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Bennett Schmanski, Chiara Scotti, Clara Vega and Hedi Benamar

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Fed Communication, News, Twitter, and Echo Chambers*

Bennett Schmanski   Chiara Scotti   Clara Vega   Hedi Benamar

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Abstract

We estimate monetary policy surprises (sentiment) from the perspective of three different textual sources: direct central bank communication (FOMC statements and press conferences), news articles, and Twitter posts during FOMC announcement days. Textual sentiment across sources is highly correlated, but there are times when news and Twitter sentiment substantially disagree with the sentiment conveyed by the central bank. We find that sentiment estimated using news articles correlates better with daily U.S. Treasury yield changes than the sentiment extracted directly from Fed communication, and better predicts revisions in economic forecasts and FOMC decisions. Twitter sentiment is also useful, but slightly less so than news sentiment. These results suggest that news coverage and Tweets are not a simple echo chamber but they provide additional useful information. We use Sastry (2022)'s theoretical model to guide our empirical analysis and test three mechanisms that can explain what drives monetary policy surprises extracted from different sources: asymmetric information (central bank has better information than journalists and Tweeters), journalists (and Tweeters) have erroneous beliefs about the monetary policy rule, and the central bank and journalists (Tweeters) have different confidence in public information. Our empirical results suggest that the latter mechanism is the most likely mechanism.

Keywords: Monetary policy, public information, price discovery.

JEL Classifications: C53, D83, E27, E37, E44, E47, E5, G1.

*Bennett Schmanski, Chiara Scotti, and Clara Vega are with the Federal Reserve Board, 20th and C Streets NW, Washington, DC 20551, USA. Hedi Benamar is with Abu Dhabi Investment Authority (ADIA), and his contributions to this research occurred while he was an economist at the Federal Reserve Board. The authors can be reached via email at bennett.a.schmanski@frb.gov, chiara.scotti@frb.gov, clara.vega@frb.gov, and hedi.benamar@adia.ae. We thank participants at the Stockholm Business School Future of Financial Information (FutFinInfo) webinar series and at the IWH-CIREQ-GW Macroeconometric Workshop on Inflation: Modelling, Forecasting and Monetary Policy Reactions in Halle (Saale); Isaiah Hull and Lars Other for an excellent discussions; and Michal Dzielinski, Diego Garcia, Hao Jiang, Abalfazl Zareei, and Tengfei Zhang for their comments. We thank Betsy Vrankovich for developing the algorithm that identifies Tweets that discuss FOMC decisions. The opinions expressed here are our own, and do not reflect the views of the Board of Governors or the views of ADIA.

1 Introduction

In the last two decades there has been an extraordinary growth in the textual data economists and investors use to forecast future outcomes (see, for example, Dessaint et al., 2022). In 2022, there were over 500 million Tweets and 25 thousand news articles published per day, on average. This wealth of information does not necessarily translate into better forecasts. Prior literature shows that news and Twitter posts can translate into biased echo chambers that in turn create asset price bubbles (Pedersen, 2022) or it can even accelerate bank runs (Cookson et al., 2023).

In this paper, we estimate monetary policy surprises (sentiment) from the perspective of three different textual sources: direct central bank communication (FOMC statements and press conferences), news articles, and Twitter posts during FOMC announcement days. We, then, investigate the information content of each of these sources. We find that news coverage of the FOMC communication is not a simple echo chamber of FOMC information but provides additional useful intelligence, above that provided by asset price movements and central bank communication itself. In contrast, Tweets correlate well with U.S. Treasury yield changes, but are not as informative regarding revisions in economic forecasts and FOMC decisions. Our analysis has implications for existing central bank communication theories. While monetary policy has become increasingly more transparent in the last three decades—with the idea that transparency enhances the effectiveness of monetary policy (Blinder et al., 2008) and it is a mechanism for democratic accountability—to this day, it has been unverified whether news and Tweets would benefit or impair the goals of increased transparency from central banks. Our results suggest that news, on average, helps central banks achieve their goals by correctly anticipating future central bank actions.

To evaluate the information related to FOMC decisions, we first collect FOMC statements, press conference transcripts, and identify all news and Tweets that discuss FOMC decisions through a keyword search.[1] Out of the over 500 million Tweets and 25 thousand news articles published on average each day in 2022, we identify that 120 thousand Tweets and 25 distinct Dow Jones wire articles discuss the central bank decision during FOMC announcement days. Next, to measure the information content of these sources (FOMC statements, press conference transcripts, news and Tweets), we use the textual analysis technique developed in Gardner et al. (2022). Specifically, we

[1] The keywords we use to identify news and Tweets that discuss the FOMC decision are listed in the Appendix.

use a dictionary based on the most common words that appear in the FOMC statements related to five topics: labor market, output, inflation, financial conditions, and future monetary policy actions. The dictionary contains two separate lists of words: a list of topic keywords (for example, "GDP," "unemployment") and a list of modifiers (for example, "increasing," "decreasing"). The algorithm pairs each keyword with the closest modifier and determines whether the combination of topic-modifier communicates good (tightening), neutral, or bad (easing) news about these topics. We repeat this analysis separately for FOMC statements, press conference transcripts, news and Tweets related to FOMC communication. By construction, the sentiment is high (low) when the FOMC is more likely to tighten (ease) monetary policy in the near future.

The four sentiment indexes—from the FOMC statements, press conference transcripts, news, and Twitter— are highly positively correlated. The high but not perfect correlation suggests that news and Twitter include a subset of the information from the Fed communication. Importantly, though, we find that daily changes in U.S. Treasury yields have higher correlation with news and Twitter sentiment indexes than with the sentiment indexes directly extracted from central bank communication. Because of the daily window of analysis, during which yields and news and Tweets can potentially interact and affect each others, we treat this analysis as correlation rather than causation.[2] Similar to the interpretation in Gardner et al. (2022) that textual sentiment extracted from direct central bank communication provides an additional monetary policy surprise measure, our interpretation is that the textual sentiment extracted from news and Twitter provide additional monetary policy surprise measures from the perspective of journalists and Twetters.

We next explore, what drives monetary policy surprises from different sources. Sastry (2022) considers three mechanisms that can explain monetary policy surprises: asymmetric information (the central bank has better information than journalists and Tweeters), journalists and Tweeters have erroneous beliefs about the monetary policy Taylor rule, and the central bank and journalists (Tweeters) have different confidence in public information.[3] To test these hypothesis we regress

[2]The analysis is conducted at the daily frequency as we do not have exact time-stamps for articles that appear both in the online and the print version of the newspaper. See section 2 for more information.

[3]In Sastry (2022)'s theoretical model there are two agents, the Fed and the market. In our setting, there are several agents, the Fed, the market, professional forecasters, journalists, and Tweeters. We treat the market, professional forecasters, journalists, and Tweeters as one type of agent different from the Fed. Sastry (2022) considers three mechanisms that can explain monetary policy surprises. In our setting, news and Twitter sentiment are positively correlated with monetary policy surprises, and we consider the same three mechanism to explain monetary policy surprises, news and Twitter sentiment.

news and Twitter sentiment on past public information related to economic growth, employment and inflation, and find that positive economic growth information predicts positive news and Twitter sentiment. According to Sastry (2022)'s theoretical model, asymmetric information cannot explain the positive correlation between sentiment and past public information. Past information can only be positively correlated with sentiment if either journalists (Tweeters) under-estimate central bank's confidence in information or they under-estimate the central bank's Taylor rule weight on information.

To distinguish between these two possibilities, we analyze the relationship between sentiment and future economic forecast revisions. If journalists (Tweeters) under-estimate central bank's confidence in public information then Sastry (2022) shows that this relationship is positive. Professional forecasters revise up (down) their economic outlook forecast after positive (negative) news sentiment because professional forecasters realize that the central bank is more confident on the positive (negative) public information than they thought before the monetary policy announcement. In the model, in the case of under-estimated confidence, markets' updated positive (negative) economic growth is larger than the negative (positive) effect higher-than-expected (lower-than-expected) interest rates have on economic growth. In contrast, if journalists (Tweeters) under-estimate the central bank's Taylor rule weight on public information then the relationship is negative. Professional forecasters revise down (up) their economic outlook forecast after positive (negative) news sentiment because they realize that their economic growth forecast was correct but the Fed is tightening more-than-expected (less-than-expected) and this will in turn lower (increase) economic growth more than they expected prior to the announcement. In the model, in the case of under-estimated Taylor rule weight on public information, there is only the negative (positive) effect from higher-than-expected (lower-than-expected) interest rates and there is no positive (negative) effect from under-estimating the precision of (confidence in) past public information.

We document a positive relationship. Positive news sentiment can forecast positive future Blue Chip revisions of GDP, GDP deflator, and unemployment rate, and survives the horse race with a number of other explanatory variables like the FOMC sentiment, the target rate surprise, and the change in Treasury yields. This result is consistent with Sastry (2022)'s third mechanism, namely journalists under-estimate central bank's confidence in public information. Interestingly, our paper suggests that a reason why the market (professional forecasters) in Sastry (2022)'s theoretical model may under-estimate central bank's confidence in public information is because journalists (not considered in Sastry (2022)'s model) do so and media affects the behavior of professional forecasters. This interpretation is consistent with literature showing that the media affects the behavior of economic agents (e.g., Doms and Morin, 2004; Carroll, 2003; Vigna and Kaplan, 2007) and is further validated by the fact that news sentiment can forecast future Blue Chip revisions of GDP, GDP deflator, and unemployment rate, *after* controlling for a number of other explanatory variables like the FOMC sentiment, the target rate surprise, the change in Treasury yields, and other variables considered in Sastry (2022).

It is important to note that studies document biases in the media. Newspapers slant stories towards readers' beliefs (e.g., Gentzkow and Shapiro, 2010; Mullainathan and Shleifer, 2005), newspapers have a political bias (e.g., Groseclose and Milyo, 2005), newspapers slant stories toward extremes (e.g., Mullainathan and Shleifer, 2005), and newspapers can be biased echo chambers that in turn create asset price bubbles (Pedersen, 2022). Journalists under-estimating central bank's confidence in public information, is another bias, that may hinder journalists' ability to predict future FOMC decisions. However, we find that the news sentiment is among the best predictors of FOMC decisions. In contrast, while Tweets correlate with U.S. Treasury yield changes, they are not as informative regarding revisions in economic forecasts and FOMC decisions. Our results clearly indicate that, even though, the news sentiment index is in part driven by journalists' under-estimating the Fed's weight on public information, it can still be informative about the Fed's future decisions. News sentiment is not a simple echo chamber of FOMC communication and is not simply describing asset price movements. It contain valuable intelligence beyond the information subsumed by asset prices and direct central bank communication.

For example, Twitter and news sentiment indexes allow us to observe when individuals and journalists focus on a particular topic more so than the FOMC and whether they interpret the information to imply more (less) tightening than the FOMC communication. On average, we observe an asymmetric reaction to tightening and easing information. Individuals and journalists agree with the FOMC statement when it comes to easing. However, individuals and journalists expect tightening a few meetings before the FOMC statement sentiment indicates tightening. Focusing on the pandemic period (January 2020 to December 2021), we observe that journalists and individuals expected tightening shortly after the 2020 recession was over, long before the FOMC statement started to indicate tightening in April 2021. During this period, we also observe that individuals and journalists focused on inflation long before the FOMC statement. Since the disagreement in sentiment coincides with individuals and journalists accurately predicting tightening in the future, we find that news sentiment is able to forecast future monetary policy decisions better than the sentiment in the FOMC statement itself. According to Pedersen (2022)'s theory, the "stubbornness" of journalists (and U.S. Treasury investors, since journalists are likely to write articles taking the yield reaction to the statement into account) is what makes the market rational. Our results suggest that in our setting, when a central bank communicates information to the market, a large professional journalist community reports on the event, and the majority of the trading is done by institutions (the minimum trade size in the U.S. Treasury market is 1 million dollars) the "stubbornness of truth" is likely to prevail.

This paper contributes to several strands of the literature. First, we contribute to the literature that emphasizes the importance of words in central bank communications, e.g. Gardner et al. (2022), Gürkaynak et al. (2005), Lucca and Trebbi (2009), and Swanson (2020). This literature focuses on the effect textual central bank communication has on interest rates, while we focus on the effect Twitter and news coverage of central bank communications has on interest rates, future FOMC decisions and investors' beliefs about the future economy. Our contribution is to show that, not only is central bank communication important, but the journalists' and investors' interpretation of this information is crucial to understand the yield reaction to FOMC decisions and to predict market expectations and the central bank's future policy stance.

Second, we contribute to the literature that studies the value of alternative data (see, for example, Dessaint et al., 2022), in particular news and social media sentiment, as well as the potential for social media data to cause asset price bubbles (Pedersen, 2022) or accelerate bank runs (Cookson et al., 2023). Our results indicate that the potential for social media sentiment to cause asset price bubbles depends on the setting. As Pedersen (2022) indicates, whether "stubbornness truth" or "stubbornness fanatism" prevails may depend on whether retail or institutional investors dominate the market, and on whether there is a central bank communicating. We add that the dominating equilibria may also depend on the prevalence of journalists, as the informative Twitter sentiment also includes Tweets from journalists; once we exclude journalists' tweets, Twitter sentiment is not very informative.

Third, we contribute to the literature that uses textual analysis techniques to extract useful variables that have predictive power. Textual analysis has gained significant ground in recent years, particularly in the study of uncertainty and of central bank and political deliberations. These analyses use a combination of methods including news search (Baker et al., 2016; Caldara and Iacoviello, 2018; Demiralp et al., 2019; Shapiro et al., 2020), machine learning techniques such as Latent Dirichlet Allocation (Hansen and McMahon, 2016; Hansen et al., 2017; Larsen and Thorsrud, 2019), dictionary methods (Loughran and McDonald, 2011; Sharpe et al., 2017; Banerjee et al., 2019; Shapiro et al., 2020; Gardner et al., 2022), or semantic orientation (Lucca and Trebbi, 2009). We contribute to this literature by showing that using a Federal Reserve-specific dictionary to sign FOMC statements, Twitter and news coverage of central bank communication works better than using the general dictionary of financial market positive and negative words of Loughran and McDonald (2011) or machine learning techniques such as Latent Dirichlet Allocation. We further contribute to this literature by showing that news sentiment during FOMC announcement days is an extremely useful predictor of investors' expectations. It is notoriously difficult to forecast investors beliefs, e.g., Patton and Timmermann (2011) and investors beliefs are sometimes biased, e.g., Ben-Rephael et al. (2021), thus our study is important because it helps us better understand what drives investors beliefs, news, and Twitter content, and when those beliefs incorporate unbiased information, information that helps forecast future FOMC decisions.

Fourth, we contribute to the literature that tries to understand the drivers of monetary policy surprises (e.g., Sastry, 2022; Bauer and Swanson, 2020; Cieslak, 2018). Consistent with this literature, we find that news sentiment is ex post predictable. This does not imply that people make "obvious" mistakes (Cieslak, 2018), instead, it highlights challenges of real-time forecasting.

The paper proceeds as follows. Section 2 introduces the data used in this study, including the derivation of the FOMC statement, press conference, Twitter and news sentiment indexes. Section 3 investigates the information contained in news and Twitter sentiment indexes through an analysis of Treasury yield changes, and forecasts of future monetary policy and investors' beliefs about future macroeconomic variables like GDP, inflation, and the unemployment rate. Finally, we conclude in Section 5.

2 Data

In this section, we describe the data and variables that we use in the analysis. First, we describe the textual data sources and explain the construction of the sentiment index for FOMC statements, press conferences, news articles, and Twitter posts. We then discuss U.S. Treasury yield data as well as investors' beliefs about macroeconomic variables. Throughout the paper we focus on the period 2000-2021.[4] Our Twitter data starts in March 2007 and the corresponding results are therefore based on the smaller sample period from March 2007 to December 2021.

2.1 FOMC Statements and Press Conferences

We use FOMC meeting dates from January 2000 to December 2021 and the corresponding release times of the statement and the press conference (see the Appendix Table A2). During our sample period there were 183 meetings and 56 press conferences. We download the text of the statements and press conferences from the Federal Reserve Board of Governors public website, www.federalreserve.gov. The Federal Reserve began to have post-meeting press conferences in 2011, after every other meeting. Only in December 2018, the Federal Reserve began to hold a press conference after each meeting of the FOMC.

2.2 News and Twitter Data

We use Factiva and Twitter to collect, respectively, news and Twitter data related to FOMC announcements. For news, we focus on Dow Jones articles covering FOMC communication and note that our results are robust to adding three other major newspaper sources: NY Times, Wall Street Journal, and Washington Post. To identify articles covering FOMC communication we automate the search for these articles using keyword searches (see, for example, Baker et al., 2016; Benamar et al., 2021) in the headline and body of newspaper articles or the body of Twitter posts. Specifically, we collect all Dow Jones articles with a headline or body containing the keywords "FOMC" or "Federal Reserve." Our Twitter sample is composed of all tweets that mention either a keyword related to the Federal Reserve, like "Fed", "FOMC", and "Powell", tag their post with a related

[4] Our sample period starts in January 2000. We could possibly start the analysis in September 1998, when the Federal Reserve started to release a statement, albeit not consistently, along with the decision. However, the statements in the early part of the period were not very informative and therefore we decided to start in 2000. Nevertheless, we note that our results are robust to including statements from November 1998 to December 1999.

hashtag or account, like "#fomc" and "@federalreserve", or contain a link to the Federal Reserve website. Retweets, quote tweets, and replies are all included.[5]

In Panel A of Figure 1, we show the number of Dow Jones news articles related to FOMC decisions over time. The graph indicates that the number of articles has increased over time. Before 2008, there were, on average, about 20 articles per day on FOMC days; after 2008, the average increases to about 60 articles a day on FOMC days. Part of the growth in media coverage is in response to an increase in information demand related to central bank actions to address the 2008 financial crisis, and part of the growth is due to Dow Jones launching new services.[6] We noticed that several Dow Jones articles contain the same sentences, so we delete duplicate sentences and our denominator in computing sentiment is the number of unique sentences shown in Panel B of Figure 1. Similarly, Panel A of Figure 2 shows the (daily) number of Tweets related to FOMC statements on FOMC days, and Panel B shows the percent of Tweets written by journalists. Tweeter data starts on January 2010 and it experiences tremendous growth in 2019.

For illustrative purposes, in figure 3 we show average volatility and average news counts per 5-minute intervals on FOMC days with a 14:00 ET FOMC statement release (for release times please see Table A2). The figure shows a sharp increase in volatility and news articles at 14:00 ET, when FOMC statements are released. Volatility and news coverage stays elevated throughout the press conference and we see another spike in news articles at around 16:00 ET, when articles that appear on the print version the next day are marked as released at 16:00 ET or later the previous day because they are released online the day of the FOMC, but the exact released time online is not recorded. The fact that the exact release time for these articles is not known could bias our results downward, because these articles could either be released before the FOMC statement is released

[5] The exact keywords we use for Twitter are: "fomc" or "federal reserve" or "@federalreserve" or "#fomc" or "#federalreserve" or "@fedresearch" or "url:federalreserve" or "to:federalreserve" or "to:fedresearch" or "retweets_of:federalreserve" or "retweets_of:fedresearch" or (("powell" or "yellen" or "bernanke") and ("fed" or "fomc" or "chair" or "governor" or "federal reserve")).

[6] Overtime Dow Jones has launched and merged news services. We observe an increase in coverage when a news service is launched, and a decrease when news services are merged. The two structural breaks worth mentioning occurred in 2008 and 2013. In June 2008, Dow Jones launched Dow Jones Newswires, which coincides with an increase in the number of articles related to the FOMC, and in October 2013 all the Dow Jones newswire services were consolidated into Dow Jones Institutional News. In We also see an increase in the number of articles by Wall Street Journal and News York Times on October 2008 following Lehman Brothers bankruptcy, so our interpretation is that the growth in articles is due to both an increase in information demand and structural changes in Dow Jones Newswire services . Prior to 2008, most of the articles come from Dow Jones Capital Markets Report and Dow Jones News Services, after 2008 most of the articles are from Dow Jones Newswires. In 2013, Dow Jones consolidated their wire services into Dow Jones Institutional News.

or very late in the day. Our manual reading of these articles indicates that these articles tend to be more in depth than the articles released right after the FOMC statement and discuss the statement, so the probability that some of these articles were released online before the statement is released is low. The pattern observed in figure 3 is similar when we include all FOMC days, but the different FOMC release times (14:00 ET or about 14:15 ET) makes it less clear that the increase in volatility and news articles coincides with the release time of the statement. In our empirical analysis we include all FOMC days and the sentiment of news articles released after the FOMC statement is released or released in the print version of the newspaper the next day, which are articles that are, most of the time, published online the day of the FOMC.

In Table 1, we show sample articles that cover the FOMC statement in the minutes after the release, articles that are released while the press-conference is held, and articles released at 19:00 or 20:00 or the next day with a more in-depth analysis. Sometimes, this in-depth analysis mentions yield movements and it could be an ex-post explanation of the yield-movements. We test these hypothesis below.

2.3 Sentiment Indexes

We construct four sentiment indexes: the FOMC statement, press conference, news, and Twitter sentiment indexes. We use the methodology developed by Gardner et al. (2022), namely, we use a user-defined dictionary of *topic-keywords* and *modifier-keywords*. We separate topic-keywords into five topics: labor market, output, inflation, financial conditions, and future monetary policy actions based on our reading of the FOMC statements over the 2000-2021 period. Words are added to each topic-keyword dictionary based on their relative frequency in a list of most frequently used words that appear in FOMC statements after dropping common stop words such as "a," "the," etc. Due to the predictable pattern of FOMC communication, Gardner et al. (2022) are able to generate a representative set of topic-keywords (7 for labor, 18 for output, 3 for inflation, and 3 for financial conditions) and phrases (24 for future monetary policy). Even though the topic-keyword dictionary is developed based on the FOMC statements, we find that this dictionary is also useful in constructing the sentiment of the Chairman's press conference, news and Twitter coverage of FOMC communications. In the Robustness section we construct sentiment using Loughran and McDonald (2011)'s dictionary and a machine learning technique that uses manually signed FOMC statements as the training sample, and the sentiment constructed using Gardner et al. (2022) has higher explanatory value than the sentiment using those two alternative methods.

For the first four topics—labor, output, inflation, and financial conditions—we pair a topic-keyword (see the Appendix of Gardner et al. (2022) for a list of topic-keywords) with the closest modifier-keyword (see the Appendix of Gardner et al. (2022) for a list of modifier-keyword) within a sentence to get the *topic-modifier* pair. Distance is measured by the number of words from the beginning of a topic-keyword to the beginning of a modifier-keyword. We then use this topic-modifier pair to sign FOMC communication depending on whether the statement indicates that the economy (output, employment, financial conditions) is expanding, neutral, or contracting, or that inflation is increasing, neutral, or decreasing. A simple mention of the word "unemployment" does not provide much information about what the FOMC believes regarding the state of the economy; similarly, using modifiers independently of the keyword might be misleading because they can have positive or negative connotations according to the keyword to which they refer. Importantly, including the context of "unemployment rate has declined" allows us to assign a signed score. By separating words into topic and modifier categories, our algorithm is more flexible at recognizing a variety of possible pairs like "unemployment rate has declined" and "unemployment rate to resume the gradual decline" without having to identify and score every possible permutation of those two words. Topics and modifiers take on values of 1, 0, and -1 based on our assessment of whether they communicate good, neutral, or bad information about economic conditions.

We calculate the *topic-modifier pair sentiment* by multiplying the topic-score with the modifier-score. For example, in the aforementioned phrase "unemployment rate has declined", "unemployment rate" and "has declined" receive both a score of -1 for an overall score of 1. In contrast, the phrase "labor market conditions have deteriorated" from the December 16, 2008 press release receives an overall score of -1, because the topic "labor market" is scored as 1 and the modifier "deteriorated" is scored as -1. See the Appendix of Gardner et al. (2022) for a list of the keywords, modifiers, and their respective scores.

The sentiment index for each source (FOMC statement, press conference, news, and Twitter) is the sum of each topic-modifier sentiment divided by the number of unique sentences after having deleted uninformative sentences (see the Appendix of Gardner et al. (2022) for a description of how they identify uninformative sentences).[7] In other words, every topic-modifier pair is evaluated independently and its score is then combined with all the others. That is, for example, the topic-modifier pair "expanding output" would receive a score of +1; when combined with "increasing inflation," the overall score for the FOMC sentiment index would be +2, but when combined with "stable inflation," the overall score would still be a +2 because the latter topic-modifier pair would be scored as zero. Of course, different weighting schemes could be considered.[8]

In Table 2 we show the correlation across these four sentiment indexes and the target rate surprise for the full sample, the Twitter sample, and the press conference sample. The sentiment correlation across sources is high, suggesting that Twitter and the news coverage may be an unbiased echo chamber of the FOMC communication, a simple repetition of the original source of information. Interestingly, the lowest correlation displayed is the one between the target surprise and the sentiment indexes, highlighting that textual information might be different from the information in the target surprise.

Despite the high correlation, Panel A of Figure 4 shows periods when the overall news sentiment (in red) differs substantially from the FOMC statement overall sentiment index (in blue). Similarly, Panel B of Figure 4 shows periods when the overall Twitter sentiment (in red) differs substantially from the FOMC statement overall sentiment index (in blue). In future sections, we investigate whether differences across sentiments are enough to identify whether news and Twitter sentiment are more informative than the FOMC statement and press conference sentiment.

2.4 U.S. Treasury Yields Data

Following prior literature that uses high-frequency (minute-by-minute) data to estimate the response of yield changes to macroeconomic news announcements to better identify the effect, we use intraday data from Bloomberg on on-the-run U.S. Treasury bills and notes with maturities 3-month, 6-month, 2-year, 5-year and 10-year, as well as Eurodollar and federal funds futures data.

[7] The textual analysis program is written in R and is available upon request.

[8] The Robustness section of Gardner et al. (2022) shows that extracting a principal component is less informative than adding the different subcomponents.

2.5 Monetary Policy Surprises and Other Variables

Another group of variables considered in our analysis are those that refer to monetary policy decisions or that are believed to affect such decisions. One such variable is the level of the federal funds rate (FFR). Indeed, Goldberg and Grisse (2013) argue that the Federal Open Market Committee (FOMC) is less likely to raise interest rates in response to positive nonfarm payroll surprises when the FFR is already high. Thus, in this situation, positive nonfarm payroll surprises should have a bigger impact on equity prices.

Because our sample contains the effective lower bound (ELB) period, in addition to the change in the FFR, we also consider a policy stance indicator that takes the value $s = -1,\ 0$, or 1 according to whether the FOMC decreases, leaves unchanged or increases the FFR and to whether it announces other unconventional policies that are tightening, neutral or accommodative, respectively. During our sample period, February 2000 to December 2021, there were (as shown in the Appendix Table A2), 183 FOMC meeting press releases, some of which were inter-meeting press releases.[9]

In the paper, we also evaluate which variables best predict FOMC decisions. The variables we use are those considered by Law et al. (2020): employment gap, inflation level, 5-year bond yield level and changes, the price-to-dividend ratio, and the VIX index as a proxy for uncertainty.[10] While the 5-year bond yield can be considered as a measure of forward guidance expectation and surprise, we also include in the analysis more direct measures of monetary policy regarding both the target rate/range and its forward guidance.

In particular, the target surprise is the difference between the announced target fed funds rate and expectations of this target derived from fed funds futures contracts (see Kuttner2001), over a 30-minute window (from 10 minutes before the FOMC announcement to 20 minutes afterward) and the path surprise is the residual from a regression of the change in yield for the fourth Eurodollar futures contract from 10 minutes before the time of the announcement to 20 minutes afterward onto the target surprise. As measures of expected future rate and forward guidance, we also employ

[9]The FOMC press-release dates shown in the Appendix Table A2 are taken from www.federalreserve.gov. We confirmed the release dates using Bloomberg, the Internet Appendix Table IA.I in Boguth et al. (2019), and the dates from Rogers et al. (2014) and Rogers et al. (2018) updated to December 2021.

[10]In our regressions, we use the value of the VIX index at the close of the day preceding the macroeconomic announcement because options used to construct the index trade from 9:15 am to 4:15 pm ET.

the expected change in the FFR implied by fed funds futures and the expected change in the FFR one-year hence implied by Eurodollar futures or the Blue Chip forecast for the FFR over the next four quarters.[11]

3 Do News and Twitter Sentiment Indexes Contain Information?

In order to disentangle the information contained in the FOMC statement, press conference, news and Twitter sentiment indexes, we look into their performance in affecting interest rates across maturities (section 3.1), in predicting future revisions of Blue Chip forecasts (section 3.2), and in predicting future FOMC policy decisions (section 3.3).

3.1 U.S. Treasury Yields

While prior literature has shown that monetary policy surprises affect short- and long-term interest rates, we are particularly interested in the value of textual information as summarized by our indexes. Following Lucca and Trebbi (2009) and Gardner et al. (2022), we therefore investigate whether the textual analysis summarized by our sentiment indexes contains information relevant for interest rates beyond the target rate surprise. To this end, we regress interest rate movements in a one-day window around the FOMC announcement on the monetary policy target rate surprise, the Gardner et al. (2022) FOMC sentiment index, and the news sentiment index:

$$\Delta y^m_{\tau,t} = \alpha + \beta_{Surp}\text{Target Surprise}_t + \beta_{Sent}\text{Sentiment}_t + \varepsilon_t, \tag{1}$$

where $y^m_{\tau,t}$ is the yield on day t at time τ of U.S. Treasury notes with maturity $m = 3$ and 6 months, 2, 5, and 10 years, or the fourth Eurodollar futures contract; the target surprise is the difference between the announced target fed funds rate and expectations of this target derived from fed funds futures contract; and Sentiment is either the FOMC sentiment index, the news sentiment or both. We define the daily yield change around the FOMC announcement as $\Delta y^m_{\tau,t} = 100\times(y^m_{\tau,t} - y^m_{\tau,t-1})$, where $y^m_{\tau,t}$ is the "closing" price (mid-quote at 4:59 p.m. ET). The one-day window captures the yield reaction to the statement, the reaction to press-conference communication, and

[11]More details on the computation of monetary policy expectations following Kuttner (2001) are in the Appendix of Gardner et al. (2022).

more detailed news coverage of both the statement and the press-conference. As we mentioned above, some articles have a time-stamp after 4:59 p.m. ET, these articles appear in the print version of the newspaper the next day and according to Factiva it is not possible to know the exact online release time. To the extent that the articles are published after 4:59 p.m. ET the coefficient on news sentiment has a downward bias. For robustness, we drop articles with time-stamps after 4:59 p.m. ET and whose release time is unknown and the results are weaker but consistent with our conclusions.

Many studies focus on explaining 30-minute yield changes because the narrower the window the better one can identify the impact of news on asset prices (Andersen et al., 2003, 2007). However, in Figure 3 we show that news articles are released throughout the day, many of which are released after the 30-minute window. We therefore prefer to compute our news and Twitter sentiment at the daily frequency, as explained in section 2.3.

Consistent with previous studies, the results in Panel A of Table 3 document a statistically significant effect of target rate surprises on short-term yields, and a substantial drop in the fraction of the variance explained for longer-term yields. Panel B shows that the FOMC sentiment also affects yields, but the novel results are in Panel C, which indicate that news sentiment has somewhat higher explanatory power (higher adjusted R^2) than the sentiment in the FOMC statement. Consistent with Gardner et al. (2022), Panel D shows that both the sentiment in the FOMC statement and target rate surprises have an effect on interest rate changes during the daily window. Panel D also contains the press conference sentiment index, computed on the text of the press conference (which occured on 56 days out of the 183 FOMC meetings as indicated in Table A2).[12] In the bottom panels of Table 3, we show that the news sentiment is statistically significant even after controlling for the target rate surprise, and the sentiment in the FOMC statement and in the press conference, suggesting that the news sentiment contains useful information that explains daily yield changes on FOMC announcement days.

In Table 4, we consider the Twitter sentiment instead of the news sentiment. As we explained before, Twitter sentiment is only available starting in March 2007, so our sample period is reduced to 120 FOMC meetings compared to 183 meetings in our full sample. In Panel C of Table 4, we

[12]We control for press conference sentiment and interact this variable with an indicator variable equal to one when there is a press conference, zero otherwise.

show that Twitter sentiment is particularly useful in explaining short-term yield changes, even when competing against target rate surprises, FOMC statement and press conference sentiment. Some of the lower explanatory value in explaining longer-term yields is probable due to the sample period and also to the Twitter sentiment being different from the news sentiment.[13]

Importantly, the analysis in this section is conducted at the daily frequency as our sentiment measures can only be computed at such frequency. Because of the daily window of analysis, during which yields and news can potentially interact and affect each others, we treat this analysis as correlation rather than causation. However, in the next section, we investigate whether the ability of news and Twitter sentiment indexes to explain interest rate changes is purely due to the dual-causality (news and Twitter affecting yields but also responding to yield movements), or whether news and Twitter sentiment indexes contain valuable information regarding investors' beliefs about future inflation and economic activity, and future FOMC decisions after controlling for yield changes.

3.2 Blue Chip Forecast Revisions

In the previous section, we documented that news and Twitter sentiment correlate with daily interest rate changes across maturities on FOMC days better than the FOMC statement and press conference sentiment. This could be because there is dual-causality between news and interest rate movements—journalists come up with an ex-post explanation of why interest rates moved—or because news and Twitter sentiment contains fundamental information. In this section, we investigate whether news and Twitter sentiment convey fundamental information beyond that reflected in interest rate movements, the FOMC statement and press conference sentiment, by investigating whether news and Twitter sentiment help predict investors' beliefs about future macroeconomic activity, unemployment and inflation.

To test this hypothesis, we rely on the framework introduced by the Fed information effect literature and we formally test whether the sentiment indexes, across different sources, have forecasting

[13]Table A3 in the Appendix, shows that the explanatory power of the news sentiment is higher than the Twitter sentiment for longer-term yield changes using the same 120 FOMC meetings when Twitter sentiment is available, but Twitter sentiment has higher explanatory power than news sentiment for shorter-term yield changes.

powers for investors' beliefs.[14] In particular, we revisit the empirical evidence by making an important point of departure from the traditional literature; namely, we consider the FOMC statement, press conference, news and Twitter sentiments as a measure of text-based monetary policy surprises, in addition to the interest-rate-based surprises previous literature considers—the target, path and LSAP (large-scale asset purchases) surprises. To do so, we use the same specification of Bauer and Swanson (2020) and other "Fed information effect" papers:

$$\begin{aligned}\text{BCrev}_{t+1} = \alpha &+ \beta_{TS}\text{Target Surprise}_t + \beta_{PS}\text{Path Surprise}_t + \\ &+ \beta_{LSAP}\text{LSAP Surprise}_t + \beta_S\text{Sentiment}_t + \beta_N\text{News}_t + \varepsilon_t,\end{aligned} \tag{2}$$

where t indexes FOMC announcement days; *Target Surprise*, *Path Surprise* and *LSAP Surprise* are the monetary policy surprises as defined in Section 2.5; Sentiment is either one or more of the sentiment indexes considered thus far, the FOMC sentiment, the press conference sentiment, and/or the news sentiment; *News* are three variables Bauer and Swanson (2020) consider, nonfarm payroll (NFP) surprises, quarterly S&P500 returns and the ADS index, a real-time macroeconomic index; and *BCrev* denotes the one-month revision in the Blue Chip consensus forecast of a given variable averaged over the one-, two-, and three-quarter-ahead horizons.[15]

During our sample period, the Blue Chip Economic Indicator surveys were conducted over the first three business days of each month until December 2000, and over the first two business day of each month after December 2000. The consensus (mean) forecast is released to the public on the 10th of each month. To make sure that the FOMC information is available to forecasters, Bauer and Swanson (2020) use forecast revisions if there was an FOMC announcement in between Blue Chip Economic Indicator surveys, and they drop forecast revisions if the FOMC announcement occurs in

[14] When the Federal Reserve surprises markets with a monetary policy decision, this shock is not only an exogenous interest rate shock, as in the monetary policy VAR literature (e.g., Christiano et al., 1996; Cochrane and Piazzesi, 2002; Faust et al., 2004b), but it can also convey either information about the state of the economy, as argued by "Fed information effect" studies (e.g., Romer and Romer, 2000; Faust et al., 2004a; Campbell et al., 2012; Nakamura and Steinsson, 2018; Cieslak and Schrimpf, 2019; Hoesch et al., 2020), or information about the Fed's response to news, as argued by Bauer and Swanson (2020). The traditional Fed information effect hinges on the results that positive target rate surprises are associated with a positive (negative) revision to GDP (unemployment rate) forecasts—that is, the opposite signs to those predicted by a standard New Keynesian model— suggesting that the Fed has superior information about the state of the economy. Recently, however, Hoesch et al. (2020) show that such information advantage mostly disappeared after 2000, and Bauer and Swanson (2020) show that, controlling for macroeconomic news, the effects of Federal Reserve monetary policy announcements on Blue Chip forecasts looks very standard, consistent with a "Fed response to news" channel rather than a "Fed information effect" channel.

[15] Our results are qualitatively similar when we replace the ADS index with the "big data" business cycle indicator of Brave et al. (2019)'s index as in Bauer and Swanson (2020).

the first seven days of the month. In panel A of Table 5, we show estimates of equation (2) for all of the dates when there is an FOMC meeting in between forecasts, and in panel B we show estimates when we drop forecast revisions if the FOMC announcement occurs in the first seven days of the month.

The results in Table 5 show, consistent with recent literature, that the target rate surprise and forward guidance have limited impact on professional forecasts during the 2000–21 period. Interestingly, professional forecasters do appear to revise their forecasts based on the news coverage of the FOMC decision. In other words, the news sentiment index is statistically significant in all of the specifications even after controlling for FOMC statement and press conference sentiment, target, forward guidance and LSAP surprises. In Table 6, we provide even more direct evidence that news sentiment contains fundamental information beyond that contain in interest rate yield changes by replacing target, forward guidance and LSAP surprises with daily interest rate movements during FOMC days. The results are qualitatively the same as in Table 5. That is, even after controlling for the information contained in the change in yields brought about by the FOMC decisions, the news sentiment index affects the evolution of the the Blue Chip forecasts for GDP, unemployment, and inflation.

3.3 Upcoming FOMC Decisions

In this section, we investigate whether news and Twitter sentiment convey fundamental information beyond that reflected in interest rate movements, the FOMC statement and press conference sentiment, by investigating whether news and Twitter sentiment help predict upcoming FOMC decisions.

FFR changes are naturally ordered in 0.25 percent increments over the range of ± 0.75 percent, prompting the use of an ordered probit model to forecast the size of the FFR change, consistent with Hamilton and Jordá (2002), Scotti (2011), and Angrist et al. (2018). However, because the period we analyze is characterized by both conventional and unconventional policies, we develop a policy stance indicator that takes the value $s = -1,\ 0,\ or\ 1$, as explained in Section 2.5.

In terms of explanatory variables, our specification is similar to that used by Angrist et al. (2018), who, consistent with Kuttner (2001), find that federal funds futures are one of the best predictors of the change in the FFR. We also include Blue Chip professional forecasts of the change in the FFR and the change in fed funds futures one year hence implied by Eurodollar futures. In addition to these variables measuring market expectations regarding target and forward-guidance (path) monetary policy changes, we also include Taylor rule-type variables—namely, inflation and the unemployment rate gap. According to the Taylor rule, the *change* in the federal funds target rate is a function of the inflation rate (minus a 2 percent long-run objective) and the change in the GDP gap (see, for example, Orphanides, 2005; Board of Governors, 2018)[16] In the literature, the monthly CPI index (or quarterly GDP deflator) and the change in the unemployment rate gap are generally used in place of inflation and the output gap change. We use real-time measures of inflation and the unemployment rate gap as suggested by Orphanides (2001) and as explained in the Data section. We also include the financial variables Law et al. (2020) show to be good predictors of future monetary policy, such as the 5-year bond yield level and changes, the price-to-dividend ratio, and the VIX.[17] And, of course, we include our FOMC sentiment index, which is meant to capture the likelihood of a change in the federal funds target rate due to a change in economic conditions since the previous FOMC meeting.

Specifically, we estimate the following probit specification at a daily frequency using observations only when there is an FOMC meeting:

$$Pr(MPD_t = s|X_{t-1}) = \Phi(X_{t-1}\mathrm{B} + \varepsilon_t), \tag{3}$$

where MPD_t is the monetary policy decision on day t when there is an FOMC announcement, measured as the policy stance variable just described, and X_{t-1} is the matrix of predictors of monetary policy decisions available as of the day before the FOMC meeting. For most variables, this means that we use their value as of $t-1$, but for the FOMC sentiment, the latest value is that corresponding to the previous FOMC meeting. In addition, Φ is the normal probability distribution.[18]

We first consider each variable's predictive power in isolation in a univariate specification. All of the variables, except for the indicator variables (recession and inverted yield curve), are standardized

[16] See the box "Monetary Policy Rules and Their Role in the Federal Reserve's Policy Process" in Board of Governors (2018).

[17] Our right-hand variable is the change in monetary policy; however, previous literature shows that both the level and the change in interest rates have predictive power, so we include both.

[18] Results are qualitatively similar when we estimate equation (3) with MPD_t being the actual FFR change $s = -0.75$, -0.5, -0.25, 0, 0.25, 0.50 or 0.75 or when we exclude the ELB period—see Table 8, columns (3)–(4).

so that the marginal effects can be interpreted as the effects of a one-standard-deviation shock to the variable. In Table 7, we show that the expected rate change implied by federal funds futures—computed as described in Section 2.5 and in the Appendix—is the best predictor of future monetary policy, with a pseudo R^2 of 0.33, followed by the news sentiment, with a pseudo R^2 of 0.29, the previous change in the monetary policy stance, with a pseudo R^2 of 0.29, and the FOMC statement sentiment index, with a pseudo R^2 of 0.25. These results are consistent with the intuitive notion that interest rate derivatives provide a very good policy forecast (Piazzesi, 2005), and that the texts of news covering FOMC decision and coming directly from the FOMC (the statement itself), as well as past FOMC actions, are good predictors of future monetary policy decisions. The VIX, the ADS index, and a recession indicator variable also turn out to be good predictors of future monetary policy stance. For ease of interpretation, we standardized all continuous variables, and the table reports the marginal effects on the probability of the FOMC making a tightening announcement for a one-standard-deviation increase in continuous variables, or for a change from 0 to 1 in discrete variables.[19] In column (1), we observe that a one-standard-deviation increase in the news sentiment increases the probability of a tightening announcement by 0.21, which is a sizable number. For comparison, a one-standard-deviation increase in the expected FFR change implied by fed funds futures (corresponding to about 25 basis points) would increase the probability of a tightening announcement by 0.25. Conversely, the probability of tightening decreases by 0.23 when the economy moves into recession.

In column (3) of Table 8, we show results from a horse race exercise where we include in the probit regression all of the variables at once. Not all variables are statistically significant in this specification: the fact that the news and FOMC statement sentiment maintain their significance in this regression is indicative of the fact that its information is not subsumed by other variables. Importantly, the marginal effect of the news and FOMC statement sentiment indexes are still sizable. A one-standard-deviation increase in the FOMC sentiment increases the probability of tightening announcement by 0.13, while a one-standard-deviation increase in the news sentiment increases the probability of tightening announcement by 0.04. Variables like the VIX index, instead, lose significance in this exercise. In the Appendix, we show that our conclusion is robust to excluding

[19]To be clear, the table shows the marginal effect not in terms of slope, but in terms of impact on the probability.

the ELB period and to forecasting federal funds target rate changes rather than using the monetary policy stance variable.[20]

The result that news sentiment forecasts future FOMC decisions as well as or better than FOMC sentiment itself is surprising because we expect the FOMC to forecast better what it will do in the future than journalists themselves. However, this is consistent with the view that there can be disagreement about monetary policy between the central bank and journalists similar to the disagreement prior literature has documented between the central bank and the private sector (see, for example, Sastry, 2022). In the next section, we investigate why news and FOMC sentiment indexes disagree.

4 What Drives Monetary Policy Surprises and Disagreement

In the previous section we established that news sentiment contains useful information that is different from that contained in the FOMC statement. In this section we investigate what drives monetary policy surprises estimated using news textual sentiment and disagreement between news sentiment and FOMC statement sentiment.

To guide our empirical analysis we use Sastry (2022)'s theoretical model. In Sastry (2022)'s model there are three periods $t = \{0, 1, 2\}$, and there is a single unknown fundamental economic growth variable, θ, normally distributed with mean zero and variances equal to τ_θ^{-1}. There are two market participants, the Fed, F, and the Market, M, which in our setting are journalists. F and M receive public information about the fundamental. In addition, F receives a private signal about the fundamental (asymmetric information). F sets the interest rate, r, based on the information it has about the fundamental (its expectation of the fundamental), and M forms an expectation about the interest rate, r. Expectations are labeled $E_{X,t}$ where $X = \{F, M\}$ indicates whose expectation it is and $t = \{0, 1, 2\}$ indicates at what time the expectation is formed.

Specifically, in period t=0, F and M receive a public signal $Z = \theta + \varepsilon_z$. F also receives a private signal $F = \theta + \varepsilon_F$. F sets interest rates using the public signal and the private signal $r = E_{F,0}[\theta]$. M makes a prediction about r, $P = E_{M,0}[r]$. In period t=1, the interest rate is reveal and the monetary policy surprise is $\Delta = r - P$. In period t=2, F and M receive another public signal $S = \theta + \varepsilon_S$ and

[20] An alternative to a probit specification would be to use the shadow rate of Wu and Xia (2016) and follow the approach used by Hansen and McMahon (2016).

employment (or output or inflation) is realized $Y = a\theta - r$ for some $a >= 1$, which implies that fundamental shocks have a positive effect on employment net of the policy response. The Fed and the market use Bayes rules to form their beliefs.

In our setting, the market are journalists. Journalists receive a public signal and observe interest rate decision r. Then they update their beliefs about future economic activity and future interest rates. We assume news sentiment captures journalists discussion of their updated beliefs. This assumption is supported by our prior empirical results, namely, news sentiment is correlated with U.S. Treasury yield changes, predicts future monetary policy decisions, and predicts professional forecast updates to economic activity and inflation.

Interestingly, in Sastry (2022) model, since the Fed receives private information, the Fed is always a better forecaster of the economy than journalists. How can then journalists provide useful information? One way they are useful, is that observing the interest rate decision in Sastry (2022)'s model is equivalent to observing a signal about the Fed's private information, $\hat{F} = F + \frac{\omega}{\delta_F^F} Z$, which is exactly equal to the Fed's private information if journalists knew the monetary policy rule, i.e., if $\omega = 0$. So journalists discussion can help investors understand F.

In Appendix D we describe in more detail the key equations in Sastry (2022) and the three mechanisms explaining how journalists can be surprised by the Fed announcement, or for $\Delta \neq 0$. The first mechanism is the Fed's private signal F, or asymmetric information; the second mechanism is journalists' (Tweeters') miss-perception in the monetary policy rule, $-\omega Z$; and the last mechanism is journalists', Tweeters' and Fed's potentially different confidence in the public signals captured by q and q^F.

To test these hypothesis, we use similar regression specifications as in Sastry (2022). In Sastry (2022), the monetary policy surprise can be written as $\Delta = \delta_F^F(F - E_{M,0}^R[\theta]) + \delta_F^F qZ + \omega Z$. Where $E_{M,0}^R[\theta] = \delta_Z^M Z$ is the rational average expectation of the market regarding the fundamental. So Sastry (2022) regresses monetary policy surprises on macro variables, Z. Since the first term is a constant, if macro variables in the regression are statistically significant, then either ω, Taylor rule miss-specification, or q under-confidence in public signals play a role. Also if q and ω are positive, it means that the market beliefs that the Fed either under-estimates the Taylor rule parameter or under-estimates the Fed's confidence in the public signal.

Following Sastry (2022), we regress news and Twitter sentiment on macro variables and estimate the following equations:

$$\text{News Sentiment}_{t+1} = \alpha + \beta_A \text{ADS}_t + \beta_S \text{S\&P500 Return}_t + \beta_N \text{NFP Surprise}_t + \varepsilon_t, \tag{4}$$

$$\text{Twitter Sentiment}_{t+1} = \alpha + \beta_A \text{ADS}_t + \beta_S \text{S\&P500 Return}_t + \beta_N \text{NFP Surprise}_t + \varepsilon_t, \tag{5}$$

where t indexes FOMC announcement days; *News Sentiment* and *Twitter Sentiment* are the monetary policy surprises estimated using news articles and Twitter posts, respectively; ADS index, is a real-time macroeconomic index, S&P500 returns are quarterly returns calculated the day before the FOMC announcement, nonfarm payroll (NFP) and GDP deflator surprises are the most recent surprises prior to the FOMC announcement.

The results in Panel A and B of Table 10 indicate that macro variables, S&P500 returns and GDP deflator surprises, in the regression are statistically significant, which means that either Taylor rule miss-specification, or under-confidence in public signals play a role. Since the coefficient on the macro variables are positive, it means that journalists and people writing tweets either **under-estimate** the Taylor rule parameter or **under-estimate** the Fed's confidence in the public signal.

Having established that the coefficient on public information are positive because of the regression, then we can rule out either one of these possibilities by looking at the relationship between Blue Chip forecast updates and news and Twitter sentiment. Table 5 indicates that Blue Chip forecasters update their forecast positively based on news and Twitter sentiment.

4.1 Disagreement between FOMC, News and Twitter Sentiment

In Panel A of Figure 5, we show our measure of disagreement, the difference between news and FOMC sentiment indexes. Positive (negative) values indicate that news coverage of the FOMC decision is more hawkish (dovish) or puts a higher (lower) probability on the Fed raising rates in the near future than the FOMC sentiment itself. The graph indicates that disagreement in sentiment tends to be positive after recessions, and negative right before a recession, suggesting that news coverage of FOMC decisions is more hawkish (dovish) than the FOMC when the state of the economy is close to a turning point (moving from a recession to an expansionary period and vice-versa).

We estimate the following equation:

$$
\begin{aligned}
\text{Disagreement}_{t+1} = \alpha + \beta_A \text{ADS}_t + \beta_S \text{S\&P500 Return}_t + \beta_N \text{NFP Surprise}_t \\
+ \beta_{Before} \text{Before Recession}_t + \beta_{After} \text{After Recession}_t + \varepsilon_t,
\end{aligned}
\tag{6}
$$

Where t indexes FOMC announcement days; *Disagreement* is the difference between news and FOMC sentiment shown in Figure 5 or the difference between Twitter and FOMC sentiment; ADS index, is a real-time macroeconomic index, S&P500 returns are quarterly returns calculated the day before the FOMC announcement, nonfarm payroll (NFP) and GDP deflator surprises are the most recent surprise prior to the FOMC announcement; *Before Recession* is an indicator variable equal to one two years prior to the recession, and *After Recession* is an indicator variable equal to one two years after the recession.

The results in Panel A and B of Table 11 columns 1-6 indicate that past S&P 500 returns and the indicator variable two-years after a recession are the best explanatory variables for disagreement. The positive coefficient on the indicator variable two-years after a recession confirms what we observed in the Figure 5, namely journalists are more hawkish than the Fed right after a recession, when the Fed is hesitant to increase interest rates but recent public information indicates that the economy is growing. The positive coefficient on S&P500 returns suggests that journalists are more hawkish than the Fed when recent past information indicates that economic growth was larger than expected.

4.2 Is Disagreement in News and FOMC Sentiment Indexes Related to Disagreement Between Federal Reserve Board Staff's Forecasts and Private Sector Forecasts?

A large literature investigates whether professional (Blue Chip) forecasts are more accurate than Federal Reserve Board staff or FOMC members' forecasts, see, for example, Berge et al. (2019), Reifschneider and Tulip (2007), Romer and Romer (2000), among others, and more recently there is a literature that tries to understand why there is disagreement (see, for example, Sastry, 2022;

Bauer and Swanson, 2020, , among others). In Figure 5 Panel B we plot the difference between news and FOMC sentiment along with the difference between Blue Chip and Greenbook interest rate forecasts four-quarters ahead.[21] The two series are positively correlated, 0.22 correlation, and tend to be positive after recessions, and negative right before a recession. Below, we explore this relationships by estimating the following equation:

$$
\begin{aligned}
\text{Disagreement}_{t+1} = \alpha &+ \beta_C(\text{CPI BC Forecast - CPI GB Forecast}_t)+ \\
&+ \beta_E(\text{Employment BC Forecast - Employment GB Forecast}_t)+ \\
&+ \beta_G(\text{GDP BC Forecast - GDP GB Forecast}_t)+ \\
&+ \beta_{FFTR}(\text{FFTR BC Forecast - FFTR GB Forecast}_t) + \varepsilon_t,
\end{aligned}
\tag{7}
$$

In Table 12 we show that the two types of disagreement are related. When the private sector forecasts higher inflation or higher interest rates than the Federal Reserve Board Staff, the media tends to be more hawkish than the Fed. In contrast, when the private sector forecasts higher employment or GDP growth than the Federal Reserve Board Staff, the media tends to be more dovish. In column (5) we show that when controlling for both disagreement about economic fundamentals and disagreement about interest rates, disagreement about economic fundamentals is more important than disagreement about interest rates suggesting that the media is more likely to underestimate the Fed's confidence on the state of the economy than to underestimate the parameters of the Fed's Taylor rule.

[21] The Federal Reserve Board staff prepare a forecast prior to each FOMC meeting. These projections were reported in a document called the Greenbook until 2010, when a change in the color of the (restructured) report's cover led it to be renamed the Tealbook. For brevity, we will refer to both as Greenbook forecasts in this paper. Greenbook forecasts are from the database maintained by the Federal Reserve Bank of Philadelphia, see Federal Reserve Bank of Philadelphia (2022). Greenbook forecasts are made public with a five year lag, and our dataset ends in 2014. Forecasts are available for different horizons, current quarter, one-, two-, three-, four- up to eight-quarters ahead. Disagreement across horizons is positively correlated, with disagreement being higher at longer-horizons. We show results using disagreement with a four-quarter ahead horizon. Our results are stronger when we use longer-term horizons (three-quarters ahead or more).

4.3 Is Disagreement in News and FOMC Sentiment Indexes Related to Uncertainty?

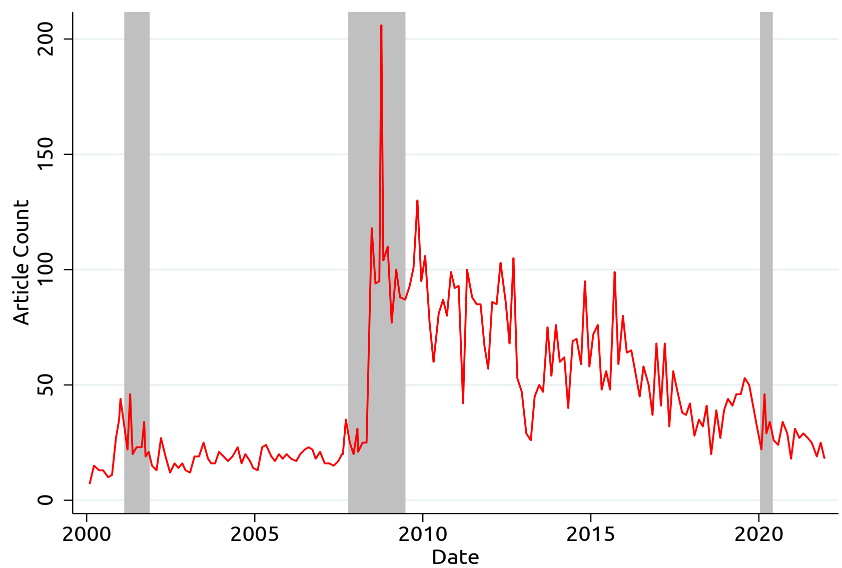
In Table 13 shows that disagreement between the news and FOMC sentiment is higher around turning points (two-years after the recession) and when there is disagreement across professional forecasters, but the other uncertainty measures are not highly correlated with disagreement.

5 Conclusion

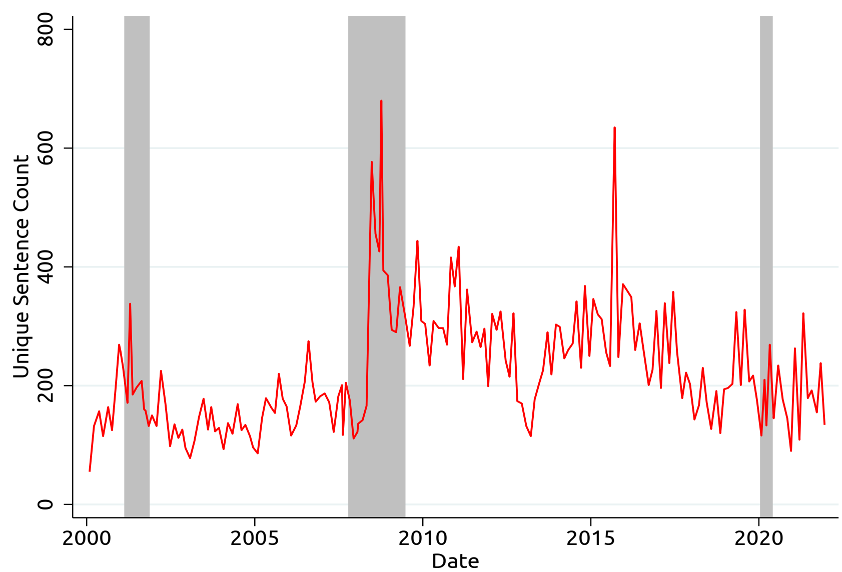
In the last two decades there has been an extraordinary growth in the use of textual data by economists and investors to forecast future outcomes. This wealth of information does not necessarily translate into better forecasts; in fact, it can translate into biased echo chambers that in turn create asset price bubbles (Pedersen, 2022). In this paper, we investigate the information content of text coming from different sources: direct central bank communication (FOMC statement and press conferences), news articles, and Twitter posts during FOMC announcement days. We find that the textual sentiment across sources is highly correlated, suggesting that, on average, news and Twitter echo central bank information. Despite this high correlation, though, we find that news and Twitter sentiment explain better daily U.S. Treasury yield changes than the sentiment coming directly from the central bank. We also find that news and Twitter sentiment are able to forecast future monetary policy decisions and investors' beliefs about future inflation and economic activity better than yield changes and the sentiment coming directly from the central bank, suggesting that news and Twitter coverage is not a simple echo chamber, it provides additional useful information.

Figure 1: Number of News Articles and Unique Sentences Related to FOMC Decision

(a) Number of News Articles Related to FOMC Decision



(b) Number of Unique Sentences Related to FOMC Decision

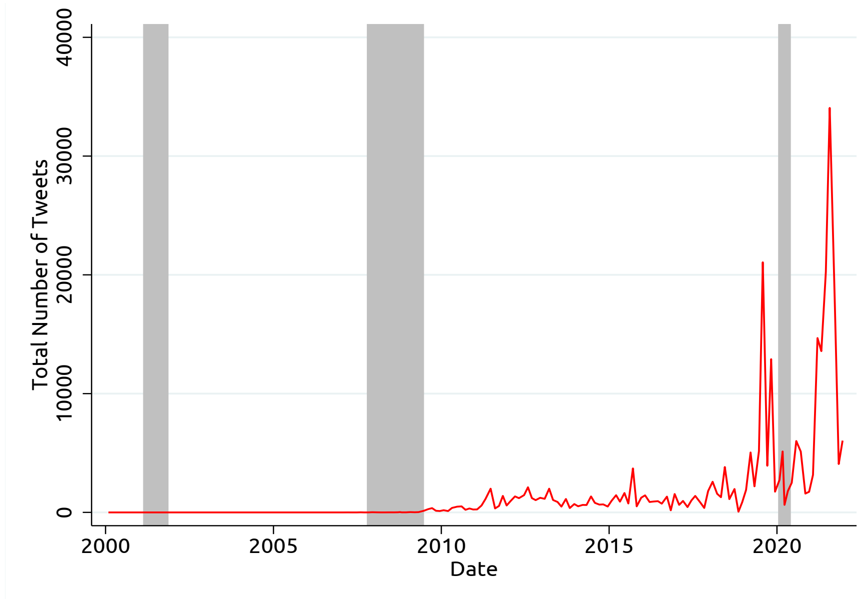


Notes: The top panel (panel a) of the figure shows the number of news articles related to the FOMC decision on days when the FOMC statement is released. The bottom panel (panel b) shows the number of unique sentences related to the FOMC decision on days when the FOMC statement is released. The sample covers 183 FOMC decisions over the 2000-2020 period. The shaded areas denote the NBER recession periods.

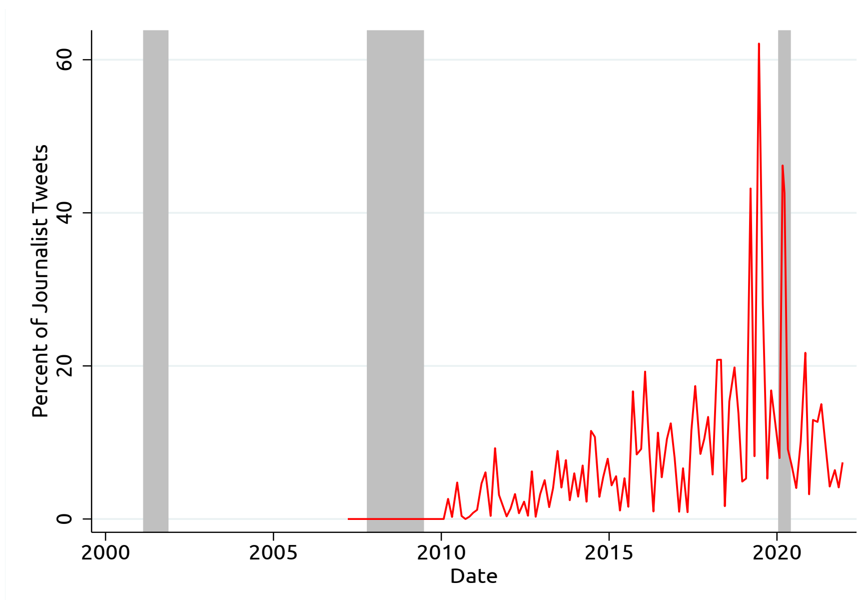
SOURCE: Authors' calculations based on Factiva. The graph only shows DJ newswire articles. FOMC dates are taken from www.federalreserve.gov.

Figure 2: Number of Tweets Related to FOMC Statement and Percent of Tweets Written by Journalists

(a) Number of Tweets Related to FOMC Statement



(b) Percent of Tweets Written by Journalists

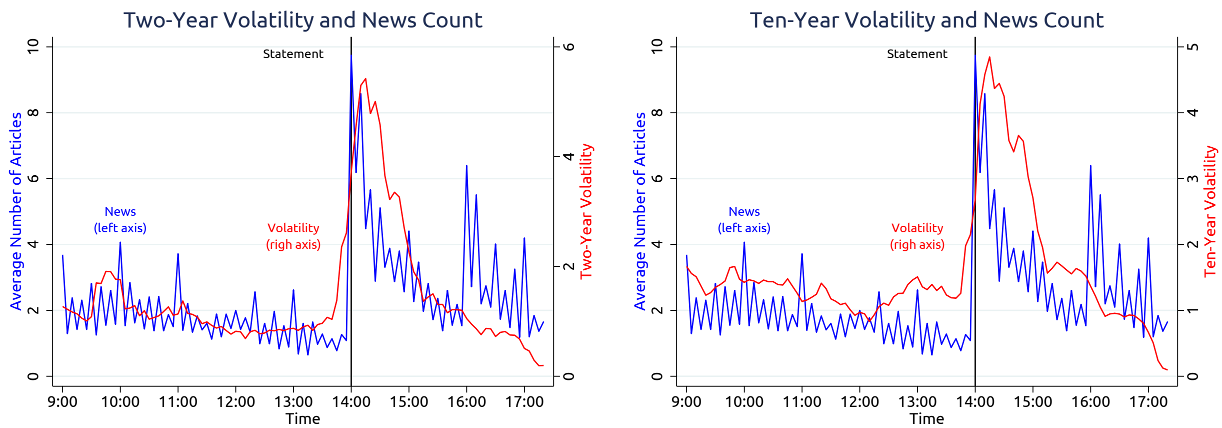


Notes: The top panel (panel a) of the figure shows the number of Tweets related to FOMC statement on days when the FOMC statement is released. The bottom panel (panel b) shows the percent of Tweets written by journalists. The sample covers 183 FOMC decisions over the 2000-2020 period. The shaded areas denote the NBER recession periods.

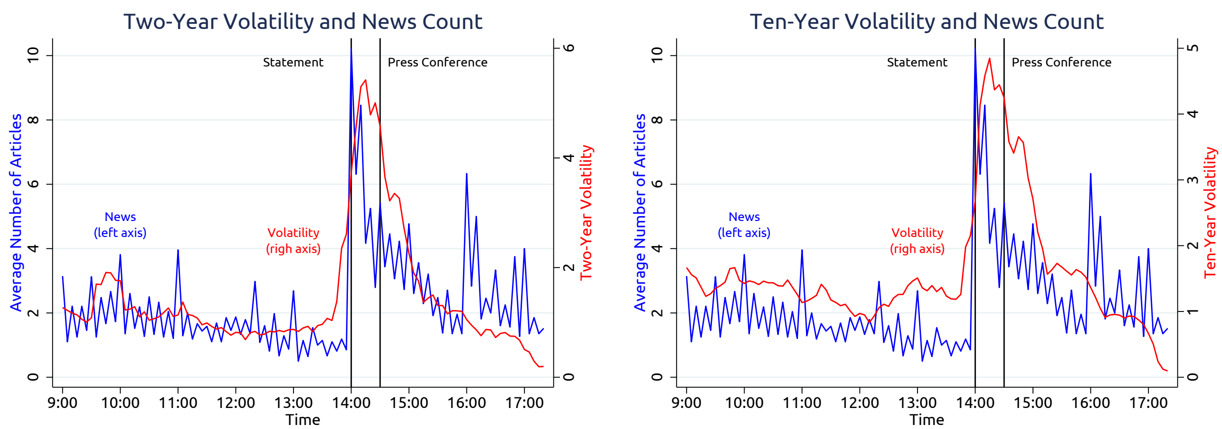
SOURCE: Authors' calculations based on Factiva. FOMC dates are taken from www.federalreserve.gov.

Figure 3: Intraday News Count and Volatility in 2- and 10-year U.S. Treasury Cash Yields

(a) All FOMC Days



(b) Press Conference Days

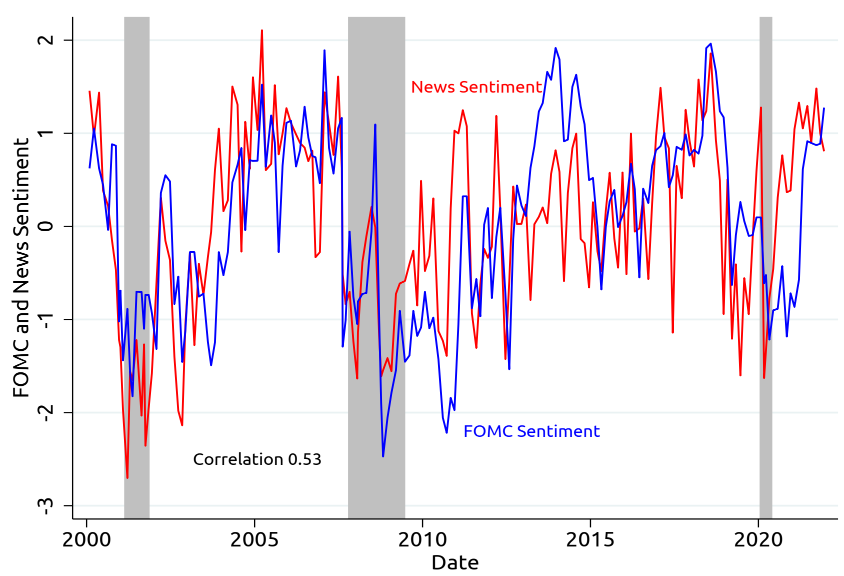


Notes: The figure shows in each panel average number of DJ news articles (blue line) and annualized yield volatility in 2-Year and 10-year US Treasury cash yield changes (red line) per 5-minute intervals on FOMC days (top panels) and on FOMC days with a Press Conference (bottom panels) from 2000 to 2021. We only keep days when the statement is released at 14:00 ET. The vertical lines indicate the time the FOMC statement is released (14:00) and the time the press conference starts (14:30).

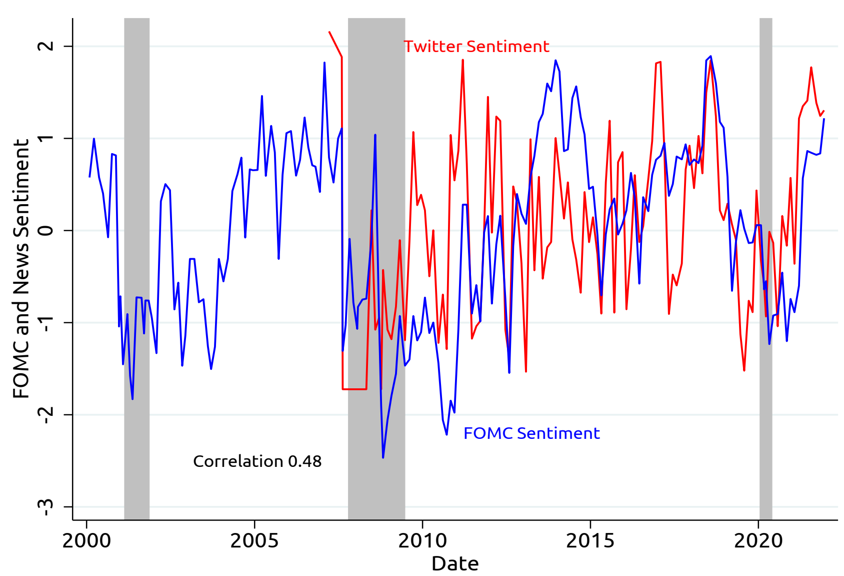
SOURCE: Authors' calculations based on Refinitiv (formerly Thomson Reuters), Factiva, and FOMC statements from www.federalreserve.gov.

Figure 4: FOMC, News and Twitter Sentiment Related to FOMC Statements

(a) FOMC and News Sentiment Indexes



(b) FOMC and Twitter Sentiment Indexes

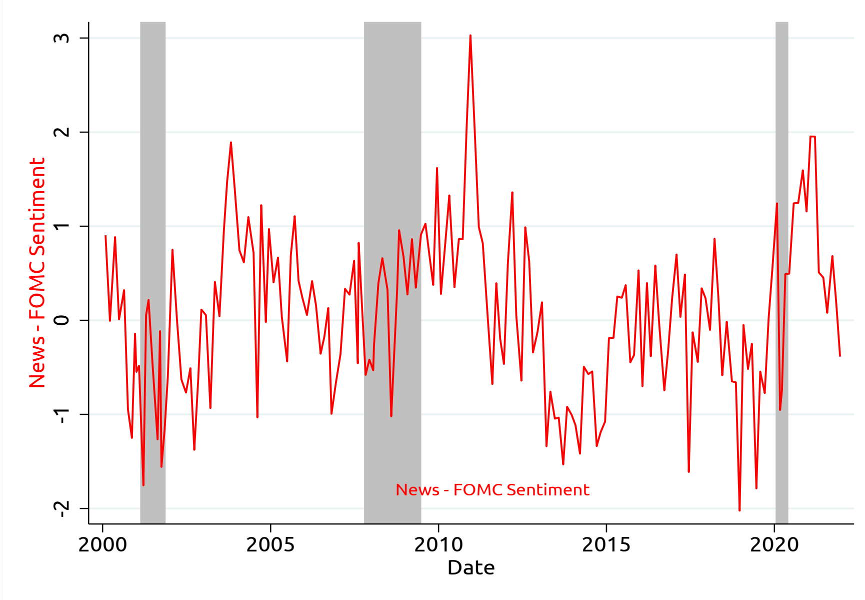


Notes: The top panel (panel a) of the figure shows the Gardner et al. (2022)'s overall FOMC statement sentiment index (blue line), and News sentiment (red line) estimated using the same methodology as in Gardner et al. (2022). The bottom panel (panel b) shows the Gardner et al. (2022)'s overall FOMC statement sentiment index (blue line), and Twitter sentiment (red line) estimated using the same methodology as in Gardner et al. (2022). The sample covers 183 FOMC decisions over the 2000-2020 period. The shaded areas denote the NBER recession periods. The correlation between Twitter and News sentiment is 0.70.

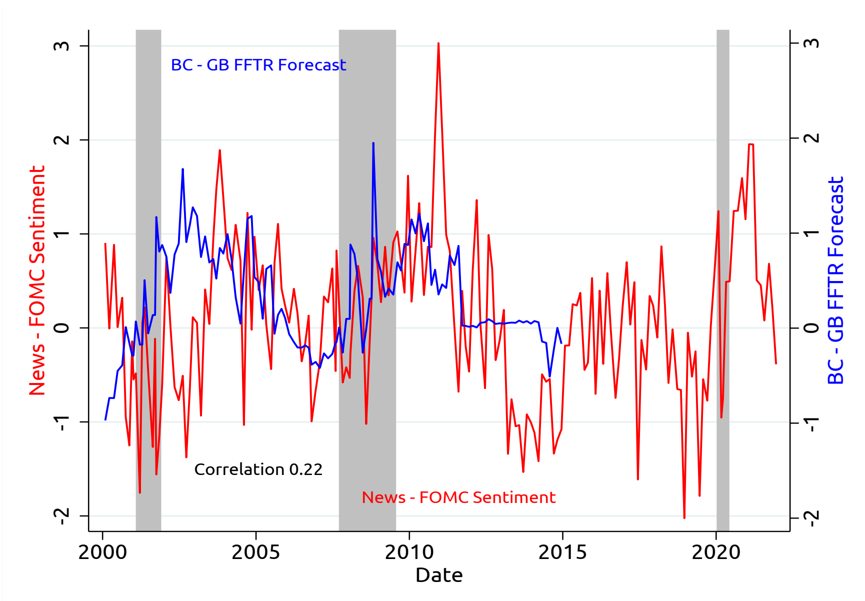
SOURCE: Authors' calculations based on Factiva. The graph only shows DJ newswire articles. FOMC dates are taken from www.federalreserve.gov.

Figure 5: Difference in Sentiment

(a) Difference between News and FOMC Sentiment Indexes



(b) Difference between News and FOMC Sentiment Indexes, and between Blue Chip and Greenbook FFTR Forecasts



Notes: The top panel (panel a) of the figure shows the difference between news and FOMC statement sentiment indexes (red line). The bottom panel (panel b) shows the difference between news and FOMC statement sentiment indexes (red line), and the difference between the Blue Chip forecast of the Federal Funds Target Rate four quarters out and the Greenbook forecast of the Federal Funds Target Rate four quarters out. The sample for the news and FOMC sentiments covers 183 FOMC decisions over the 2000-2020 period, while the Greenbook and Blue Chip forecast covers 126 FOMC decisions over the 2000-2014 period. The shaded areas denote the NBER recession periods. The correlation between the two differences shown in Panel b is 0.22.

SOURCE: Authors' calculations based on Factiva. The graph only shows DJ newswire articles. FOMC dates are taken from www.federalreserve.gov.

Table 1: Examples of Articles Released on FOMC Days

Articles released at 2:00 pm
The Federal Reserve met broad expectations and lowered its overnight-target rate range by a quarter percentage point to between 2% and 2.25%. The decision drew support from all but two policymakers with votes on the rate-setting Federal Open Market Committee. In its statement, the Fed described the economy in strong terms. But it also said "in light of the implications of global developments for the economic outlook as well as muted inflation pressures" lowering rates now is the right move. This is the first rate cut of Chairman Jerome Powell's tenure as Fed leader, and first easing since the end of 2008, when central bankers lowered rates to near zero levels.

Articles released at 2:30 pm
Fed leader Jerome Powell said the rate cut should be viewed as a "mid-cycle adjustment" to monetary policy that will help the economy perform as the Fed wants. Powell said he believes the entire evolution of the Fed's policy outlook this year, with a move from a hawkish to dovish path, have helped the economy. The rate cut "will work" to help the economy. He added a rate cut "seems to work through confidence channels" as well as through lowering the cost of short-term borrowing.

Articles released after 7:00 or the next day
Yields, which decline when bond prices climb, slid and the dollar gained following the Fed decision and press conference. Weak economic data and a decline in oil prices Thursday then boosted concerns about the outlook for global growth and the Fed's ability to stimulate inflation. A strengthening dollar tends to weigh on global growth while also sapping inflation by making imported goods less expensive. Yields began falling early in the session, with German government debt yields dropping to fresh lows after reports showed continued sluggish manufacturing data from Germany and the eurozone. They extended the decline after the Institute for Supply Management said Thursday that U.S. manufacturing activity slowed in July to the lowest since before the 2016 election. Demand accelerated after the 10-year Treasury yield fell below 2%, which some investors see as an important level. "Breaking through 2% seems to have brought in some buyers," said Don Ellenberger, head of multisector strategies at Federated Investors. The gap between the yields on five-year Treasury inflation-protected securities and fixed-coupon U.S. government debt, which reflects the bond market's expectation for the average rate of inflation through 2024 – fell to about 1.5% from roughly 1.6% Wednesday, according to Tradeweb. With economic growth decelerating it will be difficult for the Fed to revive inflation or boost expectations for consumer prices to rise, said Dec Mullarkey, a managing director at SLC Management. "They haven't moved the needle – there's a lot of skepticism." Analysts said investors are questioning how much a one-quarter-percentage-point drop in borrowing costs will cushion a broader slowdown driven by concerns about trade, which affects business investment and can hamper companies with global supply chains – factors outside the Fed's control. Some investors are worried about how quickly Fed Chairman Jerome Powell can move to provide additional support for the economy after two Fed officials dissented in Wednesday's vote to reduce rates, analysts said. The dollar held steady Thursday, with currency investors interpreting the Fed's move as a fine-tuning of the economy rather than a signal of a prolonged cycle of rate cuts, analysts said. The WSJ Dollar Index recently declined by less than 0.1% after rising 0.2% in earlier trading. Federal funds futures show that investors are putting odds of about 45% that the Fed lowers rates two more times this year. That is down from about 55% a week ago, according to CME Group data.

Notes: The table provides examples of articles released at different times of the day.

SOURCE: Authors' calculations, Factiva (Dow Jones, NY Times, WSJ, and Washington Post) and www.federalreserve.gov.

Table 2: Correlation Across Sentiment Measures

Panel A: Full Sample					
	Target Surprise	FOMC Statement Sentiment	News Sentiment		
Target Surprise	1.00				
FOMC Statement Sentiment	0.20	1.00			
News Sentiment	0.26	0.63	1.00		
Observations	183				
Panel B: Twitter Sample					
	Target Surprise	FOMC Statement Sentiment	News Sentiment	Twitter Sentiment	
Target Surprise	1.00				
FOMC Statement Sentiment	0.19	1.00			
News Sentiment	0.29	0.57	1.00		
Twitter Sentiment	0.21	0.49	0.69	1.00	
Observations	120				
Panel C: Press Conferencer Sample					
	Target Surprise	FOMC Statement Sentiment	News Sentiment	Press Conference Sentiment	Twitter Sentiment
Target Surprise	1.00				
FOMC Statement Sentiment	0.19	1.00			
News Sentiment	0.26	0.37	1.00		
Press Conference Sentiment	0.00	0.51	0.64	1.00	
Twitter Sentiment	0.13	0.46	0.65	0.67	1.00
Observations	56				

Notes: We estimate the correlation across sentiment measures using data from 2000 to 2021 (Panel A). Twitter data starts in March 2007 (Panel B) and the first press conference is held in April 2011 (Panel C). There are 183 FOMC meetings, 95 of them are covered by Twitter, and 56 of them had a press conference.

SOURCE: Authors' calculations based on Bloomberg Finance LP, Bloomberg Terminals (Open, Anywhere, and Disaster Recovery Licenses), Factiva (Dow Jones, NY Times, WSJ, and Washington Post), Twitter, and FOMC information from www.federalreserve.gov.

Table 3: Response of Interest Rates to News Sentiment

	(1) 3-Month	(2) 6-Month	(3) Eurodollar	(4) 2-Year	(5) 5-Year	(6) 10-Year
Panel A: Target Rate Surprise						
Target Surprise	0.813***	0.730***	0.247***	0.524***	0.323***	0.189**
	(0.0563)	(0.0520)	(0.0605)	(0.0786)	(0.100)	(0.0806)
Observations	183	183	183	183	183	183
Adjusted R^2	0.535	0.521	0.084	0.198	0.054	0.029
Panel B: FOMC Statement and Press Conference Sentiment						
FOMC Statement Sentiment	2.384***	2.154***	0.580	0.879	0.767	0.367
	(0.601)	(0.548)	(0.478)	(0.662)	(0.778)	(0.619)
Press Conference	-1.001	-0.675	0.423	0.333	0.747	0.936
	(1.087)	(0.990)	(0.864)	(1.197)	(1.407)	(1.119)
Observations	183	183	183	183	183	183
Adjusted R^2	0.080	0.079	0.011	0.012	0.009	0.007
Panel C: News Sentiment						
News Sentiment	3.051***	2.760***	1.302***	1.848***	1.752**	1.355**
	(0.558)	(0.508)	(0.451)	(0.625)	(0.739)	(0.588)
Observations	183	183	183	183	183	183
Adjusted R^2	0.142	0.140	0.044	0.046	0.030	0.028
Panel D: Target Rate Surprise, FOMC Statement and Press Conference Sentiment						
Target Surprise	0.781***	0.701***	0.242***	0.523***	0.315***	0.187**
	(0.0568)	(0.0525)	(0.0621)	(0.0807)	(0.103)	(0.0826)
FOMC Statement Sentiment	1.150***	1.047***	0.198	0.0529	0.269	0.0724
	(0.430)	(0.397)	(0.470)	(0.611)	(0.778)	(0.626)
Press Conference	-0.491	-0.217	0.581	0.674	0.953	1.057
	(0.761)	(0.703)	(0.832)	(1.082)	(1.377)	(1.108)
Observations	183	183	183	183	183	183
Adjusted R^2	0.553	0.539	0.089	0.199	0.058	0.035
Panel E: Target Rate Surprise and News Sentiment						
Target Surprise	0.756***	0.677***	0.216***	0.492***	0.279***	0.151*
	(0.0560)	(0.0518)	(0.0622)	(0.0810)	(0.103)	(0.0829)
News Sentiment	1.634***	1.490***	0.897**	0.926	1.228	1.072*
	(0.408)	(0.378)	(0.453)	(0.591)	(0.752)	(0.605)
Observations	183	183	183	183	183	183
Adjusted R^2	0.573	0.559	0.104	0.208	0.068	0.046
Panel F: FOMC Statement, Press Conference and News Sentiment						
FOMC Statement Sentiment	0.580	0.558	-0.330	-0.422	-0.435	-0.649
	(0.725)	(0.662)	(0.592)	(0.820)	(0.970)	(0.770)
Press Conference	-1.920*	-1.488	-0.0404	-0.330	0.135	0.418
	(1.066)	(0.973)	(0.870)	(1.205)	(1.426)	(1.133)
News Sentiment	3.002***	2.655***	1.514**	2.165***	2.001**	1.691**
	(0.732)	(0.668)	(0.597)	(0.827)	(0.979)	(0.777)
Observations	183	183	183	183	183	183
Adjusted R^2	0.159	0.154	0.046	0.048	0.031	0.033
Panel G: Target Rate Surprise, FOMC Statement, Press Conference and News Sentiment						
Target Surprise	0.748***	0.672***	0.220***	0.498***	0.286***	0.159*
	(0.0563)	(0.0522)	(0.0627)	(0.0817)	(0.104)	(0.0836)
FOMC Statement Sentiment	0.177	0.197	-0.448	-0.690	-0.589	-0.735
	(0.516)	(0.479)	(0.575)	(0.749)	(0.954)	(0.766)
Press Conference	-1.035	-0.693	0.220	0.259	0.473	0.606
	(0.760)	(0.705)	(0.847)	(1.103)	(1.406)	(1.129)
News Sentiment	1.707***	1.491***	1.133*	1.303*	1.505	1.416*
	(0.529)	(0.490)	(0.589)	(0.767)	(0.978)	(0.785)
Observations	183	183	183	183	183	183
Adjusted R^2	0.578	0.562	0.107	0.212	0.071	0.052

Notes: We estimate the response of 3-, 6-month, eurodollar, 2-, 5-, and 10-year US Treasury yield changes to news sentiment and FOMC statement sentiment using data from 2000 to 2021. The dependent variable is the daily yield change. The regression also includes a constant term. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

SOURCE: Authors' calculations based on Bloomberg Finance LP, Bloomberg Terminals (Open, Anywhere, and Disaster Recovery Licenses), Factiva (Dow Jones, NY Times, WSJ, and Washington Post), and FOMC information from www.federalreserve.gov.

Table 4: Response of Interest Rates to Twitter Sentiment

	(1) 3-Month	(2) 6-Month	(3) Eurodollar	(4) 2-Year	(5) 5-Year	(6) 10-Year
Panel A: Target Rate Surprise						
Target Surprise	0.824***	0.736***	0.371***	0.630***	0.603***	0.458***
	(0.0737)	(0.0601)	(0.0677)	(0.108)	(0.133)	(0.129)
Observations	120	120	120	120	120	120
Adjusted R^2	0.514	0.560	0.203	0.223	0.149	0.097
Panel B: FOMC Statement and Press Conference Sentiment						
FOMC Statement Sentiment	1.693***	1.359***	0.485	0.241	0.935	0.565
	(0.602)	(0.518)	(0.442)	(0.720)	(0.839)	(0.791)
Press Conference	-0.718	-0.347	0.449	0.597	0.687	0.855
	(0.914)	(0.786)	(0.671)	(1.094)	(1.274)	(1.202)
Observations	120	120	120	120	120	120
Adjusted R^2	0.063	0.056	0.018	0.005	0.017	0.012
Panel C: Twitter Sentiment						
Twitter Sentiment	2.520***	1.907***	0.647	0.696	1.568*	1.614**
	(0.571)	(0.498)	(0.438)	(0.712)	(0.825)	(0.774)
Observations	120	120	120	120	120	120
Adjusted R^2	0.142	0.111	0.018	0.008	0.030	0.036
Panel D: Target Rate Surprise, FOMC Statement and Press Conference Sentiment						
Target Surprise	0.798***	0.718***	0.369***	0.646***	0.595***	0.457***
	(0.0748)	(0.0612)	(0.0692)	(0.111)	(0.136)	(0.132)
FOMC Statement Sentiment	0.784*	0.540	0.0638	-0.496	0.258	0.0449
	(0.438)	(0.358)	(0.405)	(0.648)	(0.795)	(0.771)
Press Conference	-0.346	-0.0121	0.622	0.898	0.964	1.068
	(0.653)	(0.535)	(0.605)	(0.967)	(1.187)	(1.151)
Observations	120	120	120	120	120	120
Adjusted R^2	0.527	0.569	0.212	0.231	0.156	0.104
Panel E: Target Rate Surprise and Twitter Sentiment						
Target Surprise	0.767***	0.698***	0.364***	0.632***	0.572***	0.418***
	(0.0714)	(0.0594)	(0.0694)	(0.111)	(0.136)	(0.131)
Twitter Sentiment	1.590***	1.061***	0.205	-0.0701	0.875	1.107
	(0.416)	(0.346)	(0.404)	(0.647)	(0.789)	(0.763)
Observations	120	120	120	120	120	120
Adjusted R^2	0.568	0.592	0.205	0.223	0.158	0.113
Panel F: FOMC Statement, Press Conference and Twitter Sentiment						
FOMC Statement Sentiment	0.619	0.597	0.318	-0.00384	0.401	-0.0779
	(0.630)	(0.553)	(0.491)	(0.800)	(0.927)	(0.871)
Press Conference	-1.780*	-1.100	0.284	0.355	0.159	0.219
	(0.904)	(0.794)	(0.704)	(1.148)	(1.330)	(1.249)
Twitter Sentiment	2.668***	1.891***	0.415	0.607	1.327	1.597*
	(0.677)	(0.595)	(0.528)	(0.860)	(0.997)	(0.936)
Observations	120	120	120	120	120	120
Adjusted R^2	0.174	0.132	0.024	0.009	0.031	0.036
Panel G: Target Rate Surprise, FOMC Statement, Press Conference and Twitter Sentiment						
Target Surprise	0.755***	0.692***	0.369***	0.649***	0.578***	0.430***
	(0.0718)	(0.0603)	(0.0704)	(0.113)	(0.138)	(0.133)
FOMC Statement Sentiment	0.0917	0.114	0.0598	-0.457	-0.00328	-0.378
	(0.455)	(0.382)	(0.445)	(0.712)	(0.873)	(0.842)
Press Conference	-1.099*	-0.476	0.617	0.940	0.681	0.607
	(0.651)	(0.547)	(0.638)	(1.021)	(1.251)	(1.207)
Twitter Sentiment	1.842***	1.134***	0.0106	-0.103	0.694	1.126
	(0.492)	(0.413)	(0.482)	(0.771)	(0.945)	(0.912)
Observations	120	120	120	120	120	120
Adjusted R^2	0.579	0.595	0.212	0.231	0.160	0.116

Notes: We estimate the response of 3-, 6-month, eurodollar, 2-, 5-, and 10-year US Treasury yield changes to news sentiment and FOMC statement sentiment using data from March 2007 to December 2021. The dependent variable is the daily yield change. The regression also includes a constant term. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

SOURCE: Authors' calculations based on Bloomberg Finance LP, Bloomberg Terminals (Open, Anywhere, and Disaster Recovery Licenses), Twitter, and FOMC information from www.federalreserve.gov.

Table 5: Response of Blue Chip Forecast Revisions to FOMC Information

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	GDP				UR				GDP Deflator			
Panel A: Keep monthly revisions when there is an FOMC meeting in between forecasts												
FOMC Sentiment		0.246**		0.0228		-0.312***		-0.0740		0.320***		0.0940
		(0.0987)		(0.102)		(0.0861)		(0.0895)		(0.0902)		(0.0944)
Press Conference Sentiment		0.0852		0.0251		0.0306		0.0719		0.110		0.0537
		(0.0834)		(0.0718)		(0.0727)		(0.0627)		(0.0754)		(0.0654)
News Sentiment	0.505***		0.245***	0.219*	-0.467***		-0.221***	-0.210**	0.505***		0.403***	0.318***
	(0.0851)		(0.0918)	(0.114)	(0.0742)		(0.0805)	(0.0993)	(0.0785)		(0.0827)	(0.103)
Target Surprise			0.000693	0.00185			0.0891	0.0928			-0.0989	-0.0967
			(0.0797)	(0.0802)			(0.0699)	(0.0700)			(0.0735)	(0.0736)
Forward Guidance Surprise			-0.0178	-0.0193			0.0436	0.0518			-0.105	-0.112
			(0.0876)	(0.0886)			(0.0768)	(0.0773)			(0.0811)	(0.0816)
LSAP			-0.105	-0.105			0.0169	0.0152			-0.0465	-0.0456
			(0.0814)	(0.0818)			(0.0714)	(0.0715)			(0.0755)	(0.0755)
NFP Surprise			-0.142***	-0.142***			0.0430	0.0436			-0.0728**	-0.0734**
			(0.0376)	(0.0378)			(0.0330)	(0.0330)			(0.0337)	(0.0337)
S&P500 Returns			0.500***	0.505***			-0.257***	-0.265***			0.0461	0.0630
			(0.0906)	(0.0925)			(0.0794)	(0.0807)			(0.0818)	(0.0829)
ADS Index			0.126	0.126			-0.325***	-0.317***			0.174***	0.172***
			(0.0796)	(0.0804)			(0.0698)	(0.0702)			(0.0275)	(0.0275)
Constant	-0.273***	-0.251***	-0.282***	-0.285***	0.0357	0.000797	0.0576	0.0470	-0.153*	-0.137	-0.116	-0.119*
	(0.0853)	(0.0916)	(0.0762)	(0.0772)	(0.0744)	(0.0799)	(0.0668)	(0.0674)	(0.0787)	(0.0833)	(0.0706)	(0.0710)
Observations	175	175	175	175	175	175	175	175	177	177	177	177
Adjusted R^2	0.169	0.057	0.362	0.363	0.186	0.075	0.368	0.374	0.191	0.109	0.377	0.385
Panel B: Drop FOMC meetings that occur within the first 7 days of the month												
FOMC Sentiment		0.244**		-0.0211		-0.351***		-0.0817		0.309***		0.112
		(0.106)		(0.108)		(0.0864)		(0.0874)		(0.0954)		(0.0991)
Press Conference Sentiment		0.0823		0.0420		0.0402		0.0634		0.140*		0.0961
		(0.0856)		(0.0724)		(0.0700)		(0.0586)		(0.0764)		(0.0660)
News Sentiment	0.510***		0.216**	0.208*	-0.468***		-0.211***	-0.194**	0.491***		0.386***	0.272**
	(0.0912)		(0.0976)	(0.119)	(0.0751)		(0.0794)	(0.0959)	(0.0843)		(0.0890)	(0.109)
Target Surprise			0.00137	0.00320			0.0230	0.0281			-0.106	-0.109
			(0.0891)	(0.0898)			(0.0725)	(0.0727)			(0.0837)	(0.0833)
Forward Guidance Surprise			-0.0135	-0.0113			0.105	0.112			-0.157*	-0.166*
			(0.0939)	(0.0949)			(0.0764)	(0.0768)			(0.0875)	(0.0874)
LSAP			-0.116	-0.117			0.0112	0.00965			-0.0380	-0.0393
			(0.0869)	(0.0875)			(0.0707)	(0.0708)			(0.0815)	(0.0809)
NFP Surprise			-0.151***	-0.151***			0.0543	0.0531			-0.0636*	-0.0633*
			(0.0416)	(0.0419)			(0.0338)	(0.0339)			(0.0360)	(0.0357)
S&P500 Returns			0.535***	0.536***			-0.181**	-0.188**			0.0824	0.106
			(0.100)	(0.103)			(0.0816)	(0.0829)			(0.0898)	(0.0901)
ADS Index			0.135	0.139			-0.422***	-0.410***			0.156***	0.154***
			(0.0951)	(0.0968)			(0.0773)	(0.0783)			(0.0276)	(0.0274)
Constant	-0.275***	-0.249**	-0.279***	-0.285***	0.0642	0.0238	0.0972	0.0857	-0.150*	-0.137	-0.109	-0.117
	(0.0915)	(0.0986)	(0.0809)	(0.0821)	(0.0753)	(0.0807)	(0.0658)	(0.0665)	(0.0846)	(0.0886)	(0.0755)	(0.0755)
Observations	152	152	152	152	152	152	152	152	154	154	154	154
Adjusted R^2	0.173	0.056	0.383	0.385	0.206	0.104	0.422	0.429	0.182	0.120	0.380	0.398

Notes: We estimate the response of Blue Chip Economic Indicators forecast revisions for GDP, the unemployment rate (UR), and the GDP price deflator to FOMC information using data from 2000 to 2022. We keep a forecast revision only if there is an FOMC meeting between forecasts, and if there are two FOMC meetings, we keep only the information from the most recent meeting. We drop forecast revisions higher than 10 standard deviations from the mean, which results in April and May 2020 forecast revisions for GDP and UR to be dropped and no GDP Deflator data is dropped. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

SOURCE: Authors' calculations based on Bloomberg Finance LP, Bloomberg Terminals (Open, Anywhere, and Disaster Recovery Licenses), Blue Chip Economic Indicators, the Aruoba-Diebold-Scotti Business Conditions Index, Factiva (Dow Jones, NY Times, WSJ, and Washington Post), and FOMC statements from www.federalreserve.gov.

Table 6: Response of Blue Chip Forecast Revisions to FOMC Information: Yield Changes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	GDP				UR				GDP Deflator			
Panel A: Keep monthly revisions when there is an FOMC meeting in between forecasts												
FOMC Sentiment				-0.0188				-0.0571				0.0883
				(0.100)				(0.0900)				(0.0950)
Press Conference Sentiment				0.0480				0.0630				0.0558
				(0.0707)				(0.0633)				(0.0661)
News Sentiment	0.505***		0.377***	0.182*	-0.467***		-0.410***	-0.198**	0.505***		0.551***	0.318***
	(0.0851)		(0.0914)	-0.102	(0.0742)		(0.0819)	(0.0999)	(0.0785)		(0.0871)	(0.104)
3-Month Yield Change		0.0959***	0.0669***	0.0484***		-0.0637***	-0.0321**	-0.00202		0.0233	-0.0191	-0.0269*
		(0.0172)	(0.0179)	(0.0171)		(0.0158)	(0.0161)	(0.0153)		(0.0176)	(0.0172)	(0.0158)
2-Year Yield Change		-0.0247	-0.0234	-0.0219		0.0186	0.0172	0.0127		-0.00416	-0.00166	0.00754
		(0.0176)	(0.0168)	(0.0152)		(0.0161)	(0.0150)	(0.0137)		(0.0178)	(0.0161)	(0.0144)
10-Year Yield Change		0.0142	0.00865	0.00215		-0.0136	-0.00752	0.000341		0.00713	-0.00187	-0.0134
		(0.0155)	(0.0149)	(0.0136)		(0.0142)	(0.0133)	(0.0122)		(0.0157)	(0.0142)	(0.0128)
NFP Surprise				-0.133***				0.0440				-0.0749**
				(0.0369)				(0.0330)				(0.0336)
S&P500 Returns				0.469***				-0.276***				0.0903
				(0.0912)				(0.0817)				(0.0848)
ADS Index				0.0775				-0.299***				0.169***
				(0.0790)				(0.0707)				(0.0273)
Constant	-0.273***	-0.0788	-0.157*	-0.208**	0.0357	-0.104	-0.0196	0.0482	-0.153*	-0.0816	-0.189**	-0.172**
	(0.0853)	(0.0909)	(0.0889)	(0.0817)	(0.0744)	(0.0831)	(0.0797)	(0.0732)	(0.0787)	(0.0921)	(0.0849)	(0.0764)
Observations	175	175	175	175	175	175	175	175	177	177	177	177
Adjusted R^2	0.169	0.156	0.233	0.391	0.186	0.090	0.207	0.371	0.191	0.012	0.199	0.381
Panel B: Drop FOMC meetings that occur within the first 7 days of the month												
FOMC Sentiment				-0.0722				-0.0486				0.0985
				(0.105)				(0.0880)				(0.0998)
Press Conference Sentiment				0.0576				0.0531				0.102
				(0.0707)				(0.0590)				(0.0666)
News Sentiment	0.510***		0.387***	0.199*	-0.468***		-0.405***	-0.177*	0.491***		0.546***	0.268**
	(0.0912)		(0.0938)	(0.115)	(0.0751)		(0.0796)	(0.0957)	(0.0843)		(0.0905)	(0.108)
3-Month Yield Change		0.108***	0.0802***	0.0552***		-0.0718***	-0.0430**	-0.0133		0.0114	-0.0272	-0.0379**
		(0.0195)	(0.0197)	(0.0188)		(0.0170)	(0.0167)	(0.0157)		(0.0201)	(0.0192)	(0.0179)
2-Year Yield Change		-0.0273	-0.0263	-0.0240		0.0214	0.0203	0.0112		-0.00662	-0.00455	0.00535
		(0.0179)	(0.0170)	(0.0154)		(0.0156)	(0.0144)	(0.0129)		(0.0184)	(0.0165)	(0.0147)
10-Year Yield Change		0.0171	0.0119	0.00264		-0.0150	-0.00963	0.00143		0.00425	-0.00381	-0.0165
		(0.0157)	(0.0150)	(0.0137)		(0.0137)	(0.0127)	(0.0115)		(0.0161)	(0.0145)	(0.0130)
NFP Surprise				-0.143***				0.0506				-0.0642*
				(0.0403)				(0.0337)				(0.0356)
S&P500 Returns				0.476***				-0.178**				0.159*
				(0.103)				(0.0864)				(0.0949)
ADS Index				0.0973				-0.389***				0.148***
				(0.0940)				(0.0785)				(0.0275)
Constant	-0.275***	-0.0531	-0.134	-0.195**	0.0642	-0.0961	-0.0114	0.0681	-0.150*	-0.0950	-0.202**	-0.196**
	(0.0915)	(0.0975)	(0.0946)	(0.0872)	(0.0753)	(0.0849)	(0.0803)	(0.0728)	(0.0846)	(0.0997)	(0.0914)	(0.0821)
Observations	152	152	152	152	152	152	152	152	154	154	154	154
Adjusted R^2	0.173	0.172	0.258	0.420	0.206	0.109	0.242	0.426	0.182	0.002	0.198	0.393

Notes: We estimate the response of Blue Chip Economic Indicators forecast revisions for GDP, the unemployment rate (UR), and the GDP price deflator to FOMC information using data from 2000 to 2022. We keep a forecast revision only if there is an FOMC meeting between forecasts, and if there are two FOMC meetings, we keep only the information from the most recent meeting. We drop forecast revisions higher than 10 standard deviations from the mean. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

SOURCE: Authors' calculations based on Bloomberg Finance LP, Bloomberg Terminals (Open, Anywhere, and Disaster Recovery Licenses), Blue Chip Economic Indicators, the Aruoba-Diebold-Scotti Business Conditions Index, Factiva (Dow Jones, NY Times, WSJ, and Washington Post), and FOMC statements from www.federalreserve.gov.

Table 7: Forecast of FOMC Monetary Policy Stance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel A: Sentiment, Expectations and the State of the Economy								
FOMC Sentiment	0.208***								
	(0.022)								
Press Conference Sentiment		0.034*							
		(0.019)							
News Sentiment			0.219***						
			(0.021)						
FFF Expectations				0.253***					
				(0.026)					
Eurodollar Expectations					0.041*				
					(0.024)				
BC Expectations						0.179***			
						(0.028)			
Δ UR Gap							-0.017		
							(0.011)		
Inflation Rate								0.035*	
								(0.021)	
ADS Index									0.016**
									(0.007)
Observations	182	182	182	182	182	182	182	182	182
Pseudo R^2	0.248	0.009	0.292	0.333	0.009	0.132	0.012	0.008	0.014
	Panel B: Past Monetary Policy Actions, the State of the Economy, Financial Variables, Uncertainty								
EBP	-0.171***								
	(0.03)								
Inverse Yield Curve		-0.205***							
		(0.034)							
Recession			-0.23***						
			(0.033)						
FFR				-0.021					
				(0.024)					
Δ Monetary Policy					0.307***				
					(0.027)				
5-Year Yield						0.029			
						(0.023)			
Δ 5-Year Yield							0.129***		
							(0.023)		
PD Ratio								0.016	
								(0.022)	
VIX									-0.176***
									(0.028)
Observations	182	182	182	182	182	182	182	182	182
Pseudo R2	0.127	0.065	0.123	0.002	0.280	0.005	0.091	0.002	0.155

Notes: We estimate an ordered probit to forecast monetary policy decisions from 2000 to 2021. The dependent variable is an indicator variable equal to -1, 0, 1 according to whether the FOMC decreased, left unchanged or increased the federal funds target rate (FFTR) or announced other unconventional policies that were tightening, neutral or easing. The table reports marginal effects on the probability of tightening for a one standard deviation increase in the independent variable, if the variable is continuous, and for an increase from 0 to 1, if the variable is an indicator variable. All of the independent variables are lagged as of the day before the FOMC meeting, except for the FOMC statement, press conference and news sentiment indexes, FFTR, and change in monetary policy stance, which are based on the most recent FOMC statement. For a detailed definition of the independent variables refer to Table A1. The change in monetary policy is the monetary policy stance variable as of the last FOMC meeting. ELB denotes the effective lower bound period. Standard errors are in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

SOURCE: Authors' calculations based on Bloomberg, Blue Chip Financial Forecasts, the Center for Research in Security Prices (CRSP), the Congressional Budget Office, the Federal Reserve Bank of Philadelphia, the Aruoba-Diebold-Scotti Business Conditions Index, the Favara et al. (2016) EBP update, Factiva (Dow Jones, NY Times, WSJ, and Washington Post), and FOMC statements from www.federalreserve.gov.

Table 8: Forecast of FOMC Monetary Policy Stance: Horse Race

	(1)	(2)	(3)
FOMC Sentiment	0.079***		0.135***
	(0.025)		(0.024)
Press Conference Sentiment	-0.026*		-0.03**
	(0.015)		(0.013)
News Sentiment	0.119***	0.073***	0.044*
	(0.024)	(0.027)	(0.026)
FFF Expectations		0.075**	0.084**
		(0.036)	(0.033)
Eurodollar Expectations		0.199***	0.217***
		(0.073)	(0.069)
BC Expectations		-0.013	-0.035
		(0.025)	(0.023)
Δ UR Gap		-0.015**	-0.013*
		(0.007)	(0.008)
Inflation Rate		0.034**	0.034***
		(0.015)	(0.012)
ADS Index		-0.036***	-0.028***
		(0.009)	(0.008)
EBP		0.034	0.003
		(0.031)	(0.028)
Inverse Yield Curve		0.022	-0.016
		(0.075)	(0.065)
Recession		-0.184***	-0.163***
		(0.039)	(0.04)
FFR		-0.321***	-0.373***
		(0.066)	(0.061)
Δ Monetary Policy	0.153***	0.061*	-0.014
	(0.031)	(0.035)	(0.036)
5-Year Yield		0.087	0.105**
		(0.057)	(0.052)
Δ 5-Year Yield		0.01	0.02
		(0.02)	(0.018)
PD Ratio		0.005	0.007
		(0.015)	(0.014)
VIX		-0.097***	-0.039
		(0.032)	(0.028)
Observations	182	182	182
Pseudo R^2	0.424	0.585	0.680

Notes: We estimate an ordered probit to forecast monetary policy decisions from 2000 to 2020. The dependent variable in columns (1) and (2) is an indicator variable equal to -1, 0, 1 according to whether the FOMC decreased, left unchanged or increased the federal funds target rate (FFTR) or announced other unconventional policies that were tightening, neutral or easing. The dependent variable in columns (3) and (4) is the federal funds target rate change. The table reports marginal effects on the probability of tightening (columns 1-2) or of 25 basis point increase (columns 3-4) for a one standard deviation increase in the independent variable, if it is continuous, and for a change from 0 to 1, if it is an indicator variable. All of the independent variables are lagged as of the day before the FOMC meeting, except for the FOMC sentiment index, FFTR, and change in monetary policy stance, which are based on the most recent FOMC statement. For a detailed definition of the independent variables refer to Table A1. The change in monetary policy is either the monetary policy stance variable as of the last FOMC in columns (1) and (2) or the change in the federal funds target rate in columns (3) and (4). ELB denotes the effective lower bound period. Standard errors are in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

SOURCE: Authors' calculations based on Bloomberg, Blue Chip Financial Forecasts, the Center for Research in Security Prices (CRSP), the Federal Reserve Bank of Philadelphia, the Aruoba-Diebold-Scotti Business Conditions Index, the Favara et al. (2016) EBP update, the Congressional Budget Office, Factiva (Dow Jones, NY Times, WSJ, and Washington Post), and FOMC statements from www.federalreserve.gov.

Table 9: Forecast of FOMC Monetary Policy Stance: Sentiment and Financial Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ Monetary Policy										0.623***
										(0.151)
FOMC Sentiment	0.714***									0.217
	(0.113)									(0.148)
Press Conference Sentiment		0.0222								-0.247**
		(0.0739)								(0.101)
News Sentiment			1.031***							0.712***
			(0.129)							(0.162)
Δ 3-Month Yield				0.511***						-0.265
				(0.0917)						(0.242)
Δ 6-Month Yield					0.522***					0.213
					(0.0909)					(0.280)
Δ Eurodollar						0.187**				-0.168
						(0.0894)				(0.141)
Δ 2-Year Yield							0.293***			0.288
							(0.0865)			(0.225)
Δ 5-Year Yield								0.162*		0.188
								(0.0874)		(0.224)
Δ 10-Year Yield									0.0734	-0.311
									(0.0870)	(0.206)
Observations	182	182	182	182	182	182	182	182	182	182
Pseudo R^2	0.133	0.000	0.247	0.093	0.098	0.012	0.032	0.010	0.002	0.368

Notes: We estimate an ordered probit to forecast monetary policy decisions from 2000 to 2020. The dependent variable in columns (1) and (2) is an indicator variable equal to -1, 0, 1 according to whether the FOMC decreased, left unchanged or increased the federal funds target rate (FFTR) or announced other unconventional policies that were tightening, neutral or easing. The dependent variable in columns (3) and (4) is the federal funds target rate change. The table reports marginal effects on the probability of tightening (columns 1-2) or of 25 basis point increase (columns 3-4) for a one standard deviation increase in the independent variable, if it is continuous, and for a change from 0 to 1, if it is an indicator variable. All of the independent variables are lagged as of the day before the FOMC meeting, except for the FOMC sentiment index, FFTR, and change in monetary policy stance, which are based on the most recent FOMC statement. For a detailed definition of the independent variables refer to Table A1. The change in monetary policy is either the monetary policy stance variable as of the last FOMC in columns (1) and (2) or the change in the federal funds target rate in columns (3) and (4). ELB denotes the effective lower bound period. Standard errors are in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

SOURCE: Authors' calculations based on Bloomberg, Blue Chip Financial Forecasts, the Center for Research in Security Prices (CRSP), the Federal Reserve Bank of Philadelphia, the Aruoba-Diebold-Scotti Business Conditions Index, the Favara et al. (2016) EBP update, the Congressional Budget Office, Factiva (Dow Jones, NY Times, WSJ, and Washington Post), and FOMC statements from www.federalreserve.gov.

Table 10: Determinants of Sentiment

	(1)	(2)	(3)	(4)	(5)
	Panel A: News Sentiment				
ADS Index	0.0830***				0.0244
	(0.0229)				(0.0245)
S&P 500 Returns		0.455***			0.424***
		(0.0607)			(0.0689)
NFP Surprise			-0.0110		-0.107*
			(0.0591)		(0.0543)
GDP Deflator Surprise				0.217***	0.158**
				(0.0701)	(0.0622)
Constant	0.0607	0.0294	0.0523	0.0972	0.0726
	(0.0717)	(0.0649)	(0.0743)	(0.0738)	(0.0653)
Observations	184	184	184	184	184
Adjusted R^2	0.067	0.236	0.000	0.050	0.278
	Panel B: Twitter Sentiment				
ADS Index	0.0416*				-0.00807
	(0.0234)				(0.0274)
S&P 500 Returns		0.350***			0.360***
		(0.0755)			(0.0918)
NFP Surprise			-0.0199		-0.0742
			(0.0588)		(0.0577)
GDP Deflator Surprise				0.210**	0.145*
				(0.0810)	(0.0776)
Constant	0.0732	0.0115	0.0670	0.129	0.0615
	(0.0885)	(0.0834)	(0.0898)	(0.0907)	(0.0881)
Observations	124	124	124	124	124
Adjusted R^2	0.025	0.150	0.001	0.052	0.189

Notes: We regress news sentiment index (Panel A) and Twitter sentiment index (Panel B) on ADS index (a real-time macroeconomic index), quarterly S&P 500 returns, non-farm payroll surprises, and GDP deflator surprises. The sample period is from 2000 to 2021. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

SOURCE: Authors' calculations based on Bloomberg Finance LP, Bloomberg Terminals (Open, Anywhere, and Disaster Recovery Licenses), the Center for Research in Security Prices (CRSP), the Aruoba-Diebold-Scotti Business Conditions Index, and FOMC statements from www.federalreserve.gov.

Table 11: Determinants of Disagreement

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: News Sentiment - FOMC Sentiment						
ADS Index	0.0316						-0.0152
	(0.0201)						(0.0220)
S&P 500 Returns		0.266***					0.243***
		(0.0558)					(0.0630)
NFP Surprise			0.0350				-0.0157
			(0.0503)				(0.0489)
GDP Deflator Surprise				0.0323			-0.0073
				(0.0612)			(0.0559)
Two-Years Before Recession					-0.2750*		-0.1000
					(0.1480)		(0.1440)
Two-Years After Recession						0.7130***	0.5710***
						(0.1340)	(0.1420)
Constant	0.0604	0.0440	0.0551	0.0638	0.1210*	-0.1290*	-0.0829
	(0.0628)	(0.0597)	(0.0632)	(0.0645)	(0.0716)	(0.0684)	(0.0827)
Observations	184	184	184	184	184	184	184
Adjusted R^2	0.013	0.111	0.003	0.002	0.019	0.135	0.208
	Panel A: Twitter Sentiment - FOMC Sentiment						
ADS Index	0.0003						-0.0297
	(0.0240)						(0.0261)
S&P 500 Returns		0.164**					0.0645
		(0.0817)					(0.0915)
NFP Surprise			0.0324				0.00005
			(0.0596)				(0.0551)
GDP Deflator Surprise				0.0224			-0.0901
				(0.0843)			(0.0746)
Two-Years Before Recession					-0.3250		0.0813
					(0.2320)		(0.2100)
Two-Years After Recession						1.2300***	1.2760***
						(0.1780)	(0.2030)
Constant	0.0631	0.0382	0.0594	0.0699	0.1230	-0.2440***	-0.3150***
	(0.0909)	(0.0901)	(0.0909)	(0.0943)	(0.0997)	(0.0888)	(0.1100)
Observations	124	124	124	124	124	124	124
Adjusted R^2	0.000	0.032	0.002	0.001	0.016	0.282	0.299

Notes: We regress disagreement, difference between news sentiment and FOMC sentiment (Panel A) or difference between Twitter sentiment and FOMC sentiment (Panel B) on ADS index (a real-time macroeconomic index), quarterly S&P 500 returns, non-farm payroll surprises, GDP deflator surprises, an indicator variable equal to one two years before a recession, and an indicator variable equal to one two years after a recession. The sample period is from 2000 to 2021. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

SOURCE: Authors' calculations based on Bloomberg Finance LP, Bloomberg Terminals (Open, Anywhere, and Disaster Recovery Licenses), the Center for Research in Security Prices (CRSP), the Aruoba-Diebold-Scotti Business Conditions Index, Factiva (Dow Jones, NY Times, WSJ, and Washington Post), and FOMC statements from www.federalreserve.gov.

Table 12: Is News and FOMC Disagreement Related to Blue Chip and Greenbook Forecast Disagreement?

	(1)	(2)	(3)	(4)	(5)
CPI BC Forecast - CPI GB Forecast	0.8607***				0.6307*
	(0.2179)				(0.3189)
Employment BC Forecast - Employment GB Forecast		-0.8375***			-0.8212***
		(0.2460)			(0.2674)
GDP BC Forecast - GDP GB Forecast			-0.3951***		-0.0932
			(0.1065)		(0.1373)
FFTR BC Forecast - FFTR GB Forecast				0.3659**	0.2139
				(0.1466)	(0.1595)
Constant	-0.3689***	0.1108	0.0115	-0.0443	-0.2953*
	(0.1258)	(0.0697)	(0.0680)	(0.0880)	(0.1650)
Observations	142	142	142	126	126
R-squared	0.1003	0.0764	0.0896	0.0478	0.1985

Notes: We regress media and FOMC disagreement, difference between news and FOMC sentiment indexes, on disagreement between Blue Chip and Greenbook forecasts. The sample period for Greenbook employment, GDP and CPI forecasts is from 2000 to 2016, and the sample period for Greenbook federal funds target rate forecasts is from 2000 to 2014. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

SOURCE: Authors' calculations based on Bloomberg Finance LP, Bloomberg Terminals (Open, Anywhere, and Disaster Recovery Licenses), Blue Chip Economic Indicators, Greenbook forecasts are from the database maintained by the Federal Reserve Bank of Philadelphia, see Federal Reserve Bank of Philadelphia (2022), Factiva (Dow Jones, NY Times, WSJ, and Washington Post), and FOMC statements from www.federalreserve.gov.

Table 13: Disagreement and Uncertainty

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Move Index	0.0005									0.0018
	(0.0012)									(0.0015)
EPU		0.0007*								0.0001
		(0.0004)								(0.0005)
MPU			-0.0002							-0.0002
			(0.0006)							(0.0006)
Two Years Before Recession				-0.1821**						-0.0407
				(0.0892)						(0.0968)
Two Years After Recession					0.3156***					0.2671**
					(0.0844)					(0.1027)
Scotti's US Uncertainty						0.0315				0.1276
						(0.0764)				(0.1768)
Dispersion Across NFP Forecasts							0.0001			-0.0006
							(0.0002)			(0.0005)
Dispersion Across GDP Forecasts								0.2397***		0.3128***
								(0.0805)		(0.1194)
Dispersion Across GDP Deflator Forecasts									-0.1499	-0.9515***
									(0.2581)	(0.3186)
Constant	0.6329***	0.5932***	0.7020***	0.7206***	0.5968***	0.6702***	0.6718***	0.5530***	0.7339***	0.6818***
	(0.1080)	(0.0636)	(0.0807)	(0.0432)	(0.0428)	(0.0426)	(0.0399)	(0.0562)	(0.1038)	(0.1602)
Observations	183	183	183	183	183	183	183	183	183	183
Adjusted R^2	0.0011	0.0150	0.0006	0.0225	0.0718	0.0009	0.0016	0.0467	0.0019	0.1379

Notes: We regress the absolute value of the difference between FOMC sentiment and news sentiment on various uncertainty measures. The regression also includes a constant term. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

SOURCE: Authors' calculations based on Bloomberg Finance LP, Bloomberg Terminals (Open, Anywhere, and Disaster Recovery Licenses), and FOMC information from www.federalreserve.gov.

References

Andersen, Torben G., Tim Bollerslev, Francis X. Diebold, and Clara Vega, 2003, Micro effects of macro announcements: Real-time price discovery in foreign exchange, *American Economic Review* 93, 38–62.

Andersen, Torben G., Tim Bollerslev, Francis X. Diebold, and Clara Vega, 2007, Real-time price discovery in global stock, bond and foreign exchange markets, *Journal of International Economics* 73, 251–277.

Angrist, Joshua D., Óscar Jordá, and Guido M. Kuersteiner, 2018, Semiparametric estimates of monetary policy effects: String theory revisited, *Journal of Business and Economic Statistics* 36, 371–387.

Aruoba, Boragan, Francis X. Diebold, and Chiara Scotti, 2009, Real-time measurement of business conditions, *Journal of Business and Economic Statistics* 27, 417–427.

Baker, Scott, Nicholas Bloom, and Steven J. Davis, 2016, Measuring economic policy uncertainty, *Quarterly Journal of Economics* 131, 1593–1636.

Banerjee, Shantanu, Michiel DePooter, Olesya V. Grishchenko, Brad Strum, and Cait Walsh, 2019, Gauging the sentiment of Federal Open Market Committee communications through the eyes of the financial press, Working Paper, Board of Governors of the Federal Reserve System.

Bauer, Michael D., and Eric T. Swanson, 2020, The Fed's response to economic news explains the "Fed information effect", Working paper 2020-06, Federal Reserve Bank of San Francisco.

Ben-Rephael, Azi, Steffen Hitzemann, and Yuanyuan Xiao, 2021, Investor (mis)reaction, biased beliefs, and the mispricing cycle, Working Paper, Rutgers University.

Benamar, Hedi, Thierry Foucautl, and Clara Vega, 2021, Demand for information, uncertainty and the response of U.S. Treasury securities to news, *Review of Financial Studies* 34, 3403–3455.

Berge, Travis J., Andrew C. Chang, and Nitish R. Sinha, 2019, Evaluating the conditionality of judgemental forecasts, *International Journal of Forecasting* 35, 1627–1635.

Blinder, Alan S., Michael Ehrmann, Marcel Fratzscher, Jakob De Haan, and David-Jan Jansen, 2008, Central bank communication and monetary policy: A survey of theory and evidence, *Journal of Economic Literature* 46, 910–45.

Board of Governors, 2018, Monetary Policy Report submitted to the Congress on February 23, 2018, pursuant to section 2B of the Federal Reserve Act, Note, Board of Governors of the Federal Reserve System.

Boguth, Oliver, Vincent Grégoire, and Charles Martineau, 2019, Shaping expectations and coordinating attention: The unintended consequences of FOMC press conferences, *Journal of Financial and Quantitative Analysis* 54, 2327–2353.

Brave, Scott A., R. Andrew Butters, and David Kelley, 2019, A new "big data" index of U.S. economic activity, *Economic Perspectives, Federal Reserve Bank of Chicago* 43.

Caldara, Dario, and Matteo Iacoviello, 2018, Measuring geopolitical risk, IFDP Notes No. 1222, Board of Governors of the Federal Reserve System.

Campbell, Jeffrey, Charles Evans, Jonas Fisher, and Alejandro Justiniano, 2012, Macroeconomic effects of Federal Reserve forward guidance, *Brookings Papers on Economic Activity* 43, 1–80.

Carroll, Christopher D., 2003, Macroeconomic expectations of households and professional forecasters, *Quarterly Journal of Economics* 118, 269–98.

Christiano, Lawrence J., Martin Eichenbaum, and Charles L. Evans, 1996, The effects of monetary policy shocks: Evidence from the flow of funds, *Review of Economics and Statistics* 78, 16–34.

Cieslak, Anna, 2018, Short-rate expectations and unexpected returns in treasury bonds, *Review of Financial Studies* 31, 3265–3306.

Cieslak, Anna, and Andreas Schrimpf, 2019, Non-monetary news in central bank communication, *Journal of International Economics* 118, 293–315.

Cochrane, John H., and Monika Piazzesi, 2002, The Fed and interest rates—a high-frequency identification, *American Economic Review* 92, 90–95.

Cookson, J. Anthony, Corbin Fox, Javier Gil-Bazo, Juan Felipe Imbet, and Christoph Schiller, 2023, Social media as a bank run catalyst, Working Paper, Arizona State University.

Demiralp, Selva, Sharmila King, and Chiara Scotti, 2019, Does anyone listen when politicians talk? The effect of political commentaries on policy rate decisions and expectations, *Journal of International Money and Finance* 95, 95–111.

Dessaint, Olivier, Thierry Foucault, and Laurent Frésard, 2022, Does alternative data improve financial forecasting? the horizon effect, Working Paper, HEC Paris.

Doms, Mark, and Norman Morin, 2004, Consumer sentiment, the economy, and the news media, Discussion Series No 2004-51, Board of Governors Finance and Economics.

Faust, Jon, Eric T. Swanson, and Jonathan H. Wright, 2004a, Do Federal Reserve policy surprises reveal superior information about the economy?, *Contributions to Macroeconomics* 4, 1–29.

Faust, Jon, Eric T. Swanson, and Jonathan H. Wright, 2004b, Identifying VARS based on high frequency futures data, *Journal of Monetary Economics* 51, 1107 – 1131.

Favara, Giovanni, Simon Gilchrist, Kurt F. Lewis, and Egon Zakrajšek, 2016, Updating the recession risk and the excess bond premium, Finance and Economics Discussion Series, Board of Governors of the Federal Reserve System.

Federal Reserve Bank of Philadelphia , 2022, Greenbook data sets, Accessed: 2022-11-17, Federal Reserve Bank of Philadelphia.

Gardner, Ben, Chiara Scotti, and Clara Vega, 2022, Words speak as loudly as actions: Central bank communication and the response of equity prices to macroeconomic announcements, *Journal of Economcetrics* forthcoming.

Gentzkow, Matthew, and Jessee M. Shapiro, 2010, What drives media slant? evidence from u.s. daily newspapers, *Econometrica* 78, 35–71.

Gilchrist, Simon, and Egon Zakrajšek, 2012, Credit spreads and business cycle fluctuations, *American Economic Review* 102, 1692–1720.

Goldberg, Linda S., and Christian Grisse, 2013, Time variation in asset price responses to macro announcements, Working Paper, National Bureau of Economic Research.

Groseclose, Tim, and Jeffrey Milyo, 2005, A measure of media bias, *The Quarterly Journal of Economics* 120, 1191–1237.

Gürkaynak, Refet S., Brian P. Sack, and Eric T. Swanson, 2005, The excess sensitivity of long-term interest rates to economic news: Evidence and implications for macroeconomic models, *American Economic Review* 95, 425–436.

Hamilton, James D., and Óscar Jordá, 2002, A model of the federal funds rate target, *Journal of Political Economy* 110, 1135–1167.

Hansen, Stephen, and Michael McMahon, 2016, Shocking language: Understanding the macroeconomic effects of central bank communication, *Journal of International Economics* 99, 114–133.

Hansen, Stephen, Michael McMahon, and Andrea Prat, 2017, Transparency and deliberation within the FOMC: A computational linguistics approach, *Quarterly Journal of Economics* 133, 801–870.

Hoesch, Lukas, Barbara Rossi, and Tatevik Sekhposyan, 2020, Has the information channel of monetary policy disappeared? revisiting the empirical evidence, Working Paper 2020-08, Federal Reserve Bank of San Francisco.

Kuttner, Kenneth N., 2001, Monetary policy surprises and interest rates: Evidence from the Fed funds futures market, *Journal of Monetary Economics* 47, 523–544.

Larsen, Vegard H., and Leif A. Thorsrud, 2019, The value of news for economic developments, *Journal of Econometrics* 210, 203–218, Annals Issue in Honor of John Geweke, Complexity and Big Data in Economics and Finance: Recent Developments from a Bayesian Perspective.

Law, Tzuo-Hann, Dongho Song, and Amir Yaron, 2020, Fearing the Fed: How Wall Street reads Main Street, Working Paper, Wharton Business School.

Loughran, Tim, and Bill McDonald, 2011, When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks, *Journal of Finance* 66, 35–65.

Lucca, David O., and Francesco Trebbi, 2009, Measuring central bank communication: An automated approach with application to FOMC statements, Working paper, National Bureau of Economic Research.

Mullainathan, Sendhil, and Andrei Shleifer, 2005, The market for news, *American Economic Review* 95, 1031–1053.

Nakamura, Emi, and Jon Steinsson, 2018, High frequency identification of monetary non neutrality: The information effect, *Quarterly Journal of Economics* 133, 1283–1330.

Orphanides, Athanasios, 2001, Monetary policy rules based on real-time data, *American Economic Review* 91, 964–985.

Orphanides, Athanasios, 2005, Historical monetary policy analysis and the Taylor rule, *Journal of Monetary Economics* 50, 983–1022.

Patton, Andrew J., and Allan Timmermann, 2011, Predictability of output growth and inflation: A multi-horizon survey approach, *Journal of Business and Economic Statistics* 29, 397–410.

Pedersen, Lasse H., 2022, Game on: Social networks and markets, *Journal of Financial Economics* 146, 1097–1119.

Piazzesi, Monika, 2005, Bond yields and the Federal Reserve, *Journal of Political Economy* 113, 311–344.

Reifschneider, David, and Peter Tulip, 2007, Gauging the uncertainty of the economic outlook from historical forecasting errors, Finance and Economics Discussion Series Divisions of Research & Statistics and Monetary Affairs, Board of Governors of the Federal Reserve System.

Rogers, John H., Chiara Scotti, and Jonathan H. Wright, 2014, Evaluating asset-market effects of unconventional monetary policy: A cross-country comparison, *Economic Policy* 29, 749–799.

Rogers, John H., Chiara Scotti, and Jonathan H. Wright, 2018, Unconventional monetary policy and international risk premia, *Journal of Money, Credit and Banking* 50, 1827–1850.

Romer, Christina D., and David H. Romer, 2000, Federal Reserve information and the behavior of interest rates, *American Economic Review* 90, 429–457.

Sastry, Karthik, 2022, Disagreement about monetary policy, Working Paper, Harvard University.

Scotti, Chiara, 2011, A bivariate model of Federal Reserve and ECB main policy rates, *International Journal of Central Banking* 7, 37–78.

Shapiro, Adam Hale, Moritz Sudhof, and Daniel J. Wilson, 2020, Measuring news sentiment, *Journal of Econometrics* .

Sharpe, Steve, Nitish Sinha, and Christopher A. Hollrah, 2017, What's the story? A new perspective on the value of economic forecasts, Finance and Economics Discussion Series No. 2017-107, Board of Governors of the Federal Reserve System.

Swanson, Eric T., 2020, Measuring the effects of Federal Reserve forward guidance and asset purchases on financial markets, *Journal of Monetary Economics* 118, 32–53.

Vigna, Stefano Della, and Ethan Kaplan, 2007, The fox news effect: Media bias and voting, *Quaterly Journal of Economics* 122, 1187–1234.

Wu, Jing Cynthia, and Fan Dora Xia, 2016, Measuring the macroeconomic impact of monetary policy at the zero lower bound, *Journal of Money, Credit and Banking* 48, 253–291.

APPENDIX

A Identifying FOMC Related News Articles and Tweets

As mentioned in the Introduction, there is a large number of Tweets and news articles published every day. In 2022, there were 500 million Tweets and 5 thousand news articles per day, on average. We therefore need an automated way to identify news articles and Tweets that discuss the FOMC decision. The format of news articles and Tweets is different, so we use a different, albeit related, set of keywords. The keywords we use to identify news that discuss the FOMC decision are: "federal reserve" or "FOMC." If any one of these keywords appear in the headline or anywhere in the body of the article, we keep the article and compute its sentiment. We considered a wider set of keywords, such as "fed," but this increased the number of false positives, articles that do not discuss the FOMC decision. For Twitter, it is somewhat easier to identify Tweets that discuss the FOMC decision because writers use hashtags and other symbols so that others can easily find their Tweets. The most common symbols used to tag Tweets related to the FOMC decision are: "@federalreserve" or "#fomc" or "#federalreserve" or "@fedresearch" or "url:federalreserve" or "to:federalreserve" or "to:fedresearch." The most common symbols to identify retweets are: "retweets_of:federalreserve" or "retweets_of:fedresearch." In addition, we use the name of the Fed chairs since the beginning of the Twitter sample: "powell" or "yellen" or "bernanke," the keywords we use to identify news: "fomc" or "federal reserve," and other common words our tabulation of frequent words used in Tweets published on FOMC days uncovered, such as "chair" or "governor" or "fed." Similar to the method we used to identify FOMC related news articles, if any one of these words appear anywhere in the body of the Tweet, we keep the Tweet and compute its sentiment.[22]

B Identifying Uninformative Sentences

In an attempt to best capture the FOMC's current description of the economy, we eliminated sentences from the sample that we deemed uninformative, such as those that expressed views on how the economy might react to future policy actions. Frequently in its statements the FOMC makes comments about changes to monetary policy, and then explains how these actions may affect

[22]We thank Betsy Vrankovich for developing the algorithm that identifies Tweets that discuss FOMC decisions

key areas such as employment or economic expansion. However, if we were to score these phrases the same way as remarks about direct expectations of future macroeconomic outcomes, they would produce scores that are opposite of what we want to measure. For example, in October 2008 the FOMC stated, "recent policy actions, including today's rate reduction, coordinated interest rate cuts by central banks, extraordinary liquidity measures, and official steps to strengthen financial systems, should help over time to improve credit conditions and promote a return to moderate economic growth." Our algorithm would pick up on the mention of "moderate economic growth" and score it positively; however, the actual conditions for output were highly negative. Removing these types of phrases is most important during the early part of our sample in which the statements are shorter, and a mismatch has a larger impact on the overall score.

To systematically identify and remove uninformative sentences, we used combinations of words and phrases that are commonly found within these types of sentences. The first type of pattern is evident in the example above. The FOMC states they will take action and explains how they hope the economy will react. A few other common patterns involve the restatement of the Fed's "dual mandate" or references to its policy toolbox. A full list of rules can be found in Gardner et al. (2022).

C Using Federal Funds Futures to Forecast Future Monetary Policy Decisions

Following Kuttner (2001), we use federal funds futures to estimate the market's expectation of the federal funds rate change at the next FOMC meeting. While there are some survey measures of expected Fed policy in the most recent sample, the use of Feds funds futures allows us to compute these expectations on particular days of interest (rather than having to use stale expectations). The use of Fed funds futures has some disadvantages, including the fact that the contract's settlement price is based on the average of the relevant month's effective overnight Fed funds rate as well as the fact that contracts are based on the effective Fed funds rate rather than the target, possibly causing discrepancies between the two rates on a daily basis.

Following Kuttner (2001) and Faust et al. (2004b) we extract a measure of the unexpected change in the target rate on date $t + 1$, relative to the forecast made on date t, using the the 1-day change in the spot-month future rate. In particular, the unexpected change in the policy rate is

$$\Delta FFR_t^u = \frac{m}{m-t}(f_{s,t}^0 - f_{s,t-1}^0), \tag{8}$$

where $f_{s,t}^0$ is the spot-moth futures rate on day t of month s, m is the number of days in the month, and ΔFFR_t^u is the 1-day surprise for date t. The idea behind this is that $day - t$ futures prices embody the expected change on (or after) date $t+1$. If the change occurs as expected, the spot rate should not change and, under the assumption of no-change in the risk premium, the change in the futures market would equal the change in the market's expectation. When using daily futures prices, an additional assumption to make is that the change on FOMC announcement days is due to an exogenous monetary policy shock, which would fail if macro releases occur on the same day as FOMC announcements—rarely the case in our sample. In addition, it is still possible that this measure contains not only exogenous monetary policy shocks but also the FOMC information advantage through earlier access to data, as discussed in Faust et al. (2004b).

D Sastry's Theoretical Model

To guide our empirical analysis we use Sastry (2022)'s theoretical model. In Sastry (2022)'s model there are three periods $t = \{0, 1, 2\}$, and there is a single unknown fundamental economic growth variable, θ, normally distributed with mean zero and variances equal to τ_θ^{-1}. There are two market participants, the Fed, F, and the Market, M, which in our setting are journalists. F and M receive public information about the fundamental. In addition, F receives a private signal about the fundamental (asymmetric information). F sets the interest rate, r, based on the information it has about the fundamental (its expectation of the fundamental), and M forms an expectation about the interest rate, r. Expectations are labeled $E_{X,t}$ where $X = \{F, M\}$ indicates whose expectation it is and $t = \{0, 1, 2\}$ indicates at what time the expectation is formed.

Specifically, in period t=0, F and M receive a public signal $Z = \theta + \varepsilon_z$. F also receives a private signal $F = \theta + \varepsilon_F$. F sets interest rates using the public signal and the private signal $r = E_{F,0}[\theta]$. M makes a prediction about r, $P = E_{M,0}[r]$. In period t=1, the interest rate is reveal and the monetary policy surprise is $\Delta = r - P$. In period t=2, F and M receive another public signal $S = \theta + \varepsilon_S$ and employment (or output or inflation) is realized $Y = a\theta - r$ for some $a >= 1$, which implies that fundamental shocks have a positive effect on employment net of the policy response. The Fed and the market (journalists) use Bayes rules to form their beliefs. Below there is a summary of the main results:

- **The Fed's beliefs**: $E_{F,0}[\theta] = \delta_F^F F + (\delta_Z^F - q^F)Z$, where δ_F^F and δ_Z^F are the optimal weights a Bayes rule puts on the private and public signal. Importantly, $q^F > 0$ encodes **under-confidence** in public information relative to Bayes rule.

- θ and the error in F and Z are normally distributed with mean zero and variances equal to τ_θ^{-1}, τ_F^{-1} and τ_Z^{-1} respectively. So the optimal weights a Bayes rule puts on the private and public signals are $\delta_F^F = \frac{\tau_F}{\tau_F + \tau_Z + \tau_\theta}$ and $\delta_Z^F = \frac{\tau_F}{\tau_F + \tau_Z + \tau_\theta}$. Bayes rule puts weight on the signals proportional to the variance of the fundamental and inversely proportional to the variance of the noise of the signal.

- **The market's or journalist's beliefs**: $E_{M,0}[\theta] = (\delta_Z^M - q)Z$, where δ_Z^M is the optimal weight a Bayes rule puts on the public signal. Importantly, $q > 0$ encodes market's **under-confidence** in public information relative to Bayes rule.

- The optimal weight a Bayes rule puts on public signal is $\delta_Z^M = \frac{\tau_Z}{\tau_Z + \tau_\theta}$

- Market's expectations about r are $E_{M,0}[r] = E_{M,0}[\delta_F^F F + (\delta_Z^F - q^F - \omega)Z]$. ω is the market's miss-specification of the policy rule's coefficient on Z. $\omega > 0$ means that the market under-estimates the weight the policy rule places on Z.

- Market's expectation about Y after r has been announced is $Y - E_{M,t}[Y] = a(\theta - E_{M,t}[\theta])$, where $t = 1, 2$, at t=1, the market and the Fed have received F and Z. At t=2, the market and the Fed have received an extra public signal, S. At t=1, after seeing r, the market forecast of Y is $Y - E_{M,1}[Y] = a(\theta - E_{M,1}[\theta]) = (\theta - E_{M,1}^R[\theta]) + \frac{\tau_0}{\tau_1} qZ - \frac{\delta_{F,1}^M}{\delta_F^F}\omega Z$, where $\tau_0 = \tau_\theta + \tau_Z$ is the initial (subjective) posterior precision, and τ_1 is the t=1 posterior precision. Sastry does not offer an expression for τ_1, but the covariance results are true as long as $\tau_0/\tau_1 > 0$ and $a > 0$ and $\delta_{F,t} > 0$ for all t.

Table A1: Variable Definitions

FOMC Sentiment	We construct the FOMC sentiment index using a user-defined dictionary of topic-keywords modifier-keywords and phrases. We separate topic-keywords and phrases into five topics: labor, output, inflation, financial conditions, and future monetary policy. The FOMC sentiment is the sum of these five topics divided by the by the square root of the number of words in the statement after having deleted uninformative sentences
FFF Expectations	Expected change in the FFR implied by Fed Funds Futures
Eurodollar Expectations	Change in the expected FFR one-year hence implied by the Eurodollar Futures
Blue Chip Expectations	Change in the Blue Chip professional forecasters expected FFR over the next four-quarters
Blue Chip Economic Indicators Expectations	The change in the Blue Chip forecast for GDP growth, DGP deflator and the unemployment rate over the next four-quarters. We use the annualized quarter-over-quarter consensus forecasts of real GDP growth and GDP price deflator, and the quarterly average of the unemployment rate in percentage points.
Change in UR Gap	The change in the difference between the (quarterly average of the monthly) real-time unemployment rate and the natural rate as released by the Congressional Budget Office (CBO)
Inflation Rate	Real-time GDP price deflator
ADS Index	Real-time values of the Aruoba et al. (2009) index
EBP	Gilchrist and Zakrajšek (2012) excess bond premium
Inv. Yield Curve	An indicator variable equal to one if the difference between the 10-year bond yield and the 2-year bond yield is negative
Recession	An indicator variable equal to one if we are in a recession according to the NBER recession dates
FFR	The federal funds rate
Treasury Yields	Yields of the on-the-run 2-, 5- and 10-year U.S. Government bonds or 3- and 6-month Treasury bills
Change in 5-Year Yield	Change in the 5-year yield since the last FOMC meeting
PD Ratio	Price-to-dividends ratio
VIX	CBOE one-month implied volatility index

Notes: The table reports a summary of the variables used in the paper.
SOURCE: Authors' calculations based on Bloomberg, Thomson Reuters Tick History, the Center for Research in Security Prices (CRSP), the Federal Reserve Bank of Philadelphia, the Aruoba-Diebold-Scotti Business Conditions Index, the Favara et al. (2016) EBP update, the Congressional Budget Office, and FOMC statements from www.federalreserve.gov.

Table A2: FOMC Dates, Statement Release Time and Press Conference Time

FOMC Date	Statement Time	PC Time	FOMC Date	Statement Time	PC Time	FOMC Date	Statement Time	PC Time
02/02/2000	14:14	NPC	08/07/2007	14:14	NPC	07/30/2014	14:00	NPC
03/21/2000	14:15	NPC	08/10/2007	9:15	NPC	09/17/2014	14:00	14:30
05/16/2000	14:13	NPC	08/17/2007*	8:15	NPC	10/29/2014	14:00	NPC
06/28/2000	14:15	NPC	09/18/2007	14:15	NPC	12/17/2014	14:00	14:30
08/22/2000	14:14	NPC	10/31/2007	14:15	NPC	01/28/2015	14:00	NPC
10/03/2000	14:12	NPC	12/11/2007	14:16	NPC	03/18/2015	14:00	14:30
11/15/2000	14:12	NPC	01/22/2008*	8:21	NPC	04/29/2015	14:00	NPC
12/19/2000	14:16	NPC	01/30/2008	14:14	NPC	06/17/2015	14:00	14:30
01/3/2001*	13:13	NPC	03/11/2008	8:30	NPC	07/29/2015	14:00	NPC
01/31/2001	14:15	NPC	03/18/2008	14:14	NPC	09/17/2015	14:00	14:30
03/20/2001	14:13	NPC	04/30/2008	14:15	NPC	10/28/2015	14:00	NPC
04/18/2001*	10:54	NPC	06/25/2008	14:09	NPC	12/16/2015	14:00	14:30
05/15/2001	14:15	NPC	08/05/2008	14:13	NPC	01/27/2016	14:00	NPC
06/27/2001	14:12	NPC	09/16/2008	14:14	NPC	03/16/2016	14:00	14:30
08/21/2001	14:13	NPC	10/8/2008*	7:00	NPC	04/27/2016	14:00	NPC
09/17/2001*	8:20	NPC	10/29/2008	14:17	NPC	06/15/2016	14:00	14:30
10/02/2001	14:15	NPC	11/25/2008	8:15	NPC	07/27/2016	14:00	NPC
11/06/2001	14:20	NPC	12/01/2008	13:45	NPC	09/21/2016	14:00	14:30
12/11/2001	14:14	NPC	12/16/2008	14:21	NPC	11/02/2016	14:00	NPC
01/30/2002	14:16	NPC	01/28/2009	14:15	NPC	12/14/2016	14:00	14:30
03/19/2002	14:19	NPC	03/18/2009	14:17	NPC	02/01/2017	14:00	NPC
05/07/2002	14:14	NPC	04/29/2009	14:16	NPC	03/15/2017	14:00	14:30
06/26/2002	14:13	NPC	06/24/2009	14:18	NPC	05/03/2017	14:00	NPC
08/13/2002	14:14	NPC	08/12/2009	14:16	NPC	06/14/2017	14:00	14:30
09/24/2002	14:12	NPC	09/23/2009	14:16	NPC	07/26/2017	14:00	NPC
11/06/2002	14:14	NPC	11/04/2009	14:18	NPC	09/20/2017	14:00	14:30
12/10/2002	14:13	NPC	12/16/2009	14:15	NPC	11/01/2017	14:00	NPC
01/29/2003	14:16	NPC	01/27/2010	14:16	NPC	12/13/2017	14:00	14:30
03/18/2003	14:15	NPC	03/16/2010	14:14	NPC	01/31/2018	14:00	NPC
05/06/2003	14:13	NPC	04/28/2010	14:14	NPC	03/21/2018	14:00	14:30
06/25/2003	14:16	NPC	06/23/2010	14:16	NPC	05/02/2018	14:00	NPC
08/12/2003	14:15	NPC	08/10/2010	14:19	NPC	06/13/2018	14:00	14:30
09/16/2003	14:19	NPC	09/21/2010	14:18	NPC	08/01/2018	14:00	NPC
10/28/2003	14:14	NPC	11/03/2010	14:16	NPC	09/26/2018	14:00	14:30
12/09/2003	14:14	NPC	12/14/2010	14:15	NPC	11/08/2018	14:00	NPC
01/28/2004	14:14	NPC	01/26/2011	14:17	NPC	12/19/2018	14:00	14:30
03/16/2004	14:15	NPC	03/15/2011	14:17	NPC	01/30/2019	14:00	14:30
05/04/2004	14:16	NPC	04/27/2011	12:32	NPC	03/20/2019	14:00	14:30
06/30/2004	14:18	NPC	06/22/2011	12:27	14:15	05/01/2019	14:00	14:30
08/10/2004	14:15	NPC	08/09/2011	14:18	14:15	06/19/2019	14:00	14:30
09/21/2004	14:15	NPC	09/21/2011	14:23	NPC	07/31/2019	14:00	14:30
11/10/2004	14:15	NPC	11/02/2011	12:32	14:15	09/18/2019	14:00	14:30
12/14/2004	14:16	NPC	12/13/2011	14:12	NPC	10/04/2019	14:00	14:30
02/02/2005	14:17	NPC	01/25/2012	12:28	14:15	10/30/2019	14:00	14:30
03/22/2005	14:17	NPC	03/13/2012	14:16	NPC	12/11/2019	14:00	14:30
05/03/2005	14:16	NPC	04/25/2012	12:33	14:15	01/29/2020	14:00	14:30
06/30/2005	14:15	NPC	06/20/2012	12:30	14:15	03/03/2020*	10:00	11:00
08/09/2005	14:17	NPC	08/01/2012	14:13	NPC	03/15/2020*	17:00	18:30
09/20/2005	14:17	NPC	09/13/2012	12:30	14:15	04/29/2020	14:00	14:30
11/01/2005	14:18	NPC	10/24/2012	14:15	NPC	06/10/2020	14:00	14:30
12/13/2005	14:13	NPC	12/12/2012	12:30	14:15	07/29/2020	14:00	14:30
01/31/2006	14:14	NPC	01/30/2013	14:15	NPC	09/16/2020	14:00	14:30
03/28/2006	14:17	NPC	03/20/2013	14:00	14:30	11/05/2020	14:00	14:30
05/10/2006	14:17	NPC	05/01/2013	14:00	NPC	12/16/2020	14:00	14:30
06/29/2006	14:16	NPC	06/19/2013	14:00	14:30	01/27/2021	14:00	14:30
08/08/2006	14:14	NPC	07/31/2013	14:00	NPC	03/17/2021	14:00	14:30
09/20/2006	14:14	NPC	09/18/2013	14:00	14:30	04/28/2021	14:00	14:30
10/25/2006	14:13	NPC	10/30/2013	14:00	NPC	06/16/2021	14:00	14:30
12/12/2006	14:14	NPC	12/18/2013	14:00	14:30	07/28/2021	14:00	14:30
01/31/2007	14:14	NPC	01/29/2014	14:00	NPC	09/22/2021	14:00	14:30
03/21/2007	14:15	NPC	03/19/2014	14:00	14:30	11/03/2021	14:00	14:30
05/09/2007	14:15	NPC	04/30/2014	14:00	NPC	12/15/2021	14:00	14:30
06/28/2007	14:14	NPC	06/18/2014	14:00	14:30			

Notes: The table reports FOMC dates, statement release times and press conference times. Starting in June 2011 the Federal Reserve started to hold a press conference after every other decisions. In December 2018, the Federal Reserve held a press conference after every pre-scheduled FOMC mmeeting. * denote inter-meeting dates, NPC denotes no press conference.

SOURCE: Authors' calculations and www.federalreserve.gov.

Table A3: Response of Interest Rates to News Sentiment: Twitter Sample

	(1) 3-Month	(2) 6-Month	(3) Eurodollar	(4) 2-Year	(5) 5-Year	(6) 10-Year
Panel A: Target Rate Surprise						
Target Surprise	0.824***	0.736***	0.371***	0.630***	0.603***	0.458***
	(0.0737)	(0.0601)	(0.0677)	(0.108)	(0.133)	(0.129)
Observations	120	120	120	120	120	120
Adjusted R^2	0.514	0.560	0.203	0.223	0.149	0.097
Panel B: FOMC Statement and Press Conference Sentiment						
FOMC Statement Sentiment	1.693***	1.359***	0.485	0.241	0.935	0.565
	(0.602)	(0.518)	(0.442)	(0.720)	(0.839)	(0.791)
Press Conference	-0.718	-0.347	0.449	0.597	0.687	0.855
	(0.914)	(0.786)	(0.671)	(1.094)	(1.274)	(1.202)
Observations	120	120	120	120	120	120
Adjusted R^2	0.063	0.056	0.018	0.005	0.017	0.012
Panel C: News Sentiment						
News Sentiment	2.520***	2.132***	1.409***	1.597**	2.311**	2.369***
	(0.666)	(0.571)	(0.488)	(0.804)	(0.935)	(0.875)
Observations	120	120	120	120	120	120
Adjusted R^2	0.108	0.106	0.066	0.032	0.049	0.058
Panel D: Target Rate Surprise, FOMC Statement and Press Conference Sentiment						
Target Surprise	0.798***	0.718***	0.369***	0.646***	0.595***	0.457***
	(0.0748)	(0.0612)	(0.0692)	(0.111)	(0.136)	(0.132)
FOMC Statement Sentiment	0.784*	0.540	0.0638	-0.496	0.258	0.0449
	(0.438)	(0.358)	(0.405)	(0.648)	(0.795)	(0.771)
Press Conference	-0.346	-0.0121	0.622	0.898	0.964	1.068
	(0.653)	(0.535)	(0.605)	(0.967)	(1.187)	(1.151)
Observations	120	120	120	120	120	120
Adjusted R^2	0.527	0.569	0.212	0.231	0.156	0.104
Panel E: Target Rate Surprise and News Sentiment						
Target Surprise	0.767***	0.699***	0.346***	0.620***	0.557***	0.397***
	(0.0750)	(0.0619)	(0.0704)	(0.113)	(0.138)	(0.133)
News Sentiment	1.321***	0.860**	0.600	0.230	1.082	1.407
	(0.499)	(0.412)	(0.468)	(0.754)	(0.920)	(0.887)
Observations	120	120	120	120	120	120
Adjusted R^2	0.542	0.575	0.214	0.224	0.159	0.116
Panel F: FOMC Statement, Press Conference and News Sentiment						
FOMC Statement Sentiment	0.356	0.368	-0.0745	-0.510	0.0178	-0.508
	(0.673)	(0.588)	(0.514)	(0.842)	(0.980)	(0.918)
Press Conference	-1.913**	-1.233	-0.0506	-0.0743	-0.133	-0.105
	(0.924)	(0.807)	(0.705)	(1.156)	(1.345)	(1.260)
News Sentiment	3.165***	2.344***	1.323**	1.776*	2.171*	2.540**
	(0.844)	(0.737)	(0.644)	(1.056)	(1.229)	(1.151)
Observations	120	120	120	120	120	120
Adjusted R^2	0.165	0.132	0.053	0.028	0.042	0.051
Panel G: Target Rate Surprise, FOMC Statement, Press Conference and News Sentiment						
Target Surprise	0.752***	0.693***	0.353***	0.634***	0.566***	0.407***
	(0.0758)	(0.0629)	(0.0716)	(0.115)	(0.141)	(0.136)
FOMC Statement Sentiment	0.190	0.215	-0.153	-0.651	-0.108	-0.598
	(0.497)	(0.412)	(0.469)	(0.752)	(0.922)	(0.888)
Press Conference	-0.946	-0.341	0.403	0.742	0.596	0.418
	(0.689)	(0.571)	(0.650)	(1.043)	(1.278)	(1.231)
News Sentiment	1.532**	0.839	0.558	0.399	0.941	1.657
	(0.644)	(0.534)	(0.608)	(0.976)	(1.195)	(1.152)
Observations	120	120	120	120	120	120
Adjusted R^2	0.549	0.578	0.218	0.232	0.161	0.120

Notes: We estimate the response of 3-, 6-month, eurodollar, 2-, 5-, and 10-year US Treasury yield changes to news sentiment and FOMC statement sentiment using data from March 2007 to December 2021, which is the sample when Twitter data is available. The dependent variable is the daily yield change. The regression also includes a constant term. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

SOURCE: Authors' calculations based on Bloomberg Finance LP, Bloomberg Terminals (Open, Anywhere, and Disaster Recovery Licenses), Factiva (Dow Jones, NY Times, WSJ, and Washington Post), and FOMC information from www.federalreserve.gov.

Table A4: Response of Blue Chip Forecast Revisions to FOMC Information

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	GDP				UR				GDP Deflator			
Panel A: Keep monthly revisions when there is an FOMC meeting in between forecasts												
FOMC Sentiment		0.317**		0.186		-0.380***		-0.194**		0.346***		0.140
		(0.129)		(0.121)		(0.111)		(0.0937)		(0.124)		(0.107)
Press Conference Sentiment		0.0769		0.0379		0.0838		0.129*		0.169		0.0989
		(0.112)		(0.100)		(0.0956)		(0.0776)		(0.106)		(0.0876)
Twitter Sentiment	0.409***		0.120	0.0142	-0.347***		-0.0782	-0.0591	0.512***		0.294***	0.176
	(0.112)		(0.108)	(0.126)	(0.0974)		(0.0844)	(0.0979)	(0.107)		(0.0963)	(0.112)
Target Surprise			-0.00426	-0.000211			0.200***	0.212***			-0.0405	-0.0366
			(0.0907)	(0.0908)			(0.0711)	(0.0704)			(0.0778)	(0.0775)
Forward Guidance Surprise			0.0539	0.0273			-0.0425	-0.0310			0.0772	0.0504
			(0.113)	(0.114)			(0.0889)	(0.0883)			(0.101)	(0.101)
LSAP			-0.168	-0.168			0.0391	0.0386			-0.137	-0.135
			(0.108)	(0.107)			(0.0846)	(0.0832)			(0.0967)	(0.0959)
NFP Surprise			-0.125***	-0.124***			0.0767**	0.0812***			-0.0692**	-0.0715**
			(0.0384)	(0.0383)			(0.0301)	(0.0297)			(0.0327)	(0.0324)
S&P500 Returns			0.632***	0.650***			-0.318***	-0.313***			0.244**	0.257**
			(0.124)	(0.124)			(0.0971)	(0.0962)			(0.104)	(0.104)
ADS Index			0.125	0.103			-0.484***	-0.471***			0.207***	0.203***
			(0.108)	(0.108)			(0.0844)	(0.0836)			(0.0337)	(0.0334)
Constant	-0.267**	-0.250**	-0.296***	-0.294***	-0.0491	-0.0862	0.0145	-0.00762	-0.222**	-0.207*	-0.176**	-0.181**
	(0.112)	(0.115)	(0.0975)	(0.0980)	(0.0973)	(0.0986)	(0.0764)	(0.0759)	(0.107)	(0.110)	(0.0869)	(0.0868)
Observations	118	118	118	118	118	118	118	118	120	120	120	120
Adjusted R^2	0.102	0.077	0.367	0.384	0.099	0.096	0.479	0.505	0.162	0.129	0.479	0.497
Panel B: Drop FOMC meetings that occur within the first 7 days of the month												
FOMC Sentiment		0.273		0.217		-0.469***		-0.130		0.344***		0.161
		(0.176)		(0.166)		(0.150)		(0.101)		(0.130)		(0.113)
Press Conference Sentiment		-0.0793		-0.0802		-0.0524		0.0503		0.223**		0.168*
		(0.144)		(0.127)		(0.122)		(0.0778)		(0.106)		(0.0875)
Twitter Sentiment	0.356**		0.154	0.105	-0.343**		-0.115	-0.0865	0.440***		0.241**	0.0885
	(0.153)		(0.141)	(0.163)	(0.136)		(0.0861)	(0.0997)	(0.116)		(0.101)	(0.112)
Target Surprise			-0.101	-0.118			0.142	0.153			-0.132	-0.117
			(0.152)	(0.154)			(0.0931)	(0.0940)			(0.109)	(0.106)
Forward Guidance Surprise			0.267*	0.249			0.0989	0.110			0.105	0.0619
			(0.156)	(0.157)			(0.0954)	(0.0963)			(0.111)	(0.109)
LSAP			-0.126	-0.127			0.0860	0.0865			-0.165	-0.162
			(0.146)	(0.146)			(0.0892)	(0.0893)			(0.104)	(0.101)
NFP Surprise			-0.0978*	-0.0972*			0.0947***	0.0944***			-0.0622*	-0.0628*
			(0.0537)	(0.0540)			(0.0328)	(0.0330)			(0.0349)	(0.0340)
S&P500 Returns			0.873***	0.863***			-0.151	-0.145			0.302***	0.311***
			(0.164)	(0.166)			(0.100)	(0.101)			(0.109)	(0.107)
ADS Index			-0.454***	-0.474***			-0.824***	-0.812***			0.189***	0.182***
			(0.123)	(0.128)			(0.0755)	(0.0783)			(0.0334)	(0.0325)
Constant	-0.166	-0.124	-0.170	-0.153	0.102	0.0871	0.139*	0.128	-0.227*	-0.230**	-0.179*	-0.195**
	(0.154)	(0.158)	(0.131)	(0.132)	(0.137)	(0.134)	(0.0800)	(0.0808)	(0.117)	(0.115)	(0.0934)	(0.0916)
Observations	103	103	103	103	103	103	103	103	104	104	104	104
Adjusted R^2	0.051	0.024	0.358	0.371	0.059	0.118	0.699	0.704	0.123	0.162	0.478	0.518

Notes: We estimate the response of Blue Chip Economic Indicators forecast revisions for GDP, the unemployment rate (UR), and the GDP price deflator to FOMC information using data from 2000 to 2022. We keep a forecast revision only if there is an FOMC meeting between forecasts, and if there are two FOMC meetings, we keep only the information from the most recent meeting. We drop forecast revisions higher than 10 standard deviations from the mean. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

SOURCE: Authors' calculations based on Bloomberg Finance LP, Bloomberg Terminals (Open, Anywhere, and Disaster Recovery Licenses), Blue Chip Economic Indicators, the Aruoba-Diebold-Scotti Business Conditions Index, Twitter, and FOMC statements from www.federalreserve.gov.

Table A5: Response of Blue Chip Forecast Revisions to FOMC Information: Yield Changes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	GDP				UR				GDP Deflator			
Panel A: Keep monthly revisions when there is an FOMC meeting in between forecasts												
FOMC Sentiment				0.137				-0.181*				0.151
				(0.116)				(0.0975)				(0.107)
Press Conference Sentiment				0.0871				0.103				0.0920
				(0.0962)				(0.0811)				(0.0875)
Twitter Sentiment	0.409***		0.210*	-0.0634	-0.347***		-0.210**	-0.0348	0.512***		0.484***	0.210*
	(0.112)		(0.115)	(0.124)	(0.0974)		(0.104)	(0.105)	(0.107)		(0.119)	(0.114)
3-Month Yield Change		0.140***	0.121***	0.0862***		-0.0922***	-0.0739***	-0.000468		0.0541**	0.0122	-0.0196
		(0.0239)	(0.0257)	(0.0256)		(0.0218)	(0.0234)	(0.0216)		(0.0262)	(0.0267)	(0.0223)
2-Year Yield Change		-0.0263	-0.0223	-0.0212		0.0184	0.0144	0.00939		0.0126	0.0222	0.0314*
		(0.0199)	(0.0198)	(0.0176)		(0.0181)	(0.0180)	(0.0148)		(0.0217)	(0.0205)	(0.0163)
10-Year Yield Change		0.00856	0.00267	-0.00124		-0.0180	-0.0121	-0.00128		0.00878	-0.00540	-0.0202
		(0.0171)	(0.0172)	(0.0154)		(0.0156)	(0.0156)	(0.0130)		(0.0186)	(0.0178)	(0.0142)
NFP Surprise				-0.103***				0.0680**				-0.0692**
				(0.0365)				(0.0308)				(0.0320)
S&P500 Returns				0.576***				-0.371***				0.251**
				(0.116)				(0.0979)				(0.104)
ADS Index				-0.000485				-0.377***				0.199***
				(0.100)				(0.0845)				(0.0322)
Constant	-0.267**	-0.00921	-0.0587	-0.147	-0.0491	-0.234**	-0.184*	-0.0213	-0.222**	-0.0900	-0.200*	-0.219**
	(0.112)	(0.112)	(0.114)	(0.105)	(0.0973)	(0.102)	(0.103)	(0.0886)	(0.107)	(0.121)	(0.117)	(0.0941)
Observations	118	118	118	118	118	118	118	118	120	120	120	120
Adjusted R^2	0.102	0.230	0.253	0.438	0.099	0.144	0.174	0.465	0.162	0.058	0.177	0.506
Panel B: Drop FOMC meetings that occur within the first 7 days of the month												
FOMC Sentiment				0.165				-0.0932				0.166
				(0.157)				(0.105)				(0.113)
Press Conference Sentiment				-0.00501				0.0360				0.167*
				(0.121)				(0.0806)				(0.0876)
Twitter Sentiment	0.356**		0.117	-0.0367	-0.343**		-0.220	-0.0862	0.440***		0.426***	0.130
	(0.153)		(0.162)	(0.161)	(0.136)		(0.151)	(0.107)	(0.116)		(0.131)	(0.117)
3-Month Yield Change		0.159***	0.148***	0.127***		-0.0952***	-0.0738**	0.00911		0.0496	0.00815	-0.0267
		(0.0355)	(0.0389)	(0.0360)		(0.0334)	(0.0364)	(0.0240)		(0.0303)	(0.0316)	(0.0262)
2-Year Yield Change		-0.0284	-0.0266	-0.0336		0.00760	0.00424	-0.00631		0.0115	0.0186	0.0273
		(0.0262)	(0.0263)	(0.0225)		(0.0246)	(0.0246)	(0.0150)		(0.0223)	(0.0214)	(0.0164)
10-Year Yield Change		0.0155	0.0118	0.0163		-0.0111	-0.00427	0.0130		0.00721	-0.00666	-0.0217
		(0.0224)	(0.0230)	(0.0197)		(0.0211)	(0.0215)	(0.0131)		(0.0190)	(0.0186)	(0.0144)
NFP Surprise				-0.0799				0.0926***				-0.0608*
				(0.0511)				(0.0341)				(0.0337)
S&P500 Returns				0.715***				-0.161				0.321***
				(0.162)				(0.108)				(0.112)
ADS Index				-0.506***				-0.786***				0.173***
				(0.121)				(0.0803)				(0.0323)
Constant	-0.166	0.136	0.104	0.0823	0.102	-0.0924	-0.0325	0.161*	-0.227*	-0.102	-0.215	-0.256**
	(0.154)	(0.157)	(0.163)	(0.142)	(0.137)	(0.148)	(0.152)	(0.0948)	(0.117)	(0.133)	(0.132)	(0.104)
Observations	103	103	103	103	103	103	103	103	104	104	104	104
Adjusted R^2	0.051	0.172	0.176	0.435	0.059	0.078	0.097	0.685	0.123	0.039	0.132	0.519

Notes: We estimate the response of Blue Chip Economic Indicators forecast revisions for GDP, the unemployment rate (UR), and the GDP price deflator to FOMC information using data from 2000 to 2022. We keep a forecast revision only if there is an FOMC meeting between forecasts, and if there are two FOMC meetings, we keep only the information from the most recent meeting. We drop forecast revisions higher than 10 standard deviations from the mean. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

SOURCE: Authors' calculations based on Bloomberg Finance LP, Bloomberg Terminals (Open, Anywhere, and Disaster Recovery Licenses), Blue Chip Economic Indicators, the Aruoba-Diebold-Scotti Business Conditions Index, Twitter, and FOMC statements from www.federalreserve.gov.

Table A6: Forecast of FOMC Monetary Policy Stance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel A: Sentiment, Expectations and the State of the Economy								
FOMC Sentiment	0.168***								
	(0.027)								
Press Conference Sentiment		0.0350**							
		(0.017)							
Twitter Sentiment			0.138***						
			(0.026)						
FFF Expectations				0.232***					
				(0.050)					
Eudodollar Expectations					-0.018				
					(0.44)				
BC Expectations						0.146***			
						(0.039)			
Δ UR Gap							-0.010		
							(0.007)		
Inflation Rate								0.018	
								(0.020)	
ADS Index									0.009
									(0.006)
Observations	119	119	119	119	119	119	119	119	119
Pseudo R^2	0.256	0.021	0.164	0.175	0.001	0.095	0.011	0.004	0.012
	Panel B: Past Monetary Policy Actions, the State of the Economy, Financial Variables, Uncertainty								
EBP	-0.116***								
	(0.032)								
Inverse Yield Curve		-0.167***							
		(0.36)							
Recession			-0.166***						
			(0.036)						
FFR				-0.110**					
				(0.044)					
Δ Monetary Policy					0.220***				
					(0.043)				
5-Year Yield						0.008			
						(0.040)			
Δ 5-Year Yield							0.120***		
							(0.029)		
PD Ratio								0.018	
								(0.033)	
VIX									-0.122***
									(0.029)
Observations	119	119	119	119	119	119	119	119	119
Pseudo R2	0.090	0.098	0.092	0.033	0.144	0.000	0.097	0.001	0.138

Notes: We estimate an ordered probit to forecast monetary policy decisions from 2000 to 2021. The dependent variable is an indicator variable equal to -1, 0, 1 according to whether the FOMC decreased, left unchanged or increased the federal funds target rate (FFTR) or announced other unconventional policies that were tightening, neutral or easing. The table reports marginal effects on the probability of tightening for a one standard deviation increase in the independent variable, if the variable is continuous, and for an increase from 0 to 1, if the variable is an indicator variable. All of the independent variables are lagged as of the day before the FOMC meeting, except for the FOMC statement, press conference and news sentiment indexes, FFTR, and change in monetary policy stance, which are based on the most recent FOMC statement. For a detailed definition of the independent variables refer to Table A1. The change in monetary policy is the monetary policy stance variable as of the last FOMC meeting. ELB denotes the effective lower bound period. Standard errors are in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

SOURCE: Authors' calculations based on Bloomberg, Blue Chip Financial Forecasts, the Center for Research in Security Prices (CRSP), the Congressional Budget Office, the Federal Reserve Bank of Philadelphia, the Aruoba-Diebold-Scotti Business Conditions Index, the Favara et al. (2016) EBP update, Twitter, and FOMC statements from www.federalreserve.gov.

Table A7: Forecast of FOMC Monetary Policy Stance: Horse Race

	(1)	(2)	(3)
FOMC Sentiment	0.124***		0.160***
	(0.029)		(0.023)
Press Conference Sentiment	-0.016		-0.029**
	(0.015)		(0.013)
Twitter Sentiment	0.080***	0.050*	0.031
	(0.025)	(0.027)	(0.024)
FFF Expectations		0.077	0.095*
		(0.066)	(0.053)
Eudodollar Expectations		0.143	0.104
		(0.127)	(0.102)
BC Expectations		0.007	-0.008
		(0.040)	(0.035)
Δ UR Gap		-0.019*	-0.013
		(0.010)	(0.010)
Inflation Rate		0.035*	0.033**
		(0.019)	(0.014)
ADS Index		-0.041***	-0.029***
		(0.011)	(0.009)
EBP		0.001	-0.035
		(0.051)	(0.044)
Inverse Yield Curve		-0.027	-0.019
		(0.113)	(0.090)
Recession		-0.135**	-0.107
		(0.058)	(0.078)
FFR		-0.346***	-0.439***
		(0.130)	(0.112)
Δ Monetary Policy	0.056	0.004	-0.108**
	(0.043)	(0.048)	(0.045)
5-Year Yield		0.189**	0.269***
		(0.089)	(0.086)
Δ 5-Year Yield		0.023	0.026
		(0.032)	(0.028)
PD Ratio		0.033	0.039
		(0.033)	(0.028)
VIX		-0.124***	-0.047
		(0.040)	(0.034)
Observations	119	119	119
Pseudo R^2	0.326	0.470	0.643

Notes: We estimate an ordered probit to forecast monetary policy decisions from 2000 to 2020. The dependent variable in columns (1) and (2) is an indicator variable equal to -1, 0, 1 according to whether the FOMC decreased, left unchanged or increased the federal funds target rate (FFTR) or announced other unconventional policies that were tightening, neutral or easing. The dependent variable in columns (3) and (4) is the federal funds target rate change. The table reports marginal effects on the probability of tightening (columns 1-2) or of 25 basis point increase (columns 3-4) for a one standard deviation increase in the independent variable, if it is continuous, and for a change from 0 to 1, if it is an indicator variable. All of the independent variables are lagged as of the day before the FOMC meeting, except for the FOMC sentiment index, FFTR, and change in monetary policy stance, which are based on the most recent FOMC statement. For a detailed definition of the independent variables refer to Table A1. The change in monetary policy is either the monetary policy stance variable as of the last FOMC in columns (1) and (2) or the change in the federal funds target rate in columns (3) and (4). ELB denotes the effective lower bound period. Standard errors are in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

SOURCE: Authors' calculations based on Bloomberg, Blue Chip Financial Forecasts, the Center for Research in Security Prices (CRSP), the Federal Reserve Bank of Philadelphia, the Aruoba-Diebold-Scotti Business Conditions Index, the Favara et al. (2016) EBP update, the Congressional Budget Office, Twitter, and FOMC statements from www.federalreserve.gov.

Table A8: Forecast of FOMC Monetary Policy Stance: Sentiment and Financial Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ Monetary Policy										0.207
										(0.247)
FOMC Sentiment	0.551***									0.352**
	(0.144)									(0.176)
Press Conference Sentiment		0.0517								-0.187
		(0.0842)								(0.119)
Twitter Sentiment			0.791***							0.667***
			(0.167)							(0.207)
Δ 3-Month Yield				0.670***						0.316
				(0.139)						(0.441)
Δ 6-Month Yield					0.598***					-0.121
					(0.145)					(0.500)
Δ Eurodollar						0.0834				-0.334
						(0.149)				(0.280)
Δ 2-Year Yield							0.201			0.471
							(0.125)			(0.335)
Δ 5-Year Yield								0.122		0.133
								(0.130)		(0.717)
Δ 10-Year Yield									0.0653	-0.282
									(0.113)	(0.511)
Observations	119	119	119	119	119	119	119	119	119	119
Pseudo R^2	0.100	0.002	0.174	0.144	0.102	0.002	0.015	0.005	0.002	0.295

Notes: We estimate an ordered probit to forecast monetary policy decisions from 2000 to 2020. The dependent variable in columns (1) and (2) is an indicator variable equal to -1, 0, 1 according to whether the FOMC decreased, left unchanged or increased the federal funds target rate (FFTR) or announced other unconventional policies that were tightening, neutral or easing. The dependent variable in columns (3) and (4) is the federal funds target rate change. The table reports marginal effects on the probability of tightening (columns 1-2) or of 25 basis point increase (columns 3-4) for a one standard deviation increase in the independent variable, if it is continuous, and for a change from 0 to 1, if it is an indicator variable. All of the independent variables are lagged as of the day before the FOMC meeting, except for the FOMC sentiment index, FFTR, and change in monetary policy stance, which are based on the most recent FOMC statement. For a detailed definition of the independent variables refer to Table A1. The change in monetary policy is either the monetary policy stance variable as of the last FOMC in columns (1) and (2) or the change in the federal funds target rate in columns (3) and (4). ELB denotes the effective lower bound period. Standard errors are in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

SOURCE: Authors' calculations based on Bloomberg, Blue Chip Financial Forecasts, the Center for Research in Security Prices (CRSP), the Federal Reserve Bank of Philadelphia, the Aruoba-Diebold-Scotti Business Conditions Index, the Favara et al. (2016) EBP update, the Congressional Budget Office, Twitter, and FOMC statements from www.federalreserve.gov.