003), and use their $UDmax$ statistic with a maximum of $K = 5$ breaks. When the test rejects the null hypothesis of no break, we estimate the number of breaks by the sequence of $\sup F(k+1|k)$ tests and estimate the break dates by globally minimizing the sum of squared residuals in eq. (1). Confidence intervals are constructed based on the asymptotic approach provided in Bai and Perron (1998), assuming serially correlated, but homogeneous residuals across segments.

Table 1: Results from multiple break tests

Horizon	UDmax	k_{supF}	k_{BIC}	Break date [90 % CI]
GDP Deflator Inflation				
Nowcast	11.99	3	3	10/1991 [10/1990 - 07/1992] 12/2002 [08/2000 - 08/2005] 09/2008 [12/2006 - 11/2009]
1 q ahead	12.16	3	3	03/1991 [05/1990 - 12/1991] 09/2003 [06/2001 - 09/2005] 06/2008 [05/2006 - 11/2009]
Avg. 2-4 q ahead	19.53	3	4	10/1990 [05/1989 - 08/1991] 03/2003 [11/1995 - 08/2008] 03/2008 [08/2003 - 04/2011]
GDP Growth				
Nowcast	13.17	1	0	03/2010 [03/2005 - 10/2013]
1 q ahead	17.98	2	2	07/1993 [10/1991 - 03/1995] 03/2000 [11/1998 - 12/2001]
Avg. 2-4 q ahead	13.95	2	2	10/1992 [02/1991 - 02/1994] 10/1999 [11/1998 - 08/2001]
Unemployment Rate				
Nowcast	4.44	0	0	
1 q ahead	4.11	0	3	
Avg. 2-4 q ahead	22.19	1	3	03/2007 [07/1990 - 12/2015]
Interest Rate				
Nowcast	84.25	1	1	06/2007 [06/2005 - 09/2007]
1 q ahead	89.76	1	1	06/2007 [02/2005 - 09/2007]
Avg. 2-4 q ahead	238.65	3	3	08/1992 [08/1984 - 07/1996] 02/2000 [02/1989 - 06/2006] 03/2007 [08/1992 - 12/2009]

Note: The trimming parameter is 0.15 and the maximum number of potential breaks is five. The HAC covariance is estimated based on Andrews (1991)'s AR(1) bandwidth selection (no prewhitening). The break dates are based on k_{supF}.

parameter equals to zero. Nevertheless, the 2002/2003 break date is robustly detected by both tests. This date is related to the major change in the FOMC communication strategy, which, in August 2003, started including time-dependent forward guidance in its post-meeting statement. This is an important break-point, documented in several studies (see Lunsford 2020).

The break dates in the early 1990s overall appear to coincide with many changes introduced by the FOMC in its communication strategy, starting with the decision to publish minutes in March 1993 and subsequently issuing statements following every meeting in May 1999. Bai and Perron (1998)'s tests also detect break-dates in the period between 2007 to 2009. These appear to be related to the release of the quarterly Summary of Economic Projections (SEP) in November 2007 (which reported ranges and central tendencies of participants' forecasts for up to three years ahead) and the subsequent quarterly press conferences related to the SEP in April 2011.

I.C Relationship to forecast accuracy

In addition to information advantage regressions, one could consider other, potentially different test statistics. In this section, we provide complementary evidence based on MSFE comparisons. Just as a preview, the results confirm our main finding: the forecasting performance is time-varying, and Greenbook/Tealbook forecasts were not significantly more accurate than the BCEI in the latest part of the sample.

It is important to clarify at the onset that information advantage regressions and MSFE comparisons are two very different ways of comparing forecasts: in general, finding that a forecast has an information advantage over a competitor does not imply that the former has a lower MSFE. In fact, information advantage regressions investigate whether a forecaster that has access to both Greenbook/Tealbook as well as BCEI forecasts will use both or will prefer only one of them. Hence, there is a tight link between information advantage regressions and the forecast combination literature. As we discuss in Section II.A in the Not-for-Publication Appendix (see also Winkler and Clemen, 1992), the optimal forecast combination (based on the MSFE measure of accuracy) weights each forecast proportionally to its forecast accuracy when the underlying forecasts are unbiased and uncorrelated. When forecasts are correlated, instead, the most accurate model still gets a higher weight in the combination, yet the weight does not reflect its accuracy because it is "distorted" by the correlation. In addition, when the forecasts are biased, it is possible that, depending on the direction and magnitude of the biases, the most accurate forecast in terms of MSFE gets a lower weight than the less accurate forecast. These insights suggest caution in interpreting the magnitude of the coefficients (that is, the weights) in the information advantage regression (see also Sims, 2002), as they cannot always be interpreted as a measure of forecast accuracy.

As the discrepancy between the forecast advantage and the relative MSFE measures may depend on the correlation between the forecasts as well as their bias, we empirically investigate them in our data. Section II.B in the Not-for-Publication Appendix shows the existence of a time-varying (and, at times, strong) cross-correlation between the central bank and private sector forecasts. The cross-correlations are particularly large for the nowcasts of the unemployment rate, real GDP growth and interest rates and have been growing over time for the latter two. In addition, Sections II.C and II.D in the Not-for-Publication Appendix show that both Greenbook/Tealbook forecasts as well as the BCEI exhibit time-varying biases and failures of rationality (see also Rossi and Sekhposyan, 2016).

Given this evidence, we complement our information advantage regressions with a time-varying analysis of forecast accuracy. Figures 3 and 4 depict rolling estimates of relative predictive accuracy, measured by the difference between the MSFEs of the BCEI consensus forecasts and the Greenbook/Tealbook forecasts,

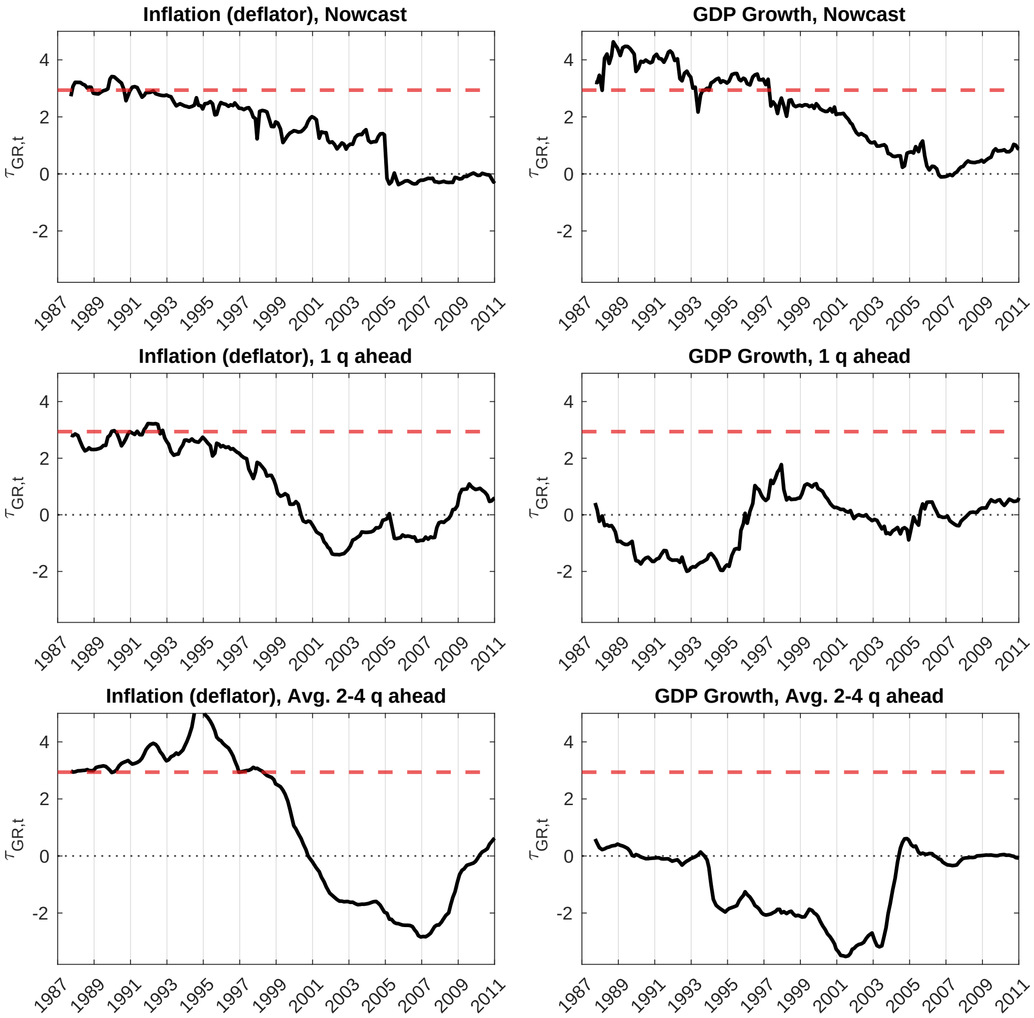

Figure 3: Forecasting performance fluctuation test: GDP growth and inflation

Note: The figure shows $\tau_{GR,t}$ based on $m = 60$ meetings rolling windows using a Newey-West covariance estimator with a truncation lag of $m^{1/4}$. Horizontal axes correspond to mid-window dates. Dashed (red) lines denote 5% critical value lines based on Giacomini and Rossi (2010)'s one-sided Fluctuation test.

scaled by its standard deviation (labeled $\tau_{GR,t}$). We implement a Fluctuation test in a regression similar to that in eq. (1), where the left-hand side is the MSFE difference and the only regressor is the constant. The null hypothesis is that the Greenbook/Tealbook and the BCEI forecasts have the same predictive accuracy; under the alternative, positive values of the test statistic indicate that the Greenbook/Tealbook predictive performance is more accurate. The dashed (red) line indicates the five percent critical value of the Giacomini and Rossi (2010) test.

The figures show that the equal predictive accuracy of these forecasts is rejected for all the variables and all horizons. The time path of the test statistic indicates that the forecast accuracy of Greenbook/Tealbook in predicting inflation worsened in the early 1990s for the nowcast and the one-quarter-ahead forecasts, while the deterioration dates to the late 1990s for the average two-to-four-quarter-ahead forecasts. For the real GDP growth rate, the central bank either had no comparative advantage in forecasting or, in the case of the nowcast, the information advantage disappeared in the late 1990s. For unemployment, the performance of Greenbook/Tealbook and BCEI forecasts is broadly the same, with some sporadic outperformance of Greenbook/Tealbook at the two-to-four-quarter-ahead horizon. In terms of the interest rate, the central bank appears to have more accurate forecasts only for the nowcast and that advantage disappears around 2003. Thus, even based on the relative forecast accuracy criterion, either the central bank had no forecasting advantage or, in some cases, the advantage disappeared even earlier than our estimates suggest, namely in the 1990s.

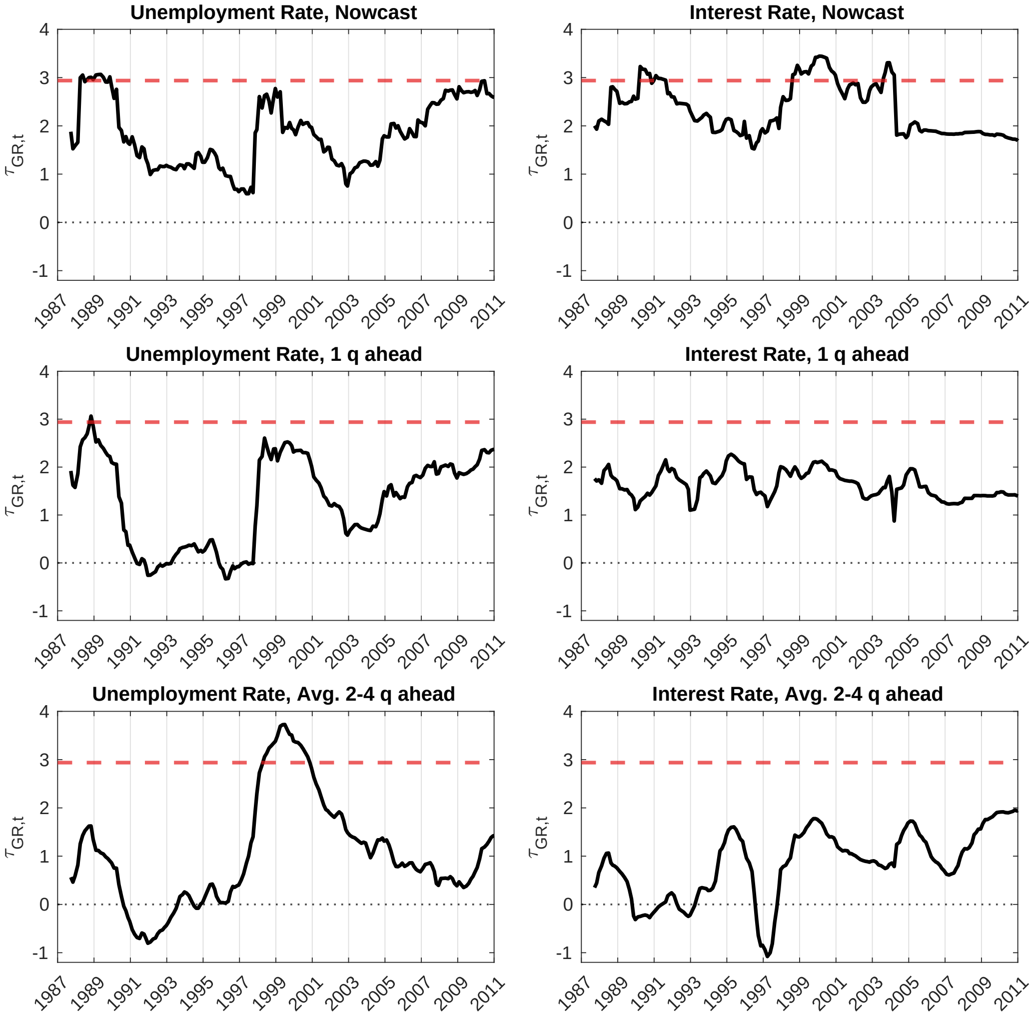

Figure 4: Forecasting performance fluctuation test: Unemployment and interest rates

Note: The figure shows $\tau_{GR,t}$ based on $m = 60$ meetings rolling windows using a Newey-West covariance estimator with a truncation lag of $m^{1/4}$. Horizontal axes correspond to mid-window dates. Dashed (red) lines denote 5% critical value lines based on Giacomini and Rossi (2010)'s one-sided Fluctuation test.

II. Do monetary policy surprises contain information effects?

The previous section provided empirical evidence that the Federal Reserve had an information advantage in predicting key macroeconomic variables historically, but lost such an advantage recently. A related and important question is whether the importance of the information channel of monetary policy has similarly decreased over time. As discussed in the introduction, the existence of the central bank information advantage is a sufficient, but not a necessary condition for the presence of the information channel of monetary policy. This is because the private sector might update its expectations on the state of the economy even if the central bank does not have an information advantage (see e.g. Morris and Shin, 2002). When studying the reaction of the economy to information effects, it is therefore important to recognize that potential time-variation in information effects might exist independently from the results we already established in Section I.. Therefore, we investigate whether high-frequency market-based surprises can be explained by the Federal Reserve's economic outlook and whether this information content has changed over time.

Similarly to our information advantage analysis in Section I., we find that, while high-frequency surprises can be historically predicted by Federal Reserve staff forecasts, this relationship has become insignificant in the recent period. Building on this finding, we then construct an updated version of Miranda-Agrippino and Ricco (2020)'s policy instrument, which is a monetary policy surprise cleaned from information available to the Federal Reserve. We explicitly take time variation into account when constructing the instrument, which is used in Section III. to estimate the response of the economy to monetary policy shocks as well as in Section IV. to establish whether professional forecasters revise their forecasts in response to monetary policy.

II.A The information content of market surprises

We start by investigating the information content of high-frequency market-based surprises identified in a short window of time around FOMC announcements. Our main objective is to establish whether market surprises are predictable by the information available to the Federal Reserve staff and whether this predictability has changed over time. High-frequency surprises are widely used in the literature on information effects and several papers highlight the importance of controlling for the Fed's private information. For example, Romer and Romer (2004) show that Greenbook/Tealbook forecasts significantly predict changes in the intended Fed Funds Rate around FOMC meetings. Campbell et al. (2017) demonstrate that the "Delphic component" of high-frequency surprises (i.e. the component that reflects the Federal Reserve's private information on current and future macroeconomic conditions) can explain the puzzling decrease in unemployment survey expectations after a monetary policy tightening (Campbell et al., 2012). Jarociński and Karadi (2018) construct an instrument for monetary policy shocks by controlling for the central bank's assessment of the economic outlook, revealed by stock market surprises. Finally, Miranda-Agrippino and Ricco (2020) construct a monetary policy shock instrument that controls for the Fed's information by extending the approach of Romer and Romer (2004) to high-frequency market-based surprises; they show that their instrument accounts for information effects across a large number of Structural VAR (SVAR) specifications. In our analysis, we follow Miranda-Agrippino and Ricco (2020)'s and Romer and Romer (2004)'s approach and study the correlation of high-frequency market-based surprises with the Federal Reserve's internal forecasts at different horizons. Specifically, we project surprises in the three month Federal Funds Futures Rate ($FF4$) on Greenbook/Tealbook forecasts of real GDP growth, GDP deflator inflation and the unemployment rate as well as their revisions for different forecast horizons, via the following regression:

$$\mathbb{S}_t = \alpha^{(h)} + \sum_j \theta_j^{(h)\prime} \begin{pmatrix} F_t^{GB}(x_{j,q+h}) \\ F_t^{GB}(x_{j,q+h}) - F_{t-1}^{GB}(x_{j,q+h}) \end{pmatrix} + \varepsilon_t^{(h)} \tag{4}$$

where $\mathbb{S}_t$ is the high-frequency market-based surprise, $F_t^{GB}(x_{j,q+h})$ denotes the h-quarter-ahead Greenbook/Tealbook forecast of variable x_j associated with the FOMC meeting at time t; $F_t^{GB}(x_{j,q+h}) - F_{t-1}^{GB}(x_{j,q+h})$ denotes the forecast revision; and $\theta_j^{(h)}$ collects the coefficients associated with the forecasts and forecast revisions of variable x_j, where j denotes the variable to be forecasted (j = GDP growth, inflation and unemployment). We estimate eq. (4) for one quarter backcasts, nowcasts as well as one- and two-quarter-ahead forecasts (i.e. $h = -1, 0, 1, 2$).

Miranda-Agrippino and Ricco (2020) find, in a similar specification over the full sample, that the null hypothesis of no correlation between the market surprises and Fed forecasts ($\theta_j^{(h)} = 0$) can be rejected. They interpret this result as evidence of an information channel. Given our findings from Section I., however, we are interested instead in studying how this correlation evolves over time. Therefore, similarly to the approach in Section I., we define the Fluctuation test statistic for the regression in eq. (4) as:

$$\mathcal{F}_{FED} = \max_t |W_t|, \tag{5}$$

with

$$W_t = m\, \hat{\theta}_t^{(h)\prime} \left\{\hat{V}_\theta^{(h)}\right\}^{-1} \hat{\theta}_t^{(h)}, \text{ for } t = m/2, \ldots, T - m/2, \tag{6}$$

where $\hat{\theta}_t^{(h)}$ and $\hat{V}_\theta^{(h)}$ are computed in rolling windows of m observations.

Data. To implement the regression in eq. (4), we choose as our baseline measure of interest rate surprises the change in the three month Fed Funds Futures in a half-hour window starting 10 minutes before and ending 20 minutes after the announcement.[11] This surprise measure was used by Gertler and Karadi (2015), Jarociński and Karadi (2018), Paul (2020) and Miranda-Agrippino and Ricco (2020). We study surprises around 234 FOMC meetings from February 1990 to December 2015 using an updated version of the Gürkaynak, Sack and Swanson (2005) dataset. While market-based monetary surprises are also available for more recent dates, our dataset is constrained by the availability of Greenbook/Tealbook forecasts, which are only released with a five-year lag.[12] The dataset contains both scheduled as well as unscheduled FOMC meetings and other important announcements. We associate each Greenbook/Tealbook forecast to the relevant FOMC announcement. For scheduled meetings, these forecasts have a direct mapping to the announcements, as they were prepared specifically for the respective FOMC meeting. For unscheduled announcements, we use the latest available Greenbook/Tealbook forecast made before the announcement and correct the forecast horizon when the target quarter of the forecasts changed. We then compute the revision of each Greenbook/Tealbook forecast as the difference between the forecast associated with the current FOMC meeting and the previous meeting, correcting the forecast horizon of the earlier forecast when necessary.[13]

Results. Figure 5 reports W_t for the regression in eq. (4) for the one-quarter backcast, the nowcast, as well as the one- and two-quarter-ahead forecasts together with the 5% critical value line for the Fluctuation test. The largest (ab-

[11] FF4 contracts exchange a constant interest for the average Federal Funds Rate over the course of the third calendar month. In most of our sample, regular policy meetings are spaced roughly six weeks apart. Therefore, the three month futures rate can be interpreted as the shift in the expected Federal Funds Rate following the next policy meeting.

[12] Greenbook/Tealbook forecasts are currently available up to December 2015.

[13] Note that by definition, the forecast revision associated with unscheduled FOMC meetings is zero as the forecasts have not been updated since the last scheduled FOMC announcement.

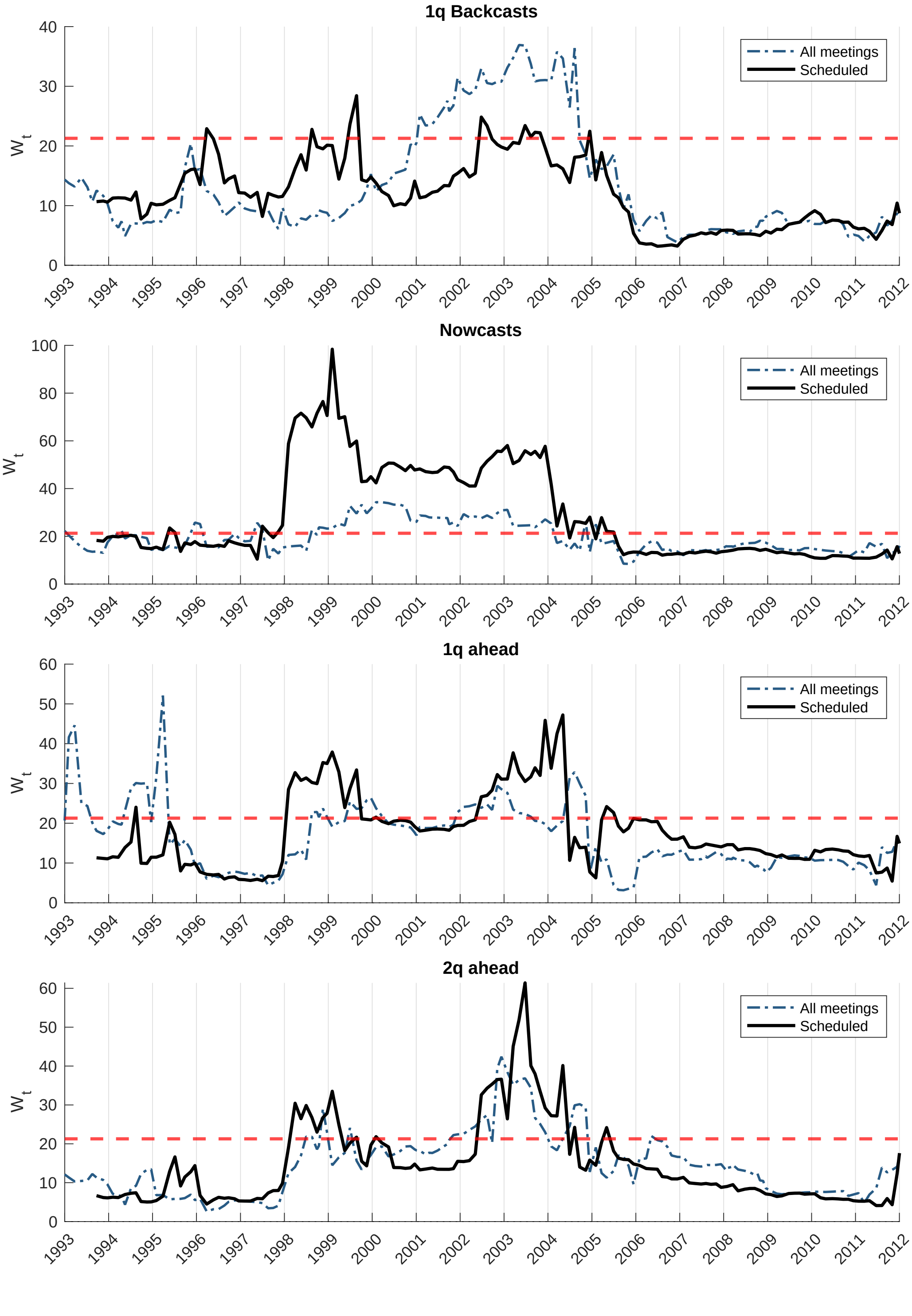

Figure 5: Information content of market-based monetary surprises

Note: The figure shows W_t from eq. (6) based on $m = 60$ meetings rolling windows using a Newey-West covariance estimator with a truncation lag of $m^{1/4}$. Horizontal axes correspond to mid-window dates. The dashed (red) line denotes the 5% critical value based on Rossi and Sekhposyan (2016)'s Fluctuation test.

solute) value of W_t is the Fluctuation statistic, $\mathcal{F}_{FED}$. When $\mathcal{F}_{FED}$ is above the critical value line, the test rejects the null hypothesis that market surprises were never predictable by the Greenbook/Tealbook forecasts. As in the previous sections, the timing reported on the x-axis is the mid-point of the rolling sample used to estimate W_t over time. The figure illustrates that high-frequency market-based surprises were significantly predictable by the Fed staff before the mid-2000s, but that the predictability disappeared in the most recent period, regardless of the forecast horizon. Importantly, the results hold for both scheduled as well as unscheduled announcements. Thus, it is important to account for information effects in the first part of the sample, but less so in the most recent period.[14]

II.B An information-robust instrument of monetary policy

In the next two sections, we study the impact of monetary policy announcements on the macroeconomy and forecasters' expectations using an information-robust instrument. Given our previous findings, namely that accounting for the Fed information is more important in the earlier than in the later part of the sample, we modify their instrument series by: (i) extending the sample to the latest available Greenbook/Tealbook data;[15] and (ii) taking the time-variation in the information content of surprises into account by estimating the instrument separately in the relevant sub-samples.

To construct the informationally-robust instrument for monetary policy shocks, we closely follow Miranda-Agrippino and Ricco (2020). First, to control for the central bank's private information, we project the FF4 surprises ($\mathbb{S}_t$) on Green-

[14] In addition to regressions at individual horizons, Miranda-Agrippino and Ricco (2020) also consider F-tests in a regression including all variables and horizons, following the specification in Romer and Romer (2004). Table 4 in the Appendix replicates the full-sample results in Miranda-Agrippino and Ricco (2020) and shows that our conclusions are robust.

[15] The original Miranda-Agrippino and Ricco (2020) series is available from February 1990 to December 2009 whereas, at the time of writing this paper, Greenbook/Tealbook forecasts are available until December 2015.

book/Tealbook forecasts as well as their revisions for macroeconomic variables at the meeting-level frequency:

$$
\begin{aligned}
\mathbb{S}_t &= \alpha + \sum_{h=-1}^{3} \theta_j' F_t^{GB}(x_{q+h}) + \sum_{h=-1}^{2} \delta_j' \left[F_t^{GB}(x_{q+h}) - F_{t-1}^{GB}(x_{q+h})\right] + \mathbb{S}_t^{MPI} \\
&= \mathbb{S}_t^{CBINFO} + \mathbb{S}_t^{MPI},
\end{aligned} \tag{7}
$$

where $F_t^{GB}(x_{q+h})$ is a vector containing the central bank's forecasts of output, inflation and unemployment. The residual of this projection ($\mathbb{S}_t^{MPI}$) is the monetary policy shock "cleaned" from the Federal Reserve's information on the economic outlook, whereas its orthogonal component ($\mathbb{S}_t^{CBINFO}$) measures the Federal Reserve's own information. Motivated by our analysis from the previous sub-section, we explicitly take instabilities into account by separately estimating the regression above in the two sub-samples before and after August 2003.

Second, we aggregate the resulting meeting-level series to a monthly frequency, as the meeting-level series are irregularly spaced and the analyses in Sections III. and IV. are conducted at the monthly frequency. Therefore, as in Miranda-Agrippino and Ricco (2020), we transform $\mathbb{S}_m^{MPI}$ and $\mathbb{S}_m^{CBINFO}$ to monthly series by summing the individual surprises occurring in each month and setting them to zero in months in which there is no FOMC announcement.[16]

Figure 6 reports our updated instrument series. The top panel shows the FF4 surprises, $\mathbb{S}_t$, at the monthly frequency while the bottom panel shows their decomposition into the information robust monetary policy instrument ($\mathbb{S}_t^{MPI}$) and the central bank's information shock ($\mathbb{S}_t^{CBINFO}$). The (red) vertical line in the bottom panel separates the two sub-samples. The correlation with the original

[16] Miranda-Agrippino and Ricco (2020) also adjust the resulting monthly instrument series to account for potential serial correlation by estimating an $AR(12)$ on the $\mathbb{S}_t^{MPI}$ series. As we construct our instrument in two sub-samples, to mitigate small sample concerns we rely on the BIC criterion to select the lag length for the $AR(p)$ process. The BIC selects $\hat{p} = 0$ for the $\mathbb{S}_t^{MPI}$ series, which is what we use to obtain our information-robust instrument. The results are robust if the lag length were selected in individual sub-samples.

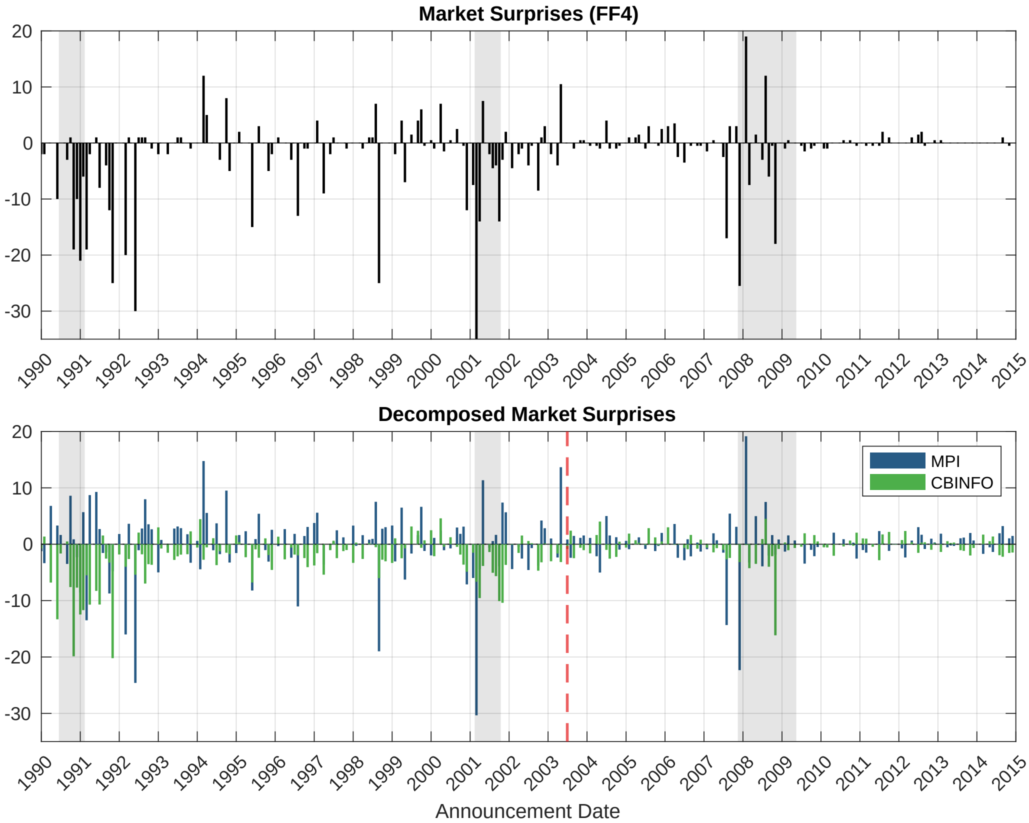

Figure 6: Contributions to the surprises in the three-month Fed Funds Futures

Note: High-frequency market-based surprises are aggregated to monthly frequency, expressed in basis points. The decomposition is based on eq. (7).

MPI shock of Miranda-Agrippino and Ricco (2020) is 0.912 for the full sample, 0.936 for the first sub-sample and 0.868 for the second sub-sample. In addition, our series preserves almost all of the large realizations of their original shock.[17]

[17]Note that the original shock is only available until December 2009 so that the second sub-sample only partially overlaps with Miranda-Agrippino and Ricco (2020)'s original sample.

III. The impact of information effects on the macroeconomy

After having established that the information content of market surprises has disappeared over time, we next turn to assessing whether the information channel played a role in the transmission of monetary policy in the U.S. and how its importance evolved over time. According to the information channel theory (Nakamura and Steinsson, 2018), in the presence of informational rigidities, informationally constrained private agents could infer from an increase in the central bank's policy rate not only that the central bank is deviating from its rule, but also that it is endogenously responding to stronger than expected future fundamentals. If the latter component is not correctly taken into account, the estimated responses to the monetary policy shock could potentially mix the response to the actual monetary policy shock and to the signal about the future state of the economy. Several papers have shown that impulse responses to high-frequency market-based surprises can be contaminated by information effects and that model-consistent impulse responses can be obtained by using an instrument that controls for the information channel (see Miranda-Agrippino and Ricco, 2020 and Jarociński and Karadi, 2018).

To investigate the information channel of monetary policy, we study impulse responses of several key macroeconomic aggregates to a monetary policy shock using a SVAR with high-frequency instruments. We consider both high-frequency surprises in the three month Federal Funds Futures Rate (FF4), as well as our updated version of the information-robust instrument discussed in Section II.. Since FF4 market surprises do not control for information effects, the implied impulse responses reflect both the effect of the change in the policy rate as well as any potential response of the economy to information effects. In contrast, the impulse responses obtained using the information-robust instrument control for the information set of the central bank, and therefore only reflect changes in the policy rate.[18] The only difference between the two impulse responses is thus whether we control for information effects or not. By comparing the impulse responses in sub-samples, we can thus assess how the information effect has changed in the recent period relative to the earlier part of the sample.

III.A The VAR model

We estimate a six-variable SVAR model where the vector of endogenous variables are the industrial production index, the unemployment rate, the consumer price index, the commodity price index, the excess bond premium by Gilchrist and Zakrajšek (2012) and the one year nominal policy rate.[19] This is the same SVAR used in Miranda-Agrippino and Ricco (2020) and it is similar to that in Coibion (2012) and Gertler and Karadi (2015). Details on the data series and their sources can be found in the Not-for-Publication Appendix.

All variables are monthly from January 1979 to December 2019. The SVAR is estimated in (log) levels with 12 lags. As discussed above, the impulse responses are identified using two external instruments: (i) the FF4 surprises ($\mathbb{S}_t$) and (ii) our updated version of the information-robust instrument of Miranda-Agrippino and Ricco (2020), $\mathbb{S}_t^{MPI}$. In both cases, the impulse responses are normalized such that the monetary policy shock increases the policy rate by one percent on impact. As discussed in the previous section, due to the lagged release of the Greenbook/Tealbook forecasts, the external instrument series is only available from February 1990 to December 2015. The impact responses in the SVAR are therefore identified from a proxy regression over the common sub-sample, February 1990 to December 2015. The VAR is estimated with standard Bayesian Normal Inverse-Wishart priors and the tightness of the prior is set as in Giannone,

[18] Because the FF4 horizon is three months, it can also capture some near-term forward guidance in addition to policy rate changes. However, it also mitigates the effect of the zero lower bound.

[19] Both the commodity price index as well as the one year nominal rate series are end-of-month values.

Lenza and Primiceri (2015).

III.B The role of information effects

Figure 7 shows the BVAR impulse responses identified using: (i) the FF4 surprises ($\mathbb{S}_t$, dashed blue line) and (ii) the information-robust series ($\mathbb{S}_t^{MPI}$, solid black line). We report impulse responses for two sub-samples: January 1979 - July 2003 and August 2003 - December 2019.[20]

First, focus on the sub-sample from January 1979 - July 2003 (left panel of Figure 7). Using the FF4 market surprises as instruments, in response to a contractionary monetary policy shock industrial production increases and unemployment decreases. However, using the information-robust instrument, we recover impulse responses that are consistent with economic theory: output decreases and unemployment increases. The large discrepancy between the responses thus corresponds to the economy's reaction to the information effects. These findings are similar to Miranda-Agrippino and Ricco (2020) for their full sample (1979 - 2014).

However, these conclusions change when we consider the second sub-sample, August 2003 to December 2019 (right panel in Figure 7). In this case, the responses based on the FF4 surprises are more in line with economic theory than in the earlier sample: output decreases and unemployment increases in the short run.

Overall, the discrepancy between the impulse responses based on FF4 and those based on the information-robust instrument is negligible in the later part of the sample, while it was substantial in the first sub-sample. Thus, we conclude that, while information effects were important historically, they are much less important in the most recent period.

[20]Specifically, note that while the impact parameters are identified in each sub-sample, the lag parameters are estimated on the full sample to improve the efficiency of the parameter estimates. Our results are robust to re-estimating the SVAR in each sub-sample separately.

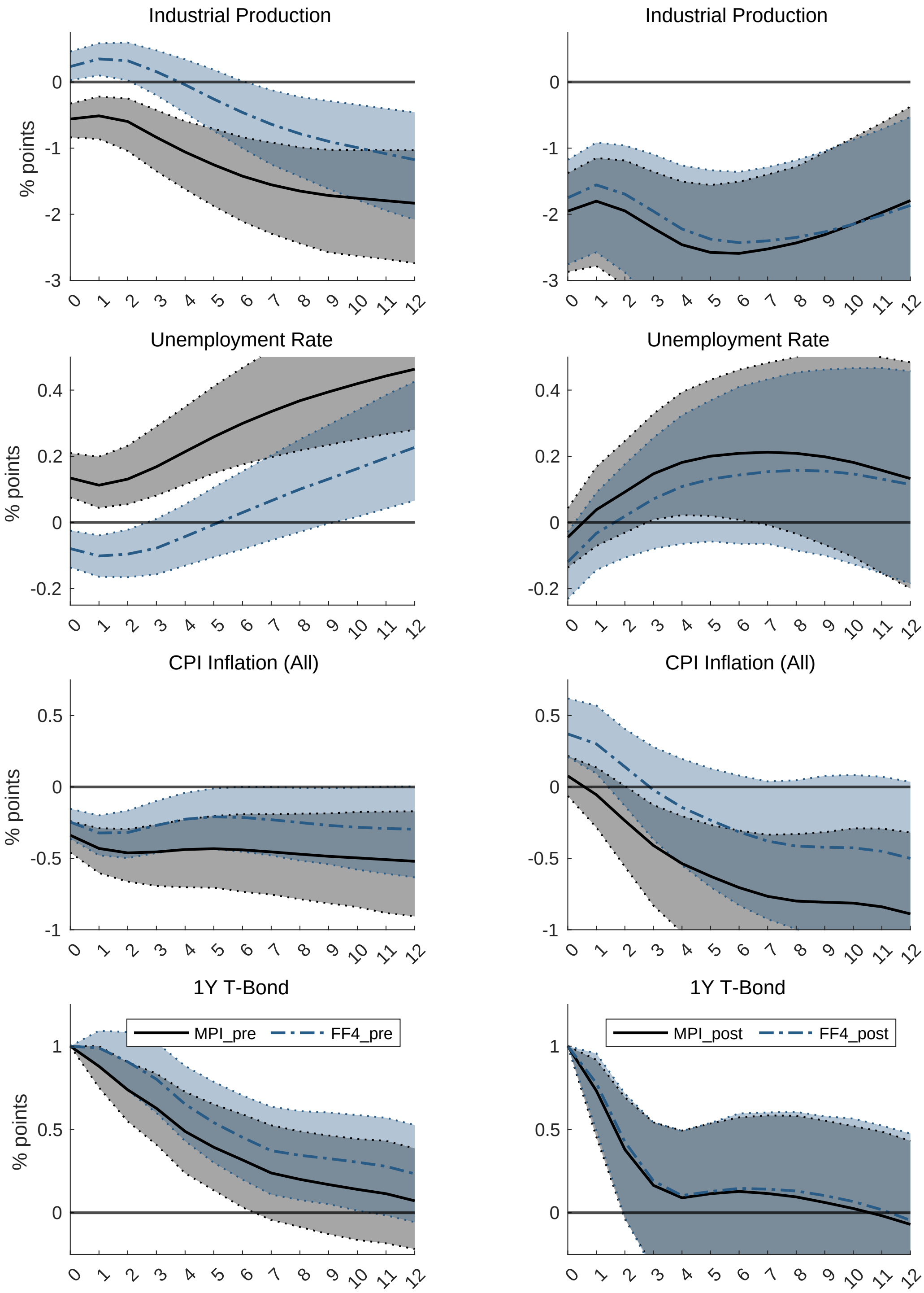

Figure 7: Responses to a monetary shock: Sub-samples

Note: Impulse responses from Bayesian SVAR with standard macroeconomic priors and external instrument identification. VAR sample: January 1979 - December 2019. Instrument samples: February 1990 - July 2003 (left panel) and August 2003 - December 2015 (right panel). Shaded areas correspond to 90 percent credible intervals.

Robustness. Figure 11 in the Appendix shows that our conclusions are robust to comparing the information-robust instrument ($\mathbb{S}_t^{MPI}$) with the associated information component, ($\mathbb{S}_t^{CBINFO}$). We also address potential misspecification concerns by repeating the analysis using a local projection approach. If the VAR is correctly specified, local projections are less efficient than BVARs but have the advantage of being robust against dynamic misspecification. Figure 12 in the Appendix shows that, although the local projection-based response bands are much larger than BVAR-based ones, our main conclusions remain robust. Finally, the Not-for-Publication Appendix shows that our conclusions remain robust regardless of whether we estimate $\mathbb{S}_t^{MPI}$ using scheduled meetings only or if we remove potential serial correlation in the shock series via an AR(12). We also show that, in our full sample, the responses based on our updated instrument are consistent with the full sample results in Miranda-Agrippino and Ricco (2020).

IV. The impact of information effects on forecasters' expectations

Finally, we characterize the response of private forecasters to monetary policy announcements. As is customary in the literature, we regress monthly revisions in the BCEI consensus forecasts on a series of high-frequency market-based surprises in Federal Funds Futures Rates around FOMC meetings. Using a similar regression with monetary policy surprises that reflect both current and future short-term rates, Nakamura and Steinsson (2018) find that the way survey forecasters update their predictions is inconsistent with standard New Keynesian models. Their results support the existence of an information channel according to which professional forecasters believe that FOMC policy surprises contain useful and otherwise unavailable information to the public. Campbell et al. (2012) come to a similar conclusion by decomposing monetary policy surprises into orthogonal "target" and "path" components. Campbell et al. (2017) show that the puzzling signs can be explained by decomposing the surprises in a "Delphic" component, associated with information releases by the central bank, and an orthogonal ("Odyssean") component: the signs remain puzzling for the former while are consistent with economic theory for the latter. Finally, Paul (2020) shows that there is little evidence of information releases in short horizon Federal Funds Futures Rate when focusing on scheduled FOMC meetings, while including unscheduled meetings leads to significant forecast revisions.

In line with the existing literature, we consider the following regression to analyze whether forecasters revise their expectations after a monetary policy announcement:

$$\Delta x^{BCEI}_{t+h|t} = \alpha + \beta\, \mathbb{S}_t + \varepsilon_{t+h} \tag{8}$$

where $\Delta x^{BCEI}_{t+h|t}$ denotes the BCEI consensus forecasts revision at horizon h between FOMC meetings and $\mathbb{S}_t$ is the FF4 surprise. We also consider an alternative specification where $\mathbb{S}_t$ is the surprise in 30 day Federal Funds Futures Rates (MP1), used in Paul (2020) and Lunsford (2020). Furthermore, to account for potential information effects in monetary policy announcements, we decompose the surprises, $\mathbb{S}_t$, into the robust monetary policy shock and the information shock described in Section II., and estimate the following regression:

$$\Delta x^{BCEI}_{t+h|t} = \alpha + \beta_1\, \mathbb{S}^{MPI}_t + \beta_2\, \mathbb{S}^{CBINFO}_t + \eta_{t+h} \tag{9}$$

where $\mathbb{S}^{MPI}_t$ is the surprise component "cleaned" from the Fed information and $\mathbb{S}^{CBINFO}_t$ is the information component (see eq. 7). We analyze this specification both in the full sample as well as in the two sub-samples identified in the previous sections.

Data. To implement the regressions in eqs. (8) and (9), we focus on the same sample of monetary policy announcements that we used to analyze the information content of monetary policy surprises in Section II.. To study the forecasters' response, we augment this dataset with a measure of revisions to the private sector forecasts which we calculate for each meeting, variable and forecast horizon as the difference between the BCEI forecasts bracketing each FOMC announcement.[21] As in Nakamura and Steinsson (2018) and Paul (2020), we drop those FOMC announcements in which the meeting date falls into the BCEI survey period (first three business days of each month until December 2000; first two business days of each month after December 2000) to ensure that the FOMC announcement are after the BCEI survey dates.[22] Further, as in Nakamura and Steinsson (2018), we focus on scheduled FOMC meetings only. This is consistent with our analysis of the information advantage from Section I.. Appendix D reports results for the sample which includes unscheduled FOMC meetings.

Results. Table 2 shows the results based on the full sample (February 1990 - December 2015). When considering FF4 surprises (first column), the sign of the coefficient β in eq. (8) is inconsistent with the responses of real GDP growth forecasts in the New Keynesian model across all forecast horizons. In contrast, for inflation, unemployment and the interest rate, all coefficients except for the one-quarter-ahead responses of inflation and the unemployment rate exhibit signs consistent with economic theory. Across all regressions, none of the coefficients

[21]Specifically, we use the same procedure as Nakamura and Steinsson (2018) and compute the forecast revision as the difference between the BCEI forecast from the month following the FOMC announcement and the forecast which falls in the same month as the FOMC announcement. Since BCEI forecasts are collected at the beginning of each month, the latter typically falls before the announcement. When the target dates of the two forecasts used to calculate the revision are different, we use the previous BCEI forecast and adjust the forecast horizon to keep the target date fixed.

[22]The strategy adopted in Nakamura and Steinsson (2018) and Paul (2020) is slightly different as they drop all FOMC meetings occuring in the first week of each month whereas we drop only those meetings occurring during the BCEI survey period, leading to a slightly larger sample. The results presented in this section are robust to adopting their strategy.

are statistically significant.[23] Hence, based on the full sample, there is no evidence that regularly scheduled monetary policy announcements lead to significant forecast revisions by private forecasters. This evidence is consistent with the results in Paul (2020), who considers the regression in eq. (8) on a similar sample. In fact, by analyzing the average of the current quarter to four-quarter-ahead responses of the BCEI to FF4 surprises, Paul (2020) also finds a positive sign for the real GDP response and negative signs for inflation and the unemployment rate and no evidence of a statistically significant reaction based on scheduled meetings (see his Appendix A.10). Our results are robust to using Paul (2020)'s shorter 30-day Federal Funds Futures surprises (MP1, see the last column of Table 2).

Next, we repeat the analysis using the surprises decomposed as in eq. (9). A comparison of the second and third columns of Table 2 with the first column highlights two important results. First, accounting for the Federal Reserve's information content corrects some of the puzzling signs: the effects of the robust (MPI) surprises, particularly at the one-quarter-ahead horizon, are more consistent with economic theory than those of FF4 surprises and yet none are significant. Second, accounting for the information content of the surprises reveals that survey participants react to the information component of FOMC announcements (CBINFO) with the expected signs and the responses are large in magnitude and statistically significant for GDP and inflation at short horizons.

Finally, Table 3 reports the forecasters' response in the same sub-samples considered in Section III.: February 1990 - July 2003 and August 2003 - December 2015. By comparing the coefficients on the FF4 surprises in both sub-samples with the ones for the full sample (reported in Table 2), we note that the coefficient signs and magnitudes in each of the sub-samples are consistent with the results obtained for the full sample. Similarly, there is no evidence of a signifi-

[23]Here we use robust standard errors since the left-hand side variable is a forecast revision, which is not correlated over time.

Table 2: Forecasters' response - Full sample, scheduled meetings

Horizon	FF4	MPI	CBINFO	MP1
GDP Growth				
Nowcast	1.02	0.93	2.51***	0.40
	(0.90)	(0.74)	(0.83)	(0.60)
1 q ahead	0.70	0.45	1.27*	0.39
	(0.67)	(0.66)	(0.67)	(0.40)
Avg. 2-4 q ahead	0.07	-0.21	-0.02	0.16
	(0.31)	(0.27)	(0.63)	(0.29)
GDP Deflator Inflation				
Nowcast	0.10	-0.22	0.74*	-0.06
	(0.42)	(0.22)	(0.41)	(0.27)
1 q ahead	-0.01	-0.08	0.51***	-0.04
	(0.20)	(0.18)	(0.17)	(0.14)
Avg. 2-4 q ahead	-0.08	-0.12	0.21	-0.05
	(0.17)	(0.14)	(0.16)	(0.11)
Unemployment Rate				
Nowcast	0.03	0.02	-0.39	0.07
	(0.22)	(0.19)	(0.17)	(0.14)
1 q ahead	-0.13	0.05	-0.67	0.06
	(0.29)	(0.25)	(0.21)	(0.20)
Avg. 2-4 q ahead	0.06	0.04	-0.49	0.18
	(0.41)	(0.31)	(0.41)	(0.26)
Interest Rate				
Nowcast	0.47	0.60	1.43***	0.19
	(0.47)	(0.56)	(0.47)	(0.33)
1 q ahead	0.78	0.87	1.99***	0.22
	(0.55)	(0.70)	(0.49)	(0.41)
Avg. 2-4 q ahead	0.61	0.79	1.29**	0.15
	(0.67)	(0.74)	(0.60)	(0.48)

Note: The results are based on scheduled FOMC meetings that do not fall into the BCEI survey period (first week of the month). Robust standard errors in parentheses.

cant reaction in any of the sub-samples. These results continue to hold for the surprises cleaned from the Federal Reserve information (MPI). In fact, there is only mild evidence that survey participants react to the discretionary component of monetary policy shocks: apart from the GDP growth response in the first sub-sample, which is significant only at a 10% level, there is no significance in either sub-sample. Similarly, the MPI responses mostly have the expected signs across the two sub-samples.[24] A striking difference between the two sub-samples is the response of interest rates' survey forecasts to the central bank's information component in monetary surprises (CBINFO): the response is highly significant in the first sub-sample and insignificant in the second one. Again, this evidence suggests that the information channel was relevant prior to 2003 but weakened substantially after that.

Robustness. We explore the robustness of our findings to including unscheduled FOMC meetings. Such meetings may be more likely to be associated with the release of a central bank's private information since they often take place as a reaction to important economic events. Tables 5 and 6 in the Appendix report results from including unscheduled meetings in the full sample and sub-sample regressions, respectively. Most of our results are robust to this change. The most important difference is that, in both the full sample as well as in the earlier sub-sample, the inclusion of unscheduled meetings leads to a significant reaction of interest rate forecasts to all surprises as well as a significant reaction of short horizon GDP growth forecasts in the earlier sub-sample. This is consistent with the findings in Paul (2020), according to whom the inclusion of unscheduled meetings leads to statistically significant coefficients while excluding unscheduled meetings leads to insignificant responses. Importantly, as Table 6 shows, the significant reaction disappears in the later sub-sample, consistently with the results presented

[24]There is one exception: the unemployment response at short horizons in the second sub-sample.

Table 3: Forecasters' response - Sub-samples, scheduled meetings

	Feb 1990 - July 2003			Aug 2003 - Dec 2015		
Horizon	FF4	MPI	CBINFO	FF4	MPI	CBINFO
GDP Growth						
Nowcast	0.87	1.42*	2.58***	1.30	0.05	4.19**
	(0.86)	(0.82)	(0.85)	(1.86)	(1.29)	(1.96)
1 q ahead	0.70	0.34	1.34*	0.84	0.32	2.85
	(0.47)	(0.59)	(0.69)	(1.52)	(1.17)	(1.77)
Avg. 2-4 q ahead	0.12	-0.36	-0.03	0.06	-0.15	1.36
	(0.29)	(0.35)	(0.71)	(0.66)	(0.31)	(1.42)
GDP Deflator Inflation						
Nowcast	-0.18	-0.15	0.26	0.51	-0.46	2.66***
	(0.37)	(0.24)	(0.40)	(0.89)	(0.42)	(0.91)
1 q ahead	-0.02	-0.04	0.50***	-0.02	-0.16	0.63
	(0.22)	(0.21)	(0.19)	(0.39)	(0.31)	(0.43)
Avg. 2-4 q ahead	-0.08	-0.11	0.08	-0.11	-0.13	0.36
	(0.23)	(0.22)	(0.18)	(0.19)	(0.15)	(0.54)
Unemployment Rate						
Nowcast	0.07	0.12	-0.47	-0.07	-0.05	-0.54
	(0.16)	(0.15)	(0.12)	(0.50)	(0.35)	(0.53)
1 q ahead	-0.12	0.16	-0.73	-0.14	-0.06	-0.73
	(0.23)	(0.21)	(0.15)	(0.66)	(0.45)	(0.71)
Avg. 2-4 q ahead	-0.09	0.06	-0.69	0.31	0.05	-0.49
	(0.20)	(0.20)	(0.19)	(1.12)	(0.57)	(1.93)
Interest Rate						
Nowcast	0.15	0.40	1.64***	1.01	0.81	1.28
	(0.37)	(0.43)	(0.56)	(1.03)	(1.11)	(0.84)
1 q ahead	0.38	0.52	2.21***	1.43	1.25	1.88*
	(0.46)	(0.51)	(0.57)	(1.21)	(1.36)	(1.00)
Avg. 2-4 q ahead	0.30	0.45	1.29**	1.25	1.09	2.43
	(0.51)	(0.54)	(0.50)	(1.69)	(1.33)	(2.30)

Note: The results are based on scheduled FOMC meetings that do not fall into the BCEI survey period (first week of the month). Robust standard errors in parentheses.

earlier in our paper.

V. Discussion

This paper explores the empirical importance of the information channel of U.S. monetary policy, paying particular attention to how it changed over time. We find that the information channel of monetary policy weakened around the early to mid-2000s since: (i) impulse responses to monetary policy shocks have the expected sign only when using the information-robust measure of monetary policy shocks before 2003, while after that the responses have the expected sign no matter whether the shock is cleaned for information effects or not; (ii) monetary policy surprises are correlated with central bank's forecasts only before 2003 but not afterward. Furthermore, the information advantage of the central bank in forecasting the state of the economy disappeared at the same time as the information channel weakened. These changes are related to improvements in the Fed's communication and transparency. Our results are robust to different estimation procedures and break tests, no matter whether we focus on scheduled or unscheduled meetings.

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Appendix

A Information advantage and forecast timing

This section provides a sensitivity analysis to the time-ordering of the Greenbook/Tealbook and Blue Chip Economic Indicator forecasts in Section I.. Recall that, in order to compare Greenbook/Tealbook and BCEI forecasts, each Greenbook/Tealbook forecast (which is specifically prepared prior to each scheduled FOMC meeting) needs to be assigned a corresponding BCEI forecast. While the BCEI forecasts are always published on the tenth of each month, the publication day of the Greenbook/Tealbook forecasts varies with the date of the FOMC meeting. To match BCEI forecasts to Greenbook/Tealbook forecasts, in Section I. we chose the BCEI forecast which occurred just before each FOMC meeting. Note that while this ensures a fixed ordering between BCEI forecasts and the FOMC announcements, it does not fix the publication order of Greenbook/Tealbook forecasts. In fact, in our dataset, there are 210 meetings for which the Greenbook/Tealbook is published after the BCEI forecast, while for 46 meetings the Greenbook/Tealbook forecast is published either on the same day as the BCEI or before.

Given the variation in the timing of Greenbook/Tealbook and BCEI forecasts, one might be concerned that a systematic change in the ordering of the forecasts over time, resulting from variation in the publication date of the Greenbook/Tealbook forecasts, might bias our findings of the informational advantage.

For example, if Greenbook/Tealbook forecasts are systematically published after BCEI forecasts in the first part of the sample while this is not the case in the later part of the sample, the loss of information advantage could simply arise from this change in timing over the sample. News arriving between the publication of the forecasts could then create systematic differences in the information sets of the private sector and the central bank or forecasters could simply have had more time to process available information in one part of the sample than in the other, incorrectly leading us to conclude that there is time-variation in the information advantage.

To assess the importance of delays between the publication of both forecasts and to inspect whether the timing undergoes a systematic change over the sample, we calculate the difference between the publication dates of the Greenbook/Tealbook and the BCEI forecasts for two alternative timing assumptions which are used to match BCEI forecasts to their Greenbook/Tealbook equivalents. Figure 8 reports boxplots for the number of days between the publication of the Green-

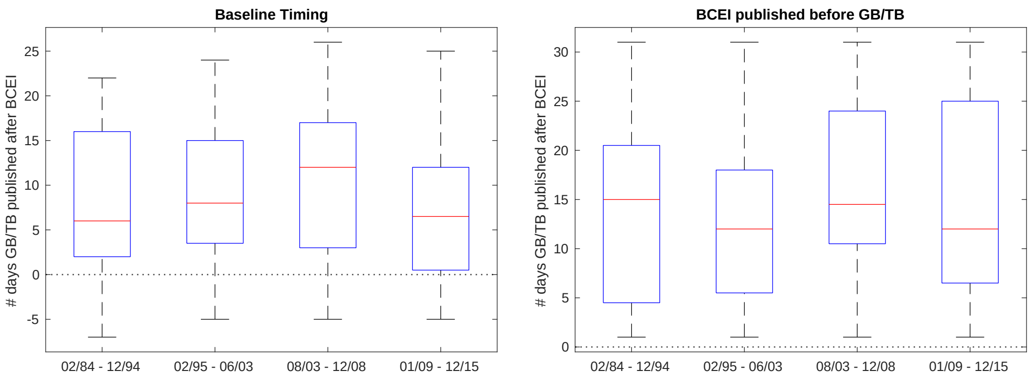

FIGURE 8: DIFFERENCE BETWEEN FORECAST PUBLICATION DATES

Note: Number of days between Greenbook/Tealbook and BCEI forecast publication for the baseline timing of Section I. and an alternative timing where the BCEI is always published before the Greenbook/Tealbook forecasts.

book/Tealbook forecasts and the BCEI forecasts. Positive values of the difference in publication dates imply that the Greenbook/Tealbook was published after the BCEI while negative values imply the reverse ordering. The difference between publication dates is computed using two different strategies for matching the BCEI forecasts: The left panel of Figure 8 reports the difference between the publication dates for the baseline timing of Section I. where BCEI forecasts are matched to FOMC announcements by ensuring that they are strictly ordered before the FOMC meeting, but without enforcing a particular ordering relative to the Greenbook/Tealbook forecasts. In contrast, the right panel of Figure 8 reports the difference between publication dates when matching forecasts such that BCEI forecasts are published strictly before their Greenbook/Tealbook counterparts.[25]

By inspecting the boxplots for the baseline timing in the left panel of Figure 8, we note several key points. First, for the majority of FOMC meetings, the Greenbook/Tealbook forecast is typically published within two weeks after the BCEI forecasts. There are some cases in which the Greenbook/Tealbook was published first. For those cases, the BCEI is typically published within a week of the Greenbook/Tealbook publication.[26] Second, the distribution of the delay in Greenbook/Tealbook forecasts relative to the BCEI forecasts has changed over time. In particular, the mean lag between BCEI and Greenbook/Tealbook publication dates increased from about 6-7 days to about 12 days for the mid-2000s sample period. However, in the most recent period, this lag decreases to 6 days. Note that this change in the timing could in principle affect the results from our information advantage tests. However, importantly, this timing change would bias our analysis towards finding an information advantage for the Fed forecasts

[25]In practice, this matching strategy implies that if a Greenbook/Tealbook publication date falls after the 10th of each month, the relevant BCEI forecasts is the one published in the same month as the Greenbook/Tealbook while for Greenbook/Tealbook forecasts which are published before the 10th of each month, the previous month's BCEI forecast is associated with the meeting.

[26]Note that at the time of "publication", the Greenbook/Tealbook forecasts are still not available to private forecasters as they are only released to the public with a five-year delay.

in the later part of the sample rather than the earlier part of the sample. As we find the opposite, namely a disappearance of the information advantage in the most recent sample, removing such potential bias would further strengthen our conclusion that there is no information advantage in recent years.

Next, compare these results with the boxplots in the right panel of Figure 8, which reports the Greenbook/Tealbook publication lag for the alternative matching strategy where BCEI forecasts are always published before Greenbook/Tealbook forecasts. We note that using this matching strategy the mean publication lag of the Greenbook/Tealbook is generally higher by about 12-15 days and there is also no systematic change in timing which could explain a loss in information advantage. Thus, under the alternative matching scheme, the Greenbook/Tealbook should on average have more information advantage compared to the baseline scheme.

To verify that a difference in timing of the forecasts does not lead to a dramatically different conclusion regarding the disappearance of the information advantage, we repeat the Information-Advantage Fluctuation test from Section I. using the alternative timing assumption where BCEI forecasts are always published before Greenbook/Tealbook forecasts. Figures 9 and 10 show the path of the $\tau_{GB,t}$ with the alternative forecast timing (blue-dashed line) compared to the baseline timing of Section I. (black solid line). The figures clearly show that the disappearance of the information advantage in the most recent sample period remains robust to changing the timing of the forecasts. Specifically, the paths of $\tau_{GB,t}$ are very close to the original ones. There is more evidence of an information advantage in the recent sample period relative to the baseline only for the nowcast and one-quarter-ahead forecasts of GDP growth and the interest rate.

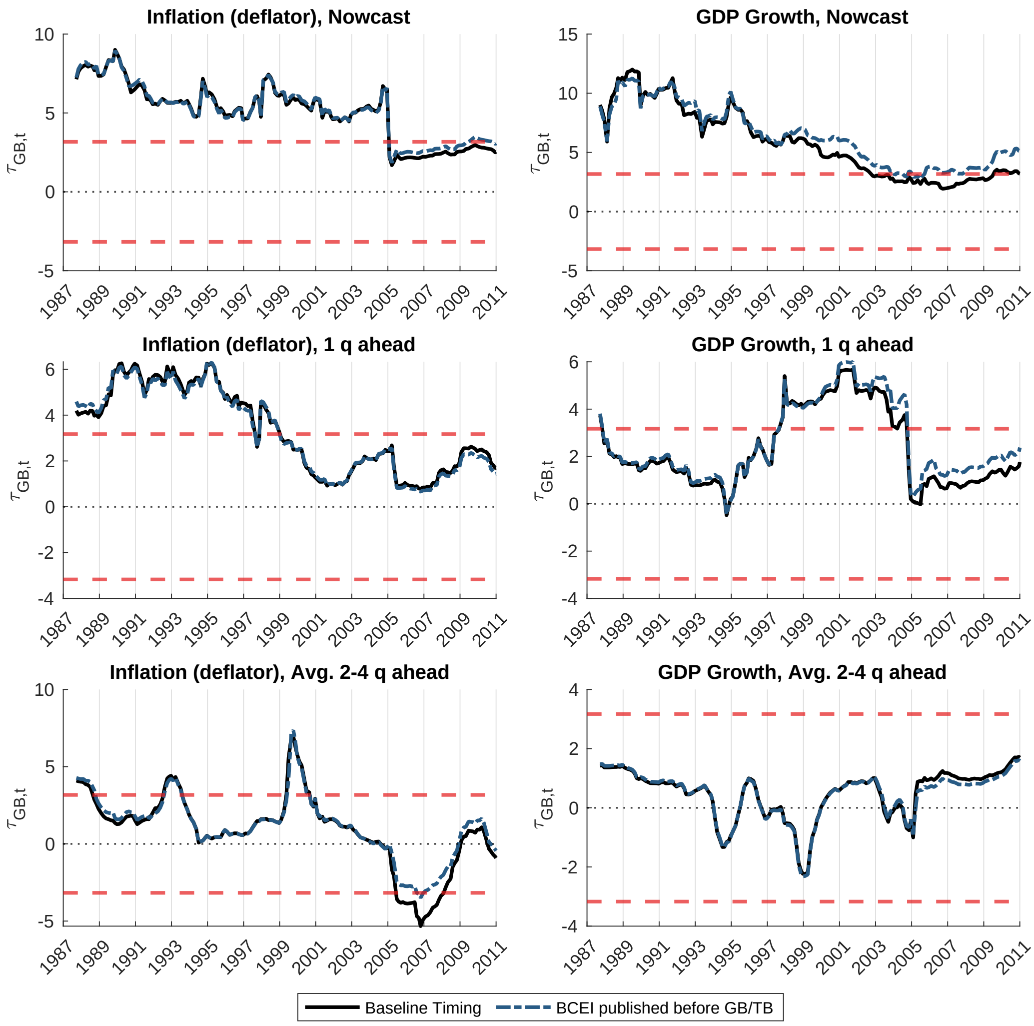

Figure 9: Information advantage timing: GDP growth and inflation

Note: The figure shows $\tau_{GB,t}$ from eq. (1) based on $m = 60$ meetings rolling windows using a Newey-West covariance estimator with a truncation lag of $m^{1/4}$. Horizontal axes correspond to mid-window dates. Dashed (red) lines denote 5% critical value lines based on Rossi and Sekhposyan (2016)'s two-sided Fluctuation test.

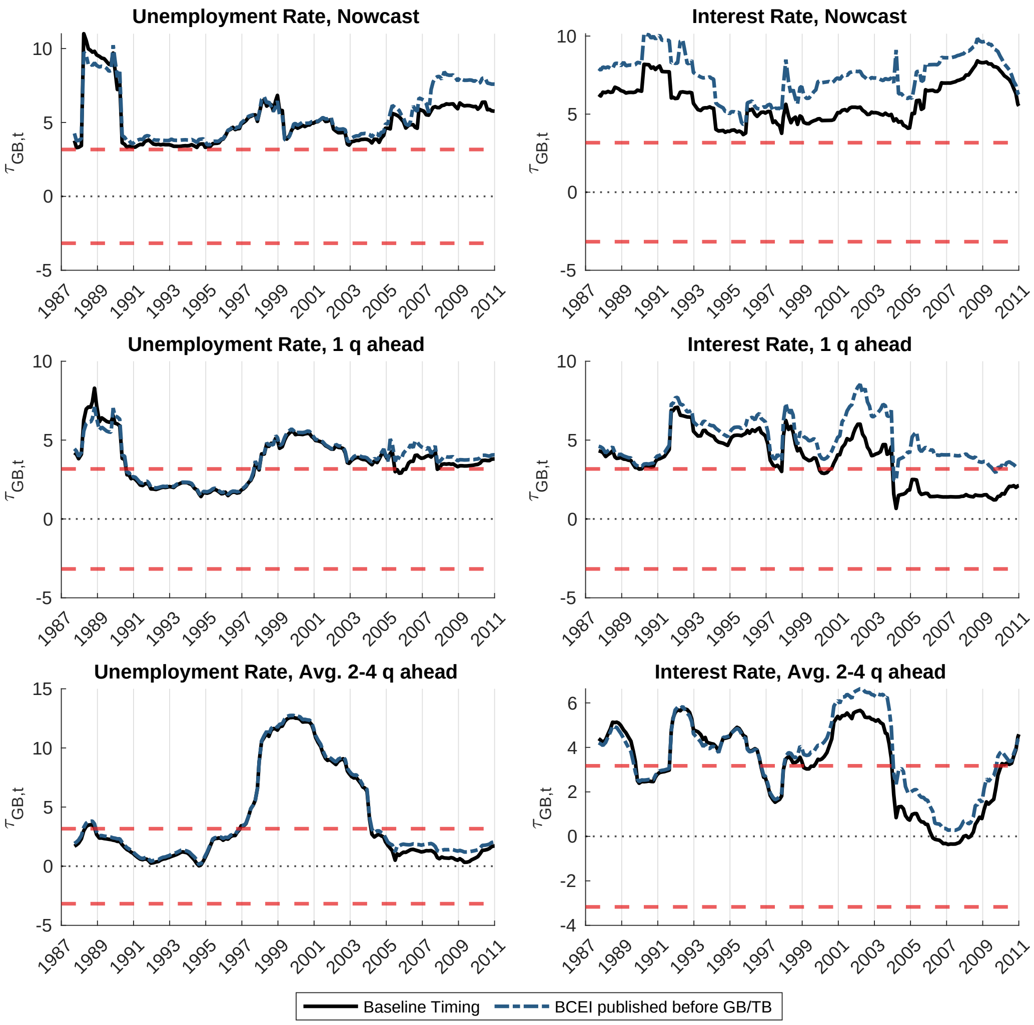

FIGURE 10: INFORMATION ADVANTAGE TIMING: UNEMPLOYMENT AND INTEREST RATE

Note: The figure shows $\tau_{GB,t}$ from eq. (1) based on $m = 60$ meetings rolling windows using a Newey-West covariance estimator with a truncation lag of $m^{1/4}$. Horizontal axes correspond to mid-window dates. Dashed (red) lines denote 5% critical value lines based on Rossi and Sekhposyan (2016)'s two-sided Fluctuation test.

B Additional evidence on the information content of high-frequency market-based surprises

In addition to the horizon-by-horizon projections reported in Section II., we also consider a specification similar to Romer and Romer (2004) which jointly includes the forecasts and their revisions for all horizons. This specification is the same used to construct the information-robust instrument in Section II..B. Miranda-Agrippino and Ricco (2020) also consider this regression and report that in their sample (1990-2009), an F-test rejects the null of joint significance of the coefficients (at the 5% level).

Table 4 below reports the same F-test for our dataset. Column (1) shows that for the sample considered in Miranda-Agrippino and Ricco (2020), we replicate their F-statistic exactly. Column (2) shows that the coefficients continue to be insignificant at the 5% level even when extending the dataset to 2015. Finally, columns (3) and (4) show that our result from Section II. continues to hold in this specification: High-frequency market-based surprises were significantly predictable by the Federal Reserve staff before the mid-2000s (the F-test rejects at 5% level), but that the predictability disappeared in the most recent period (the F-test does not reject at 5% level).

Table 4: Projection on Fed information (all horizons)

	Feb 1990 - Dec 2009	Feb 1990 - Dec 2015	Feb 1990 - Jul 2003	Aug 2003 - Dec 2015
F	1.651	1.598	2.170	1.575
p	0.039	0.046	0.004	0.070
N	186	234	127	107

Note: The table shows F-tests, p-values and number of observations from regressing the FF4 surprises on all the forecasts and at all horizons. F-statistics and p-values are based on heteroskedasticity-robust standard errors. Note that column (1) is the original sample of Miranda-Agrippino and Ricco (2020).

C Additional SVAR evidence

We assess the robustness of our SVAR conclusions in Section III. by carrying out two additional exercises.

Figure 11 compares impulse responses obtained using the information-robust instrument ($\mathbb{S}_t^{MPI}$) to the associated information component ($\mathbb{S}_t^{MPI}$) for the two sub-samples considered in Section III.. Our conclusion that information effects were important historically, but much less important in the most recent sample period is robust to this change: In the earlier sub-sample, the two sets of impulse responses have the opposite sign for real activity variables, and their differences are even more pronounced. In contrast, in the later sub-sample, both impulse responses become indistinguishable. In addition, the information component shows large estimation uncertainty in the later part of the sample. This is consistent with the result established in Section II. that the information associated with the economic outlook of the Federal Reserve becomes less relevant in the most recent period.

Figure 12 addresses potential misspecification concerns by repeating the analysis using a local projection approach rather than a BVAR. As the figure shows, our conclusion from Section III. continues to hold, even though the confidence bands obtained from the local projections are much larger than the BVAR credible intervals.

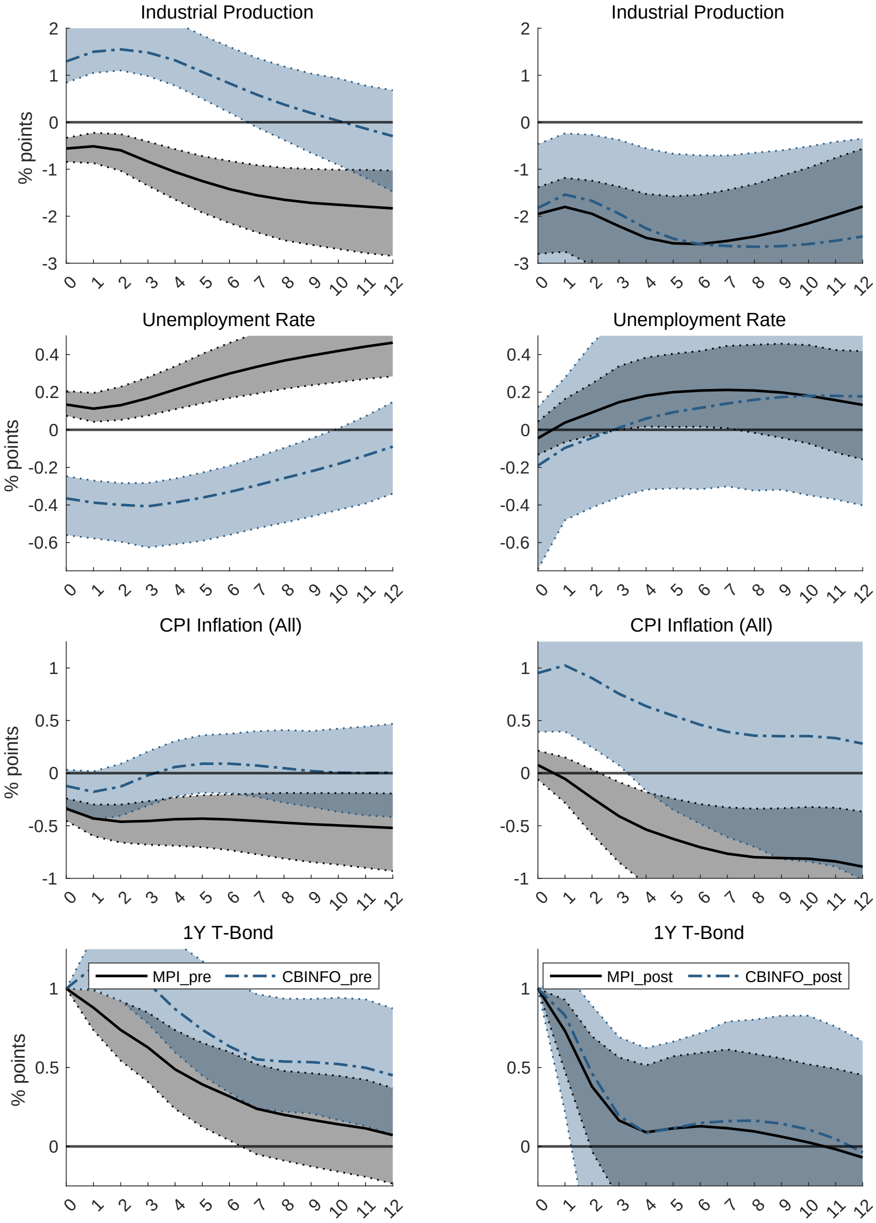

FIGURE 11: RESPONSES TO A MONETARY SHOCK: DECOMPOSITION

Note: Impulse responses from Bayesian SVAR with standard macroeconomic priors and external instrument identification. VAR sample: January 1979 - December 2019. Instrument samples: February 1990 - July 2003 (left panel) and August 2003 - December 2015 (right panel). Shaded areas correspond to 90 percent credible intervals.

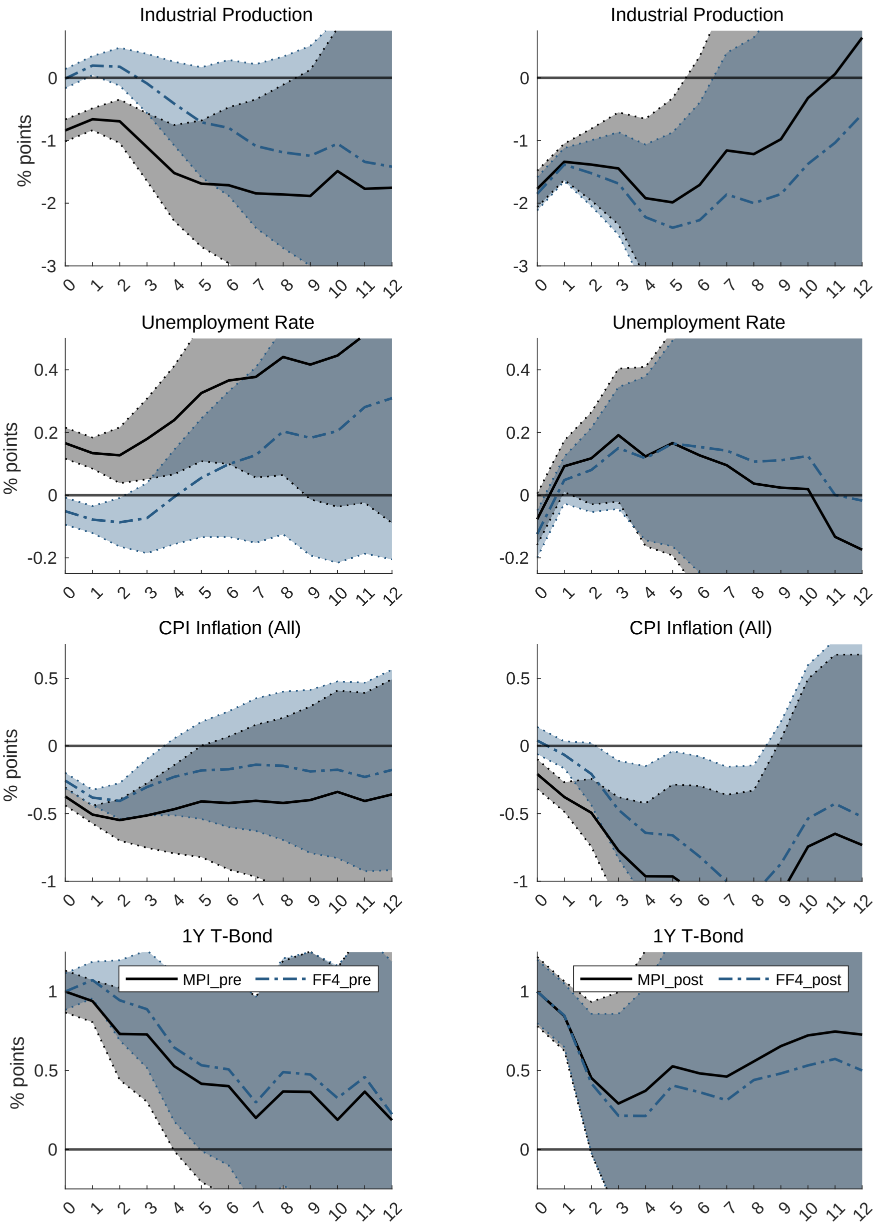

FIGURE 12: RESPONSES TO A MONETARY SHOCK: LOCAL PROJECTION

Note: Impulse responses from local projections (LP) with external instrument identification. LP sample: January 1979 - December 2019. Instrument samples: February 1990 - July 2003 (left panel) and August 2003 - December 2015 (right panel). Shaded areas correspond to 90 percent confidence intervals.

D Additional evidence on the impact of information effects on forecasters' expectations

We explore the robustness of our findings in Section IV. to including unscheduled FOMC meetings. The latter are more likely to be associated with the release of central bank's information as they often take place as a reaction to important economic events.

Tables 6 and 6 report the results. Consistent with the findings in Paul (2020), the inclusion of unscheduled meetings leads to a larger number of statistically significant coefficients compared those based on scheduled meetings. Importantly, Table 6 shows that most of the significance disappears in the second sub-sample. Overall, the coefficient estimates are similar to those based on scheduled FOMC meetings.

Table 5: Forecasters' response - Full sample, all meetings

Horizon	FF4	MPI	CBINFO	MP1
GDP Growth				
Nowcast	1.20**	0.39	2.74***	1.57**
	(0.60)	(0.57)	(0.89)	(0.67)
1 q ahead	0.66	0.14	1.26**	0.89***
	(0.40)	(0.44)	(0.63)	(0.33)
Avg. 2-4 q ahead	-0.12	-0.17	-0.07	-0.02
	(0.18)	(0.20)	(0.58)	(0.13)
GDP Deflator Inflation				
Nowcast	0.15	-0.19	0.81**	0.10
	(0.23)	(0.19)	(0.38)	(0.13)
1 q ahead	0.12	-0.12	0.57***	0.11
	(0.14)	(0.14)	(0.17)	(0.10)
Avg. 2-4 q ahead	-0.04	-0.15	0.27*	0.02
	(0.09)	(0.10)	(0.15)	(0.07)
Unemployment Rate				
Nowcast	-0.20	-0.05	-0.47	-0.22
	(0.12)	(0.13)	(0.16)	(0.09)
1 q ahead	-0.22	0.04	-0.78	-0.24
	(0.15)	(0.16)	(0.21)	(0.14)
Avg. 2-4 q ahead	-0.15	0.02	-0.66	-0.31
	(0.20)	(0.18)	(0.39)	(0.19)
Interest Rate				
Nowcast	1.08***	0.74**	1.57***	0.98***
	(0.31)	(0.34)	(0.41)	(0.19)
1 q ahead	1.32***	0.84*	2.06***	1.15***
	(0.37)	(0.43)	(0.44)	(0.24)
Avg. 2-4 q ahead	0.99**	0.78*	1.40***	1.01***
	(0.40)	(0.44)	(0.51)	(0.27)

Note: The results are based on all (scheduled and unscheduled) FOMC meetings that do not fall into the BCEI survey period (first week of the month). Robust standard errors in parentheses.

Table 6: Forecasters' response - Sub-samples, all meetings

	Feb 1990 - July 2003			Aug 2003 - Dec 2015		
Horizon	FF4	MPI	CBINFO	FF4	MPI	CBINFO
GDP Growth						
Nowcast	1.26*	0.54	2.62***	1.13	-0.09	4.58**
	(0.65)	(0.61)	(0.91)	(1.31)	(1.28)	(1.93)
1 q ahead	0.65**	0.08	1.26*	0.97	0.23	3.11*
	(0.32)	(0.35)	(0.66)	(1.09)	(1.17)	(1.83)
Avg. 2-4 q ahead	-0.11	-0.18	-0.02	0.07	-0.19	1.59
	(0.19)	(0.24)	(0.67)	(0.40)	(0.31)	(1.41)
GDP Deflator Inflation						
Nowcast	0.06	-0.08	0.32	0.36	-0.52	2.85***
	(0.23)	(0.22)	(0.37)	(0.56)	(0.43)	(0.88)
1 q ahead	0.13	-0.09	0.52***	0.05	-0.20	0.77*
	(0.16)	(0.16)	(0.20)	(0.28)	(0.33)	(0.44)
Avg. 2-4 q ahead	-0.06	-0.15	0.13	-0.05	-0.16	0.58
	(0.11)	(0.12)	(0.16)	(0.13)	(0.16)	(0.57)
Unemployment Rate						
Nowcast	-0.22	-0.06	-0.55	-0.18	-0.02	-0.62
	(0.10)	(0.11)	(0.12)	(0.33)	(0.35)	(0.53)
1 q ahead	-0.21	0.07	-0.84	-0.24	-0.02	-0.84
	(0.12)	(0.13)	(0.18)	(0.44)	(0.45)	(0.70)
Avg. 2-4 q ahead	-0.21	-0.00	-0.80	-0.03	0.10	-0.80
	(0.12)	(0.11)	(0.26)	(0.68)	(0.57)	(1.93)
Interest Rate						
Nowcast	1.14***	0.72***	1.76***	0.93	0.78	1.37
	(0.26)	(0.21)	(0.48)	(0.92)	(1.11)	(0.84)
1 q ahead	1.30***	0.69***	2.26***	1.41	1.22	1.97*
	(0.31)	(0.25)	(0.51)	(1.11)	(1.35)	(1.01)
Avg. 2-4 q ahead	0.90***	0.66**	1.39***	1.29	1.07	2.60
	(0.26)	(0.28)	(0.49)	(1.31)	(1.32)	(2.29)

Note: The results are based on all (scheduled and unscheduled) FOMC meetings that do not fall into the BCEI survey period (first week of the month). Robust standard errors in parentheses.