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Gauging the Sentiment of Federal Open Market Committee Communications through the Eyes of the Financial Press*

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July 3, 2025

Abstract

We apply natural language processing tools to news articles in the financial press to construct a sentiment index — an index of the perceived semantic orientation of monetary policy communications around scheduled Federal Open Market Committee (FOMC) meetings. To that end, we develop several dictionaries that capture various monetary policy tools: conventional monetary policy, asset purchases, and forward guidance. The surprises in the sentiment index around FOMC meetings announcements explain variation in major asset prices classes between May 1999 and November 2022. Sentiment index surprises are important for explaining the variation in asset prices beyond monetary policy surprises.

JEL Classification: E00, E40, E58, G12
Keywords: Textual analysis, semantic orientation, sentiment index, Federal Reserve, FOMC, hawkish, dovish, asset prices, policy expectations, conventional monetary policy, asset purchases, forward guidance, zero-lower-bound, COVID.

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1 Introduction

Over the past decades, central bank communications have changed significantly as central banks around the world have put more and more emphasis on transparency. For example, through the early 1990s, monetary policy decisions by the Federal Reserve's Federal Open Market Committee (FOMC) were not announced to the public. As such, market participants had to infer whether the FOMC had changed its policy stance from the open market operations conducted by the Federal Reserve Bank of New York. In contrast, currently the FOMC uses a wide range of communication tools — including policy statements and press conferences following the conclusion of each FOMC meeting, the release of the Summary of Economic Projections (SEP) at every other meeting, as well as testimonies and speeches by the Fed Chair and FOMC members — to convey its views on U.S. economic developments and its monetary policy stance. Other central banks around the globe have similarly increased their transparency over time.

Consequently, central bank communications are constantly in the spotlight and heavily scrutinized by various media outlets, in particular, by the financial press. As then-member of the Federal Reserve Board and FOMC Ben Bernanke emphasized in his remarks during the American Economic Association meeting (Bernanke, 2004) "*... because the world is complex and ever changing, policy actions alone, without explanation, will never be enough to provide the public with the information it needs to predict policy actions. Words are also necessary.*" Not surprisingly, the variation in the tone, or sentiment, of central banking communications has attracted a lot of attention among academic researchers and market participants alike.

Our paper is related to the literature on central banking communications (see, e.g., Woodford, 2005; Blinder et al., 2008, for a comprehensive overview). More recently, the relevant literature particularly focused on the bag-of-words approach. The studies include, for example, Baker et al. (2016) who relate frequency of relevant words related to economic policy uncertainty, whereas Husted et al. (2020) similarly construct monetary policy uncertainty index, and Caldara and Iacoviello (2022) construct the geopolitical risk index. A specific part of this literature is related to measurement of semantic orientation of central bank communications. This literature falls into two broad categories: Researchers in this area use natural language processing (NLP) tools to study either the textual content of direct central banking communications (Romer and Romer, 2004; Meade et al., 2015; Acosta and Meade, 2015; Cannon, 2015; Hansen et al., 2018; Gardner et al., 2022; Acosta, 2023; Schmeling and Wagner, 2025) or public perceptions and interpretations of the central bank communications (Lucca and Trebbi, 2009; Carvalho et al., 2016; Schmanski et al., 2023).[1] Our work falls into the second category.

[1] Schmanski et al. (2023) uses both direct communications and news articles, including Twitter, to measure monetary policy surprises related to sentiment.

Recent work on semantic orientation of central bank communications is part of a much larger and rapidly growing literature in economics and finance that focuses on extracting quantitative signals and measures from a range of sources containing written words, with applications to constructing uncertainty measures (e.g., Baker et al., 2016; Husted et al., 2020), predicting stock returns (Born et al., 2014; Azar and Lo, 2016; Heston and Sinha, 2020), predicting future firm earnings (Druz et al., 2020), measuring the value of economist forecasts (Sharpe et al., 2023), and — economic sentiment (Shapiro et al., 2022), among many others.[2]

In this paper, we contribute to the textual analysis literature that focuses specifically on central bank communications by constructing an index that measures semantic orientation of perceived FOMC communications around FOMC meetings. In particular, we construct a sentiment index (SI) from a corpus of relevant published articles collected from the premier news resource Dow Jones Factiva. The corpus of articles for our study consists of all relevant news articles from six major financial press outlets published in event windows of different lengths around FOMC meetings between May 1999 and November 2022. There are two benefits of assessing sentiment of policy communications via press articles. The first one is that it allows us to circumvent the complex task of assessing the sentiment of direct Fed communications, as official FOMC communications are notably complex and have become more complex over time (see, e.g., Hernandez-Murillo and Shell, 2014). The second one is that looking at the media articles before and after the FOMC meetings allows us to construct surprises in the sentiment and relate these surprises to changes in asset prices around FOMC communications — something that is not possible to do when looking only at the FOMC released statements.

Our sample period starts from the May 1999 FOMC meeting and ends with the November 2022 FOMC meeting. Thus, it includes diverse periods of monetary policy communications: the GFC, following zero-lower-bound period, subsequent monetary policy normalization, the COVID-19 pandemic and post-pandemic periods. As we discuss later, the presence of these periods in our sample also reveals the limitations of many existing methodologies used to assess the sentiment of FOMC communications, particularly the lack of words for capturing hawkish and dovish sentiment associated with forward guidance and asset purchases.

To address ever increasing complexity in monetary policy communications, our approach differs from existing studies in novel and significant ways. First, we collect the relevant stories from Dow Jones Factiva. Then we categorize the stories into four *topic-keywords* categories, based on general mentions of the monetary policy by the financial press (*General*), or specific mentions of monetary policy conduct in various regimes, whether they are related to conventional monetary policy (*Policy Rates*), or to unconventional policies such as asset purchases or forward guidance,

[2]A recent overview and introduction to the use of "text" as an input to economic research is given in Gentzkow et al. (2019).

naturally called (*Asset Purchases*) and (*Forward Guidance*). Second, we create *modifier-keywords* dictionaries related to each of the topic-keywords category. Modifier-keywords, in general, reflect and determine semantic orientation of topic-keywords (such as hawkish or dovish characterization of topic-keywords) based on the monetary policy actions and tools related to each topic. This distinction appears to us extremely important as different monetary policy regimes may (will) have different modifiers that characterize tightening or easing stance in the monetary policy. As one of the most obvious examples, a hawkish characterization of the monetary policy (e.g., *increase [rates]*) during the conventional monetary policy regime when the Fed is using the fed funds rate as its main policy tool may become dovish characterization during the unconventional monetary policy regime (e.g., *increase [purchases]*) when asset purchases become one of the main tools, as during Large Scale Asset Purchase (LSAP) programs during the Global Financial Crisis (GFC). Third, we construct the sentiment index (SI) for each relevant story. This allows us to account for the length of a story and to weigh the frequency of modifier-keywords in each individual story, giving larger weights to stories that have a substantive discussion of the FOMC's expected or realized policy stance compared to stories where the policy action is barely mentioned. We then aggregate the SIs of individual stories in the FOMC-specific SI in the window that starts on Monday of the week of the FOMC and ends at midnight on Wednesday after the FOMC.[3] Fifth, we use a more elaborate set of rules to deal with the complexity of text and in particular how to handle verb tenses, and negations that can change the meaning of hawkish words to dovish and vice versa.

In the second part of our paper we gauge the SI informational content. To do so, we use SI changes around the FOMC statement release time as a measure of sentiment surprises and in a simple linear regression framework, we examine whether surprises in SI help explain movements in a range of asset prices in arrow event windows around the releases of the FOMC statements.[4] We find that they do. Our empirical results indicate that SI performs reasonably well in terms of explaining movements in prices of money market futures contracts, nominal and inflation-linked Treasury securities, equity indexes, and foreign currency pairs, all of which are measured in the narrow intraday event windows around FOMC meetings. Moreover, they do so even after we control for the presence of monetary policy surprises, based on (see, e.g., Bauer and Swanson, 2023). Our results are robust to controlling for the Global Financial Crisis (GFC) and for the zer-lower-bound (ZLB) period.

We also analyze SI informational content separately during several subsample periods and report these results in Appendix B. These subsample periods are the pre-GFC sample 1999-2009, un-

[3]As a robustness exercise, we consider several other time frames around FOMC communications, over which we collect and score our stories.

[4]In recent years, the SEP have been released at the same time with the FOMC statement. See Appendix A for more details.

conventional monetary policy periods of 2009-2015, the COVID-19 pandemic, and post-pandemic sample 2020-2022. We find that most of the explanatory power of SI surprises is concentrated in the pre-GFC period, and we also find that SI surprises have explanatory power during the post-COVID period. Our index is relatively mute during the unconventional monetary policy period. This result may be attributed in part to the fact that policy communications became notably more transparent in our second sample period: In April 2011 the Federal Reserve then-Chairman Bernanke started conducting press conferences following the conclusions of the FOMC meetings after every other meeting, and Chairman Powell currently conducts press conferences after conclusion of every FOMC meeting.

In addition to comparing our index's ability to explain asset price movements in narrow windows around FOMC meetings, we also compare the performance of our SI to several alternative indexes developed by other researchers, mostly at other central banks. We reconstruct the methodologies of Lucca and Trebbi (2009, developed at the Federal Reserve Bank of New York), Cannon (2015, developed at the Federal Reserve Bank of Kansas City), Carvalho et al. (2016, developed at the Federal Reserve Bank of San Francisco), Apel and Grimaldi (2012, developed at the Riksbank), and Nyman et al. (2018, developed at the Bank of England). We compare the various indexes and assess their informational content for explaining asset price movements.

The rest of the paper is organized as follows. Section 2 describes the financial press stories and the financial market data sets. Section 3 describes our methodology and construction of our FOMC communications sentiment index, Section 4 discusses our index in terms of both its level and its surprises, Section 5 discusses our regression results with the index surprises and provides a comparison with other indexes, and Section 6 concludes.

2 Data

2.1 Factiva corpus of relevant media articles

Our sample starts with the May 1999 FOMC meeting when the Committee first began issuing statements following each FOMC meeting, irrespective of whether the Committee had changed the stance of monetary policy or not.[5] Our sample ends with the November 2022 FOMC meeting. In total, there are 188 scheduled FOMC meetings in our sample.[6]

[5] Prior to May 1999, the FOMC only released a statement when it had decided to change the stance of monetary policy. The FOMC began to do so following the February 4, 1994 meeting. Before that, the FOMC had not issued any statements at all.

[6] The FOMC meeting calendar and FOMC statements can be found at `https://www.federalreserve.gov/monetarypolicy/fomccalendars.htm`. During our sample period the FOMC has also held several unscheduled meetings. We did not include these in our analysis, because our methodology requires to have news stories published the before the FOMC statement release in order to construct the surprise in press sentiment around FOMC

We select corpus for our study from articles available in Dow Jones Factiva, a global news database that contains content from over 30,000 sources, including licensed publications, websites, and blogs. We focus on six outlets: the *Associated Press*, the *Financial Times*, the *New York Times*, *Reuters News*, the *Wall Street Journal* (both in print and online), and the *Washington Post*. The reason for this specific and, arguably, limited selection of sources is that these major outlets had consistently covered central banking communications since the start of our sample in 1999.[7]

The following Factiva filters are used to select a corpus for our study. First, for the paper to be included in our sample, it must contain one or more of the following keywords: *FOMC, Federal Reserve, or Federal Open Market Committee.* Second, we exclude stories that discuss non-financial industries (or industries not directly related to the financial sector), such as agriculture; automotive; basic materials and resources; energy; health care and life sciences; industrial goods; leisure, arts and hospitality; media and entertainment; real estate and construction; retail and wholesale; technology; telecommunication services; transportation and logistics; utilities; and consumer goods. Third, we exclude articles published in all regions other than the United States.

We select Factiva stories in a five-day window around each FOMC statement release, from Sunday midnight to Friday midnight of the week when the FOMC meeting takes place. We then narrow down the event window to four alternative shorter windows over which we select stories for the SI construction. Figure 2 shows the timeline for each event window around the FOMC statement release on Wednesday at 2:00 p.m.[8]

The starting time for each event window is Sunday midnight. The set of stories that fall within the window from Sunday midnight to the release of the statement constitutes our sample of "before stories" (indicated by the red section of the timelines in Figure 2). — stories written before the release and should contain expectations about the upcoming FOMC communications. The end time of considered event windows varies: midnight on Thursday, midnight on Wednesday, close-of-business on Wednesday, and 30 minutes after the release on Wednesday. Naturally, these "after" windows have increasingly fewer stories in them (indicated by the blue section of the timelines in Figure 2).[9]

statement releases.

[7] Although our smaller set goes against the typical big data principle that more data tends to be better, we chose the smaller set of sources for their full-sample availability. In this way, we potentially reduce the presence of noise by excluding minor and less relevant news outlets. Furthermore, because we had to manually collect stories from Factiva, we leave testing of our index methodology on Factiva's full set of sources for further research.

[8] We refer to the statement release day and time as Wednesday 2:00 p.m. for simplification in this Figure. However, the day and the timing of the releases of FOMC statements varied in our sample. We account for this details on our calculation of the sample and provide these details in Appendix A.

[9] We consider the stories in our sample that are published exactly at the time of the statement release (in the case of Figure 2, at 2:00 p.m.), as the ones published *after* the release as they were most likely written during the embargo period when certain members of the press already had access to the FOMC statement.

Our preferred event window is the middle one in the picture. It starts on Sunday midnight and ends on the FOMC meeting day midnight. This event window provides a reasonable balance between having stories that specifically describe the post-FOMC policy stance (and not affected by other events or shocks, such as macroeconomic releases that may sway the sentiment in wider windows shown in the top and second top of the Figure) and having a sufficient number of stories in the "after" window to create an after-SI.

Table 1 reports the number of stories for each of these event window specifications. The first line in each panel of this table reports the total number of stories downloaded from Factiva for six outlets and the number of stories for individual outlets in the corresponding event window. The second line reports the number of stories after we remove duplicate stories.[10] The third line reports the number of stories in the corpus after we remove time non-stamped stories on the day of the FOMC, because they cannot be used in constructing surprises in the SI. The fourth and final line in each panel reports the number of remaining relevant stories — the stories that contain at least one of the words defined in the dictionary of entity words from table 2 and at least one of the topic keywords from table 3. In our preferred event window (from Sunday midnight to Wednesday midnight, reported in Panel C), our search criteria and filters result in a total of 8,878 stories released around the 188 FOMC meetings in our sample. On average, there are about 47 news stories per meeting from which we derive the FOMC-specific SI.

Figure 3 shows granular information about the composition of our corpus. The stacked bars in Panel A shows the total number of stories per media outlet for each individual FOMC meeting. In general, we observe that the coverage of FOMC meeting-related news is quite dense. Press coverage of the FOMC communications increased dramatically during the financial crisis and again towards the end of 2015, when the FOMC began its most recent tightening cycle. Panel B provides information about the average number of stories per FOMC meeting per each individual media outlet. In our sample, *Reuters News* has the most number of stories per meeting, on average, followed by the *Associated Press*, then the *Wall Street Journal*, the *Financial Times*, the *New York Times*, and lastly the *Washington Post*.

Figure 4 shows the distribution of the published stories over the 10-hour window followed by the release of the FOMC statement for *Reuters News*, *Associated Press*, and the *Wall Street Journal*. The vertical grey bar indicates the timing of the press conference. Our post-meeting window captures a good amount of after stories, especially for *Reuters News* stories. As top panel shows, *Reuters News* mostly releases publications in the first half an hour after the statement release, while the peak of the stories published by *Associated Press* and the *The Wall Street Journal* occurs

[10] We define duplicates as stories with identical metadata, i.e., stories that have identical authors, titles, and an outlet. If the metadata is the same, we then check the cosine similarity of the frequency of words used in the story. If the cosine of the frequency vectors is greater than 0.95, then we flag the story as duplicate and remove it.

approximately between two to four hours of the statement release, as the middle and the bottom panels show.[11]

2.2 Financial market data

We examine variation in several asset classes in relation to SI surprises and monetary policy (MP) surprises. For policy sensitive rates, we use implied rates on federal funds (FF) futures contracts one to six months ahead and Eurodollar (ED) futures contracts 1 to 4 quarters ahead. For nominal Treasury securities, we use yields on 3- and 6-month Treasury bills, as well as yields for 2-, 5-, 10-, and 30-year on-the-run nominal Treasury securities. For real rates, we use 5- and 10-year yields on Treasury Inflation-Protected Securities (TIPS). We also look at 5-, 10-year, and 5-year 5 years ahead inflation compensation, defined as the difference between nominal and TIPS yields of comparable maturities. For equity prices, we use Standard & Poor's (S&P) 500 and NASDAQ Stock Market equity indexes. Finally, we also look at the responses of Bloomberg's DXY dollar index, as well as the euro-dollar (EURO), and yen-dollar (YEN) currency pairs.[12] We look at the intraday changes in these securities around the FOMC statement releases. All intraday data is from Bloomberg. We examined three intraday windows in measuring changes in asset prices: a tight event window, defined as the change in quotes 10 minutes before the release of the FOMC statement to 20 minutes afterwards; a wide event window, defined as the change in quotes 15 minutes before the release of the FOMC statement to 45 minutes afterwards; and a close-of-business (COB) window, defined as the change in quotes 10 minutes before the FOMC statement release to close-of-business (COB), which we take as 3:45 p.m. Tight and wide windows follow Gurkaynak et al. (2005). The COB window also captures the market reaction to the post-meeting press conference in the second half of our sample. Our main results below are presented for the tight event window.[13]

3 Methodology

In this section we discuss how we build our corpus of relevant articles from the financial press and, from that, construct our FOMC communications sentiment index.

In Section 3.1 we discuss the construction of SI: Specifically, we outline a selection of entity

[11] We find that after the FOMC day and up to the end of the FOMC week, a significant number of additional stories that cover monetary policy communications, become available. However, these stories are outside of our preferred window.

[12] The DXY dollar index is defined as the spot U.S. dollar (USD) rate relative to a weighted average of six major currencies (euro, Japanese yen, British pound, Canadian dollar, Swedish krona, and the Swiss franc).

[13] Results that use wide and COB event windows are used as robustness checks. They are not reported but available upon request.

keywords that determine relevant sentences in the stories, a selection topic and modifier keywords, we describe how we determine the backward-looking and forward-looking sentences, and how we deal with negations. In Section 3.2 we discuss how we construct sentiment surprises.

3.1 Sentiment index construction

We process each story in our sample separately as we find first relevant sentences in each story. For each story we first remove stop words and punctuation and then lemmatize the remaining words, as it is commonly done in the NLP literature. Specifically, we use the `WordNetLemmatizer` available in the Natural Language Toolkit (NLTK) module in Python.[14] As the first step, we find sentences that contain entity words. If the sentence contains an entity word, we look for a topic-specific keyword. Next, if the sentence also contains a topic-specific keyword, we look whether the temporal orientation (backward- or forward-looking) is correct (according to whether the sentence is belongs to the story in the before- or the after-FOMC category) following the appropriate dictionary. If it is correct, we keep this relevant sentence, if not, we discard it. We then look for modifier keywords from the topic-specific dictionary and negotiations that change the semantic orientation of the modifier. Figure 1 presents the summary of these methodological step. Below, we describe these steps in detail:

Entity keywords. Table 2 reports the entity keywords and their overall count in our sample. We apply entity words to search for relevant sentences. For our analysis we keep only those sentences in the stories that have at least one entity word in them. The entity words are supposed to ensure that the topic that we are picking is related to monetary policy communications specifically. Most common entity words are *fed*, *federal reserve*, and *official* found 21,465, 5,715, and 2,735 times, respectively, in our sample.

Topic keywords. After the sentences that contain the entity keywords have been selected, we search for the topic-specific keywords in these sentences. We build a separate dictionary for a separate topic. There are a total of four dictionaries associated with four topics, specifically: *General*, *Policy Rates*, *Asset Purchases*, and *Forward Guidance*. Table 3 reports the topic-specific keywords in four dictionaries and their count in the sample. The topic keywords are used as a context-switching tool that next point to a specific dictionary for modifier keywords (which we characterize as either hawkish or dovish words). As was discussed in Section 1, the verb *increase* can have a hawkish meaning in a policy-rate context, whereas it can have

[14] For a description of NLTK `WordNetLemmatizer` module, see https://www.nltk.org/_modules/nltk/stem/wordnet.html and Miller (1995).

a dovish meaning in an asset- purchases context.[15] As table 3 reports, the *Policy Rates* dictionary has 25,167 keywords followed by the *General* dictionary (16,147 keywords), then by the *Asset Purchases* dictionary (9,555 keywords), and, finally, by the *Forward Guidance* dictionary (4,229 keywords).

Forward- and backward-looking rules. Once we determined to which topic a particular sentence belongs, we look at the temporal allocation of this sentence, namely, whether the sentence is forward- or backward looking. We proceed as follows. First, we divide all stories around each FOMC meeting into those that occur before the meeting — *the before-stories* — and those that occur after the meeting — *the after-stories* — by looking at the date and the time stamp of each story. Next, we apply a classification function to ensure that the *before* stories reflect only forward-looking information. However, we keep relevant sentences with both backward- and forward-looking directionality in the *after* stories to reflect the surprise about the past meeting as well as surprises about expected future policy actions (a so-called *path* surprise). Thus, the *before* stories should reflect only expectations about upcoming and future meetings at t, $t+1$, $t+2$, and so on. While, the *after* stories should reflect both information about the most recent meeting or policy action at time t as well as the path surprise about the meetings at $t+1$, $t+2$, and so on.[16] To determine the directionality of a particular sentence, we have two dictionaries of words that are used to classify a sentence as either forward- or backward- looking. These dictionaries are listed in table 5. For forward-looking classification of sentences, we run two independent checks:

- If a sentence has any word that is in our forward-looking dictionary, it is classified forward-looking.
- If a sentence has a modal verb (*will, could, might, may, should, can, and must*) — not accompanied by another verb in past tense (e.g., *could have*) — it is classified as forward-looking.

For backward-looking classification of sentences, we run three checks:

- The sentence must not have been classified as forward-looking.
- If the sentence has a word in our backward-looking dictionary, it will be classified as backward-looking.
- If a sentence has a past-tense verb, it will be classified as backward-looking.

[15] This is in contrast to Gardner et al. (2022) who keep the same modifier-keywords dictionary for each topic-keyword they study.

[16] Also here our methodology differs from Lucca and Trebbi (2009) who simply drop the past tense to remove any reference to the policy action at time t in all of their stories.

If a sentence is not classified as either forward- or backward-looking, it is dropped and not considered relevant.

Modifier keywords and negations. Table 4 reports the counts of each of the hawkish and dovish words in the sample. They are grouped by the context. Conditional on the context-switch, hawkish words increase the sentiment of a story (leaning towards more positive SI), while dovish words decrease the sentiment of a story (leaning towards more negative SI). For each modifier dictionary, we also report the total number of negations that would switch hawkish characterization into dovish characterization and vice verse. Words like *not*, and verbs than end with *n't* make up most of the negation phrases that occur in our corpus. Our strategy for handling negations is simple: the sentence is searched up to three words before the modifier word, and if a negation is detected, the orientation of the modifier word is flipped (multiplied by -1). Similar to negations, the polarity of nearby words may flip the meaning of a modifier word but we did not find that polarity checks changed our results.[17]

Using a set of relevant sentences defined above in a story s that has W_s words in total, and H_S and D_s hawkish and dovish words, we construct a sentiment score SL_S for each story as:

$$SL_s \equiv \log\left(\frac{H_s}{W_s}+1\right) - \log\left(\frac{D_s}{W_s}+1\right) = \log\left(\frac{W_s+H_s}{W_s+D_s}\right) \tag{1}$$

with SL_s the sentiment level for story s and W_s the total number of words in the story.[18] We have thus defined SL_s as the log-difference between the number of hawkish and dovish words relative to the length of the story.

We then define the overall sentiment index level for meeting t as the average of the story-specific sentiment levels SL_s during the chosen time window:

$$SI_\tau \equiv \frac{1}{N_\tau}\sum_{s\in S_\tau} SL_s \tag{2}$$

In constructing our sentiment index this way we score each story separately therefore and weight stories equally. As a result, our approach is different from many studies in the literature that do not distinguish between stories and simply use a bag-of-sentences approach where sentences are

[17] For example, consider a hypothetical sentence "The Fed failed to raise rates." The verb *raise* by itself is hawkish, but the preceding negative polarity word *failed* changes the meaning of the phrase to being dovish. In contrast, if one of the modifier keywords is preceded by a positive polarity word, the meaning of a that modifier will not be changed. As an example, consider the hypothetical sentence "The Fed successfully raised rates". Here the adjective *successfully* has positive polarity. Therefore, it will be ignored. In our corpus, there were very few instances of modifier orientation changes based on polarity (via Loughran and McDonald (2011) dictionary). The index does not significantly change based on the presence or absence of a polarity check or changing polarity dictionaries.

[18] We add one in the log function to preclude situations where a story has only hawkish or only dovish words.

weighed equally in the overall corpus. Instead, for each story we weight the number of hawkish or dovish words by the total number of words in the story. We find such a weighting scheme more intuitive as it takes into account the context of the story in which hawkish and dovish words appear. For example, once would expect a single relevant hawkish or dovish sentence in an otherwise irrelevant story to be less informative about perceived FOMC sentiment than a story of the same length that contains multiple relevant sentences.

3.2 Sentiment index surprises construction

Whereas we average over all the stories in a window for determining the sentiment *level*, for the *surprises* in the SI index we distinguish between the stories published before and after the FOMC statement release. In particular, we compute SI surprise as the difference between SI_{before} and SI_{after}, the SI levels computed for the corpus stores published before the FOMC statement release and afterwards in a specific window:

$$\Delta SI_\tau \equiv SI_{after} - SI_{before} = \frac{1}{N_{after}} \sum_{s \in S_{after}} SL_s - \frac{1}{N_{before}} \sum_{s \in S_{before}} SL_s, \tag{3}$$

with S_{before}, N_{before} and S_{after}, N_{after} referring to the set and the number of *before* and *after* stories, respectively, for a meeting τ.

In computing surprises (3) we discard all stories from our sample that are released on the day of the FOMC statement without a time stamp. We do so because we cannot determine with certainty whether a particular article came out before or after the statement release. The third rows in each of the panels of table 1 shows the effect to the size of the our corpus of filtering out these time-non-stamped stories.[19]

4 Sentiment index and surprises

Figure 5 shows the SI level in Panel A and SI surprises in Panel B, following the base-case event window from midnight on Sunday to midnight on the day of the statement release. For illustrative purposes, index levels in Panel A are scaled to be between -1 and 1, with zero indicating a neutral sentiment stance, and -1 the most dovish sentiment level across all FOMC meetings. Surprises in Panel B are standardized and expressed in standard deviation units. The grey bars represent NBER-identified recessions.

[19] In our five-day corpus of no-duplicate stories, there are 11 stories out of 18,271 stories that are not time stamped on the same day as the FOMC statement release, which constitutes only about 0.06 percent of our sample. Note that the lack of an accurate release time is specific to the *Financial Times* and the *New York Times*. Stories from all other outlets tend to be properly time-stamped.

The level of our index appears to accurately captures the state of the business cycle and the stance of monetary policy during that cycle. Prior to recessions, the stance of monetary policy is perceived as hawkish as the FOMC is hiking rates. However, when a recession approaches, sentiment about the FOMC's policy stance quickly turns sharply dovish and bottoms out during recessions as the FOMC aggressively cuts rates and then keeps rates low to spur an economic recovery. There are two interesting periods to highlight in particular.

First, during the ZLB period approximately from 2010 to late 2014, the sentiment index hovers around neutral. This is somewhat surprising given that the FOMC actively used a range of accommodative policy tools during that period, in particular, asset purchases and forward guidance. It is likely that this period was also marked by an increasing number of central banking communications aimed to clarify the policies and increase transparencies.

Second, at the end of the sample there is a sharp reversal in sentiment from being hawkish (positive sentiment) to becoming dovish (negative sentiment). That accurately coincides with the recent chances in the FOMC policy stance from tightening policy in 2018 to easing in 2019.[20] The SI subsequently reversed its trend and became positive when the Fed engaged in the aggressive post-COVID tightening cycle with the aim to curb historically high inflation. Interestingly, our sentiment index appears to lead U.S. recessions. It is falling to negative territories shortly before the start of recessions.

Sentiment index surprises similarly appear intuitive. Going into recessions the FOMC surprises markets on the dovish side. For example, in the middle and second half of 2018 and in the post-COVID period of 2022 we see more positive surprises, meaning that the financial press was surprised by the more-hawkish-than-expected stance of policy. This lines up well with financial market commentary around some of the FOMC meetings in the latter part of 2018.

5 Informational content of surprises in the SI

We next explore the informational context of our SI level surprises for explaining movements in a broad range of asset prices around the FOMC meetings. Our empirical setup is motivated by the findings of Bernanke and Kuttner (2005) who document that equity prices significantly react to changes in monetary policy. To that end, in our analysis we first gauge the reaction in policy-sensitive derivatives, such as money market futures rates, nominal and inflation-linked Treasury yields, measures of TIPS-based breakeven inflation, equity prices, and several currency pairs relative to the dollar, to changes (surprises) in the SI. Finding notable significance, we then run a second round of regressions where we control for traditional financial-market-based measures of monetary policy surprises.

[20] The Fed cut policy rates for the first time in ten years since 2009 at the July 2019 FOMC meeting.

5.1 Empirical results

Our benchmark regression is as follows. Let Δy_t be the change in policy-sensitive rates, yields, equity prices, or currency prices in the event window.[21] Again, in the base-case the event window runs from midnight on Sunday to midnight on the day of the FOMC meeting. We then regress

$$\Delta y_t = \alpha + \beta_1 \Delta SI_\tau + \beta_2 MP_t + \epsilon_t, \tag{4}$$

where MP_t is the monetary policy shock used in Bauer and Swanson (2023), measured as the orthogonalized monetary policy surprises in the first principal component of the one- to four-quarter ahead Eurodollar(ED) futures rates in the 30-minute window around the FOMC meeting announcements starting 10 minutes before each FOMC announcement and ending 20 minutes afterwards.[22] The stochastic error term ϵ_t captures the effect of other factors that influence the asset in question. The changes in asset prices are defined from intraday quotes in the same event window.[23]

We also include postGFC and ZLB dummy variables in our basic regressions, to account for different economic environments following the GFC and during ZLB periods:

$$\Delta y_t = \alpha + \beta_1 \Delta SI_\tau + \beta_2 MP_t + \lambda_{Event} + \epsilon_t, \tag{5}$$

where $\lambda_{Event} = \{\lambda_{postGFC}, \lambda_{ZLB}\}$. $\lambda_{postGFC}$ dummy is defined as one from the December 2008 FOMC meeting to the November 2022 FOMC meeting and zero otherwise and λ_{ZLB} dummy is defined as one from the December 2008 FOMC meeting to the October 2015 FOMC meeting and from the April 2020 FOMC meeting to the January 2022 FOMC meeting and zero otherwise. We run regressions (4) and (5) using SI and MP surprises. Sections 5.1.1 and 5.1.2 describe the results of tables 6 through 10. Panels A of these tables report regression results of various asset classes with respect to SI and MP surprises for the full sample period that correspond to regression (4) results. Panels B and C of these tables report regression (5) results, that account for either the post-GFC period or the ZLB bound, respectively. In addition, we report regressions (4) results for specific sub samples in Appendix B.

[21] Changes for rates are all recorded in basis points, while changes in equities and currencies are computed in percent.

[22] The orthogonalization is conducted with respect to changes in macroeconomic and financial variables around the FOMC window. The authors argue that such monetary policy surprises are a cleaner and a more informative measure of monetary policy surprises when information that is potentially related to changes in macroeconomic and financial variables around the FOMC announcement is removed from these surprises. For a detailed description of the MP_t measure, see Bauer and Swanson (2023).

[23] We also conducted robustness checks using the wider event window definition and obtained broadly similar results. Results are available upon request.

5.1.1 SI surprises and changes in policy-sensitive rates

Table 6 reports baseline regression results from (4) for the federal funds futures (FF1, FF2, ..., FF6) contracts one to six months ahead. The left-hand side variable of the regression (4) corresponds to changes in the federal funds futures contracts 10 minutes before to 20 minutes after the release of the FOMC statement. First, as panel A shows, the response of the fed funds futures contracts reflects the surprise in sentiment; the sentiment surprise coefficient β_1 is positive and statistically significant for fed funds futures contracts four to six months out (FF4 to FF6), despite a strongly significant coefficient for monetary policy surprise at all six horizons. In other words, positive (or, hawkish) sentiment surprises are associated with positive movements in future policy-sensitive rates and negative (or, dovish) sentiment surprises are associated with negative movements in future policy-sensitive rates. Second, the response of the fed funds futures contracts to a change in media sentiment following the FOMC announcement is statistically significant at the five-percent level for FF5 and FF6 and at the ten-percent level for FF4 contracts. The MP surprise drives out significance of the sentiment surprise for the very near term contracts, namely, FF1 through FF3, but not for contracts at longer horizons. Interestingly, the explanatory power of the sentiment and monetary policy surprises increases with horizon and notably higher at longer (FF4 through FF6) than ta the shorter (FF1 through FF3) horizons. Our results are robust to accounting for the GFC and ZLB dummies, which suggests that the results are not driven by these particular periods in our sample.

Table 7 reports results for the Eurodollar futures ED1 through ED4, one to four quarters ahead. These results broadly follow results reported in table 6, but these results are even stronger. The SI surprise is strongly significant for contracts ED2 through ED4 at the 1 percent level of statistical significance. Further, the SI surprise is not driven away by the MP surprises. The R^2 in these regressions is very high, from 67 to 76 percent, across horizons. Like in table 6, results in table 7 are robust when we account for the GFC or ZLB periods.

Overall, the results in tables 6 and 7 are consistent as they both point out to the significance of information contained in SI beyond the very near-term (ED2 to ED4 contracts). This suggests that SI surprises have a complimentary information for the "path" part of changes in the policy-sensitive rates, while MP surprises are the main driver in changes in the ED1 contract.

5.1.2 SI surprises and changes in other asset classes prices

Table 8 reports regression (4) results for nominal Treasury yields implied by the 2-, 5-, and 10-year Treasury futures contracts. We find that SI surprises around FOMC announcements are important for predicting movements in nominal Treasury yields at all considered horizons, despite strong significance of MP shocks and regardless of the sample period (that is, whether we control for the postGFC or ZLB periods, or not). The predictive content in both Si and MP diminishes with horizon as R^2 falls from about 70 percent for the 2-year Treasury futures contract to about 33 percent for the 10-year contract.

Table 9 reports regression results for one-the-run 5- and 10-year TIPS yields and 5- and 10-year inflation compensation as well as five-year fine-year ahead inflation compensation. SI surprises appear to explain movements in 5- and 10-year TIPS yields regardless of the sample period, but not in the inflation compensation series. Interestingly, MP surprises are strongly significant in explaining variation in TIPS yields but not in inflation compensation at any horizon. There are may be two reasons for that. First is a mechanical reason: both nominal yields and TIPS yields react to SI and MP surprises with similar regressions coefficients, especially for 5-year yields, so their effect on inflation compensation could be washed out because inflation compensation is defined as nominal minus TIPS yields of comparable maturities. Second reason is an economical one: insignificance of the MP and SI surprises for explaining changes in inflation compensation around the FOMC meeting announcements serves as an evidence of relatively well anchored inflation expectations, in general, in our sample. This result is not changed when include postGFC or ZLB dummies in the regressions, as shown in Panels B and C, respectively.

Table 10 reports regression results related to changes in the S&P 500 and NASDAQ equity indexes as well as changes in the DXY, EURO, and YEN. First, we find that SI surprises matter little explaining movements in equity prices around the FOMC announcement windows and that MP surprises are very strong with a negative coefficient sign. This means that in our sample, on average, monetary policy acts strongly via a discount rate channel: A positive monetary policy surprise lowers equity prices because of higher discount rates, and a more-restrictive-than-expected monetary policy. According to the results in Panels B and C, $\lambda_{postGFC}$ and λ_{ZLB} are slightly positive post-GFC or ZLB periods, thus, in those subperiods, stock prices fall slightly less, than in the usual periods of monetary policy. These findings are directionally consistent with Bernanke and Kuttner (2005) who show that the unanticipated tightening (or easing) in monetary policy is associated with a decline (or increase) in broad stock indexes. Turning to regressions with currency indexes on the left-hand side, we find that SI surprises explain changes in DXY index with a positive sign, regardless of whether we control for the postGFC and/or ZLB periods or not. A positive surprise in sentiment increase the value of the dollar. We also find that positive sentiment surprise decreases the value of EURO index. The value of YEN index is relatively mute to SI surprises.

In Appendix B, we take a micro view of SI relevance for explaining variation in asset prices and report regression results for specific six subsample of the full sample period from May 1999 to November 2022.

5.1.3 Comparison with other indexes

In addition to constructing SI that takes into account different periods of unconventional monetary policy periods, we replicated five alternative methodologies developed by economists at various central banks and run regressions (4). We summarize these methodologies and regression results briefly in Appendix C. The indexes constructed using five available methodologies are shown in Figure C1.[24] We find that our index is most highly correlated with the BoE index (correlation is around 0.8), then with the LT index (correlation is around 0.6), then with the KC Fed (correlation is around 0.5). The correlation of our index surprises with either Riksbank or SF Fed are very low.

6 Conclusion

In this paper we constructed a sentiment index of monetary policy communications using texts in financial press articles published around the FOMC meetings from the May 1999 FOMC meeting to November 2022 FOMC meeting, a period that covered 188 scheduled meetings. We found that surprises in the sentiment index around the FOMC meetings have additional explanatory power for movements in asset prices, beyond a financial market-based measure of the monetary policy surprises. Our sentiment surprises also have some informational content for asset price movements in the post-COVID period. We have compared our results with other alternative indexes and find that our index has higher explanatory power for movements in various financial asset prices around FOMC meetings, even when we control for financial market-based measures of monetary policy surprises. The reason for our sentiment index being more informative than existing sentiment indexes is that we constructed policies-specific dictionaries that treat conventional monetary policy, quantitative easing, and forward guidance policies separately. Each of these dictionaries calls for a different set of modifiers of the monetary policy stance, either hawkish or dovish. This methodology was not considered before and should be considered when various sentiment indexes are constructed with the aim of obtaining additional information about monetary policy stance beyond financial market-based measures.

[24]By plotting the Riksbank index, we subtracted one from the Riksbank index to make it more comparable to other indexes.

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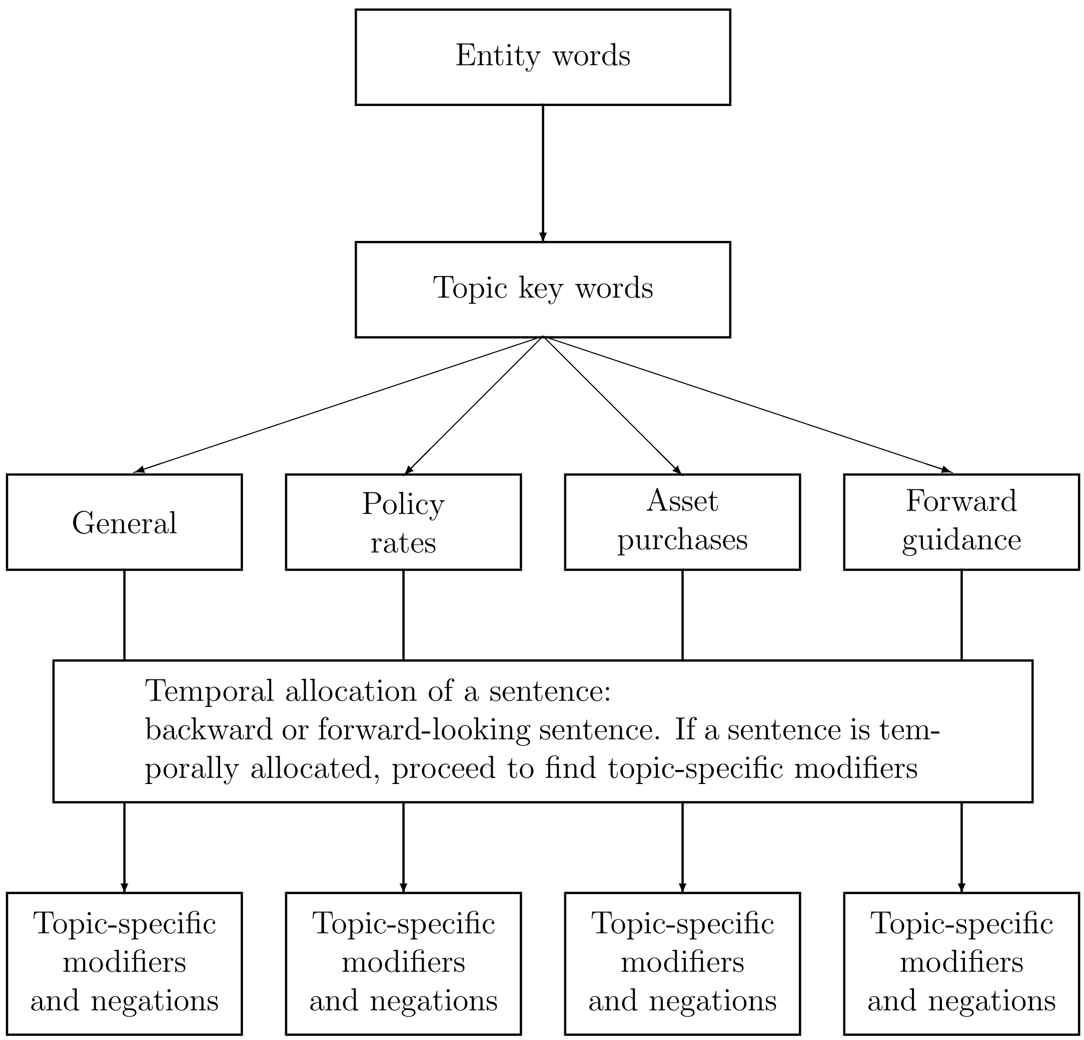
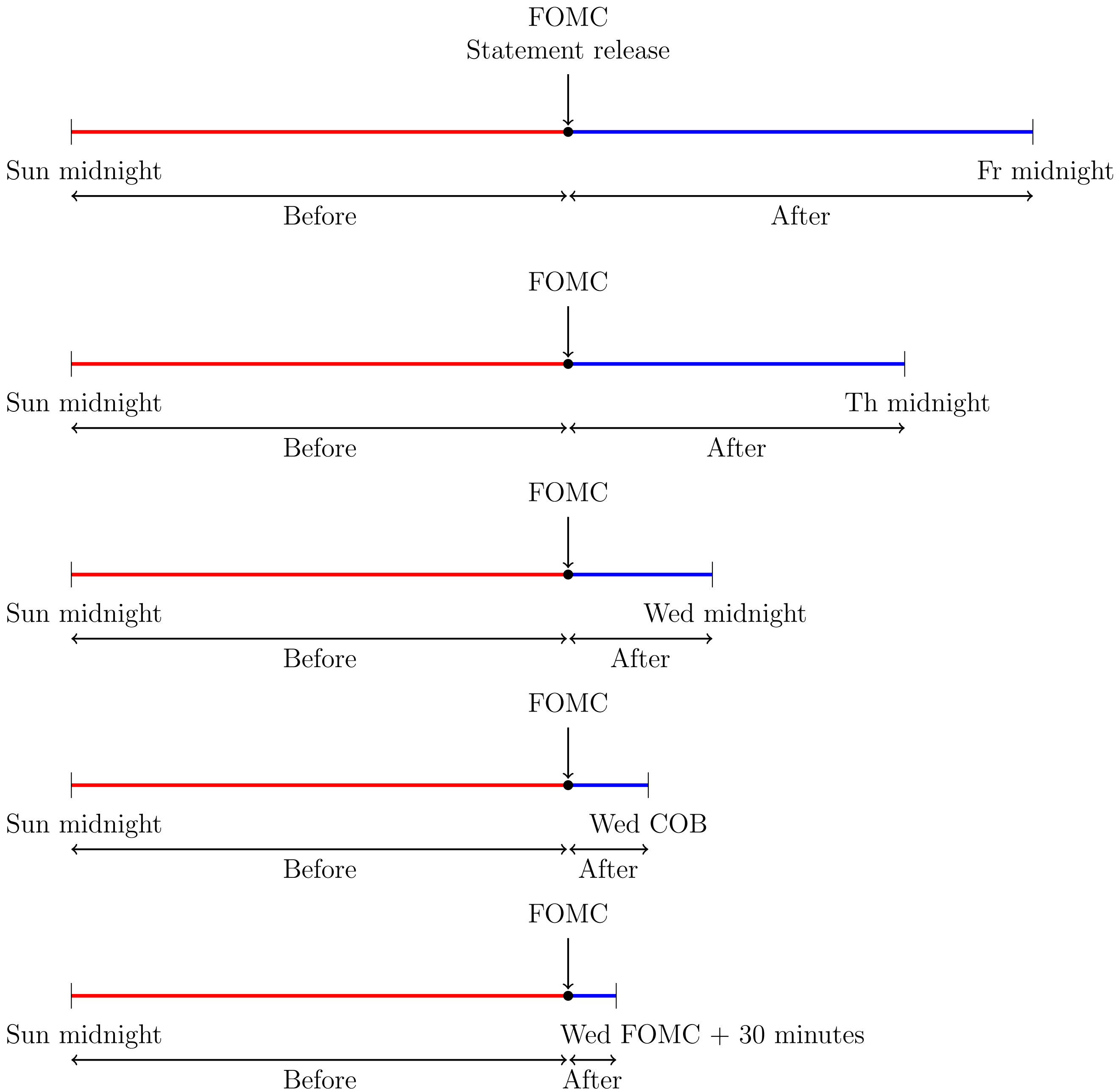
Figure 1: Methodology Summary for Identifying and Determining the Semantic Direction of a Relevant Sentence



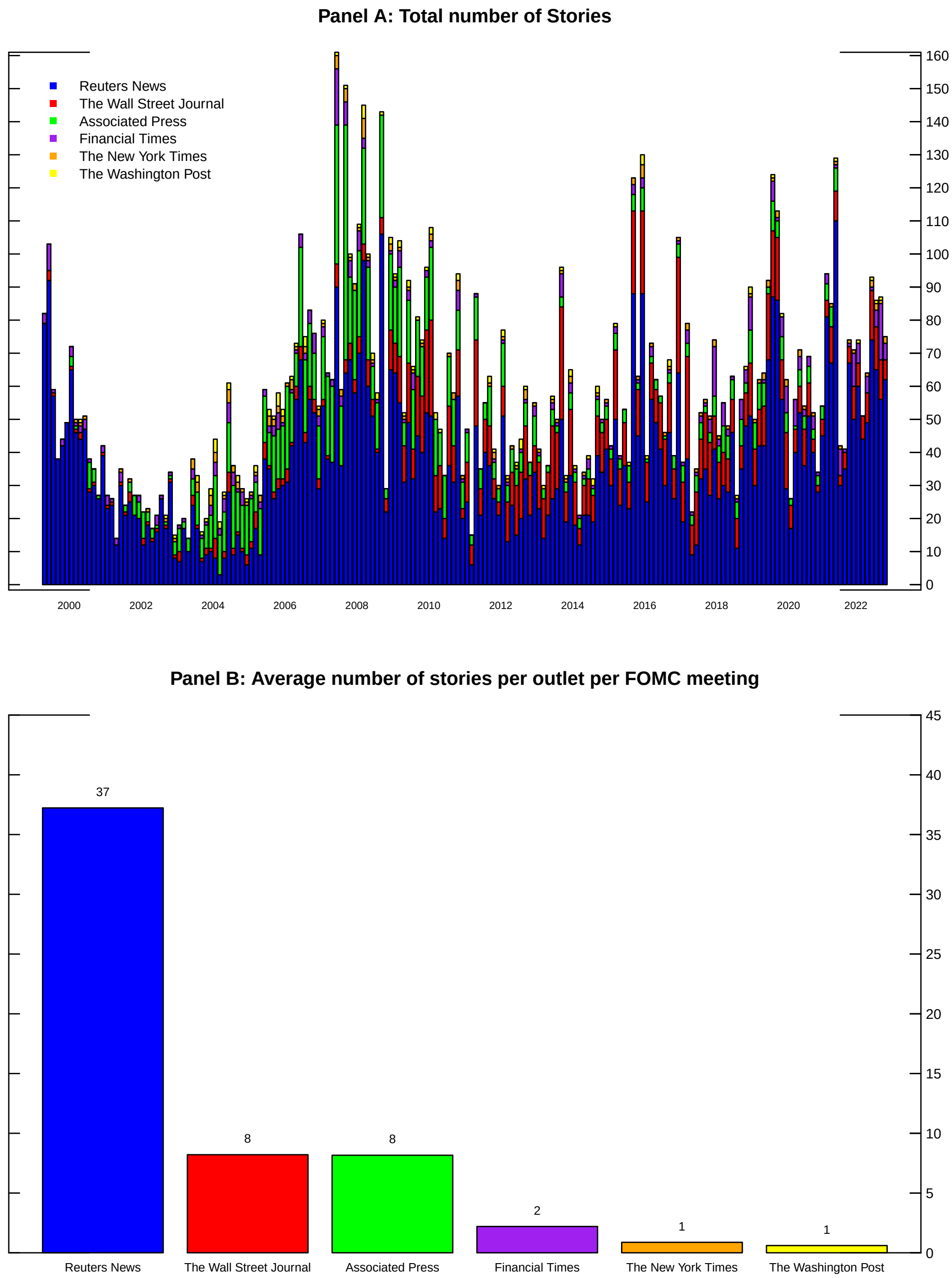
Notes: The figure presents the methodology summary for identifying and computing the semantic orientation of relevant sentences in financial media coverage of monetary policy communications around the Federal Open Market Committee (FOMC) statement releases after scheduled meetings, according to the description of Section 3.

Figure 2: Timing of the Sentiment Index Construction



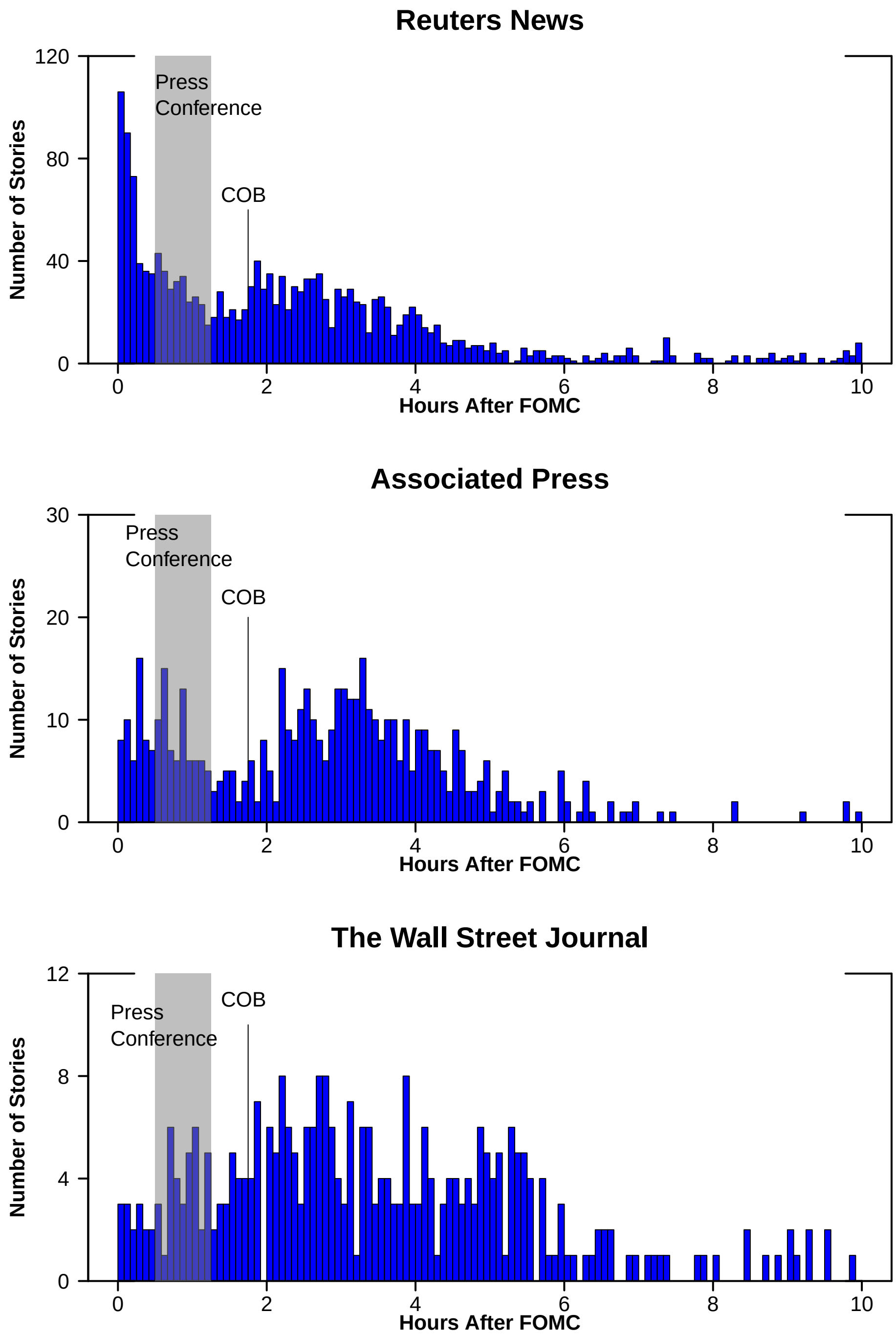
Notes: This figure shows five alternative event windows around the release of the Federal Open Market Committee (FOMC) statement, for which the surprise in the sentiment index constructed. The timing of the start point for each of the five event windows is Sunday midnight before the statement release. The period between the release of the FOMC statement and the end of the event window differs. Going from top of the page to the bottom: For the event window shown on top, the end point corresponds to Friday midnight after the FOMC statement release; For the second event window − to Thursday midnight after the statement release; For the event window shown in the middle − to Wednesday midnight after the statement release; For the fourth event window − to Wednesday, 3:45 p.m.; For the event window shown at the bottom − to (usually Wednesday) 30 minutes after the statement release. The time before and after the statement release is shown in red and in blue, respectively.

Figure 3: Distribution of News Sources and Corpus Stories



Notes: The figure shows the media coverage of monetary policy communications around the Federal Open Market Committee (FOMC) statement releases after scheduled meetings. The top panel shows the total number of Factiva stories in our sample per media source and per FOMC meeting. The bottom panel reports the average number of stories per media source per FOMC meeting. The stories in our sample are collected from Factiva using the search criteria described in Section 2.1. The sample period consists of the 188 scheduled FOMC meetings between May 18, 1999, and November 2, 2022.
Source: Dow Jones, Factiva; authors' calculations.

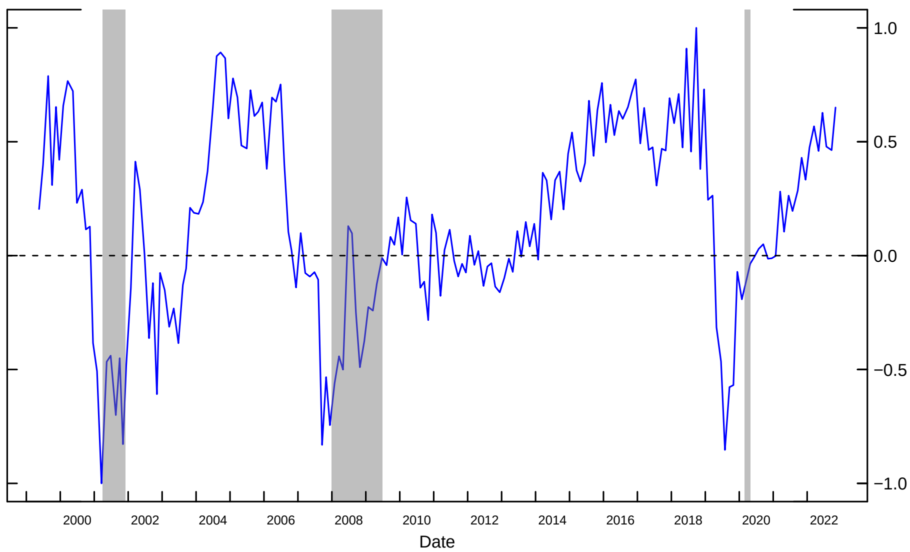
Figure 4: Distribution of Post-meeting News Publications



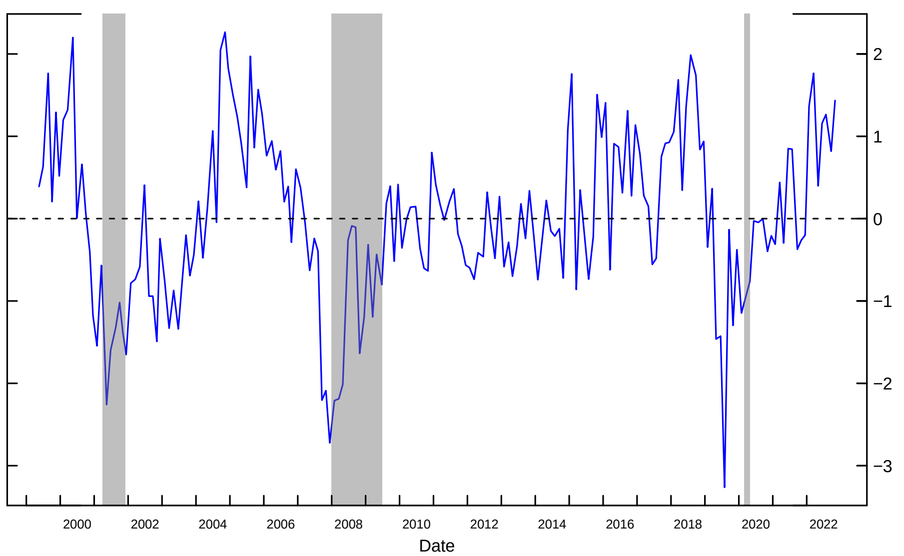
Notes: The figure shows the temporal distribution of news publications up to 10 hours following the Federal Open Market Committee (FOMC) statement release, at the five-minute intervals. The distribution is shown for outlets that always have time-stamped stories in our sample: *Reuters News*, *Associated Press*, and the *Wall Street Journal*, in Panels A, B, and C, respectively. The vertical tripwire "COB" on each chart corresponds to the close-of-business timing. The vertical gray-shaded bar on each chart represents the timing of the Chair's press conference. The sample period consists of the 188 scheduled FOMC meetings between May 18, 1999 and November 2, 2022.
Source: Dow Jones, Factiva; authors' calculations.

Figure 5: Sentiment Index and Surprises

Panel A: Sentiment Level



Panel B: Sentiment Surprise



Notes: This figure shows sentiment index (SI) level and SI surprises around the Federal Open Market Committee (FOMC) communications, in Panels A and B, respectively. The SI and SI surprises are shown for the event window that extends from Sunday midnight before the FOMC statement release to the midnight of the FOMC meeting day. The sample period consists of the 188 scheduled FOMC meetings between the May 1999 FOMC meeting and the November 2022 FOMC meeting. The frequency is FOMC. The gray-shaded bars indicate the National Bureau of Economic Research recessions.
Source: Dow Jones, Factiva; authors' calculations.

Table 1: Summary of Financial Press Articles

Number of articles by outlet	Total	Reuters	AP	WSJ	FT	NYT	WP
Panel A: 5-day window, FOMC week							
All	19687	11124	2174	3459	1770	759	401
Net Of duplicates	18271	10745	2095	3043	1395	649	344
Net of time-non-stamped	18260	10735	2094	3043	1395	649	344
Net of irrelevant stories	15911	9026	1848	2843	1255	624	315
Panel B: 4-day window: Sun midnight to Thu FOMC week							
All	16409	9229	1952	2881	1354	653	340
Net Of duplicates	15067	8908	1887	2465	981	543	283
Net of time-non-stamped	15056	8898	1886	2465	981	543	283
Net of irrelevant stories	13019	7407	1668	2294	869	522	259
Panel C: 3-day window: Sun midnight to FOMC midnight							
All	12015	7270	1596	1926	778	275	170
Net Of duplicates	10738	6999	1535	1511	414	165	114
Net of time-non-stamped	10736	6997	1535	1511	414	165	114
Net of irrelevant stories	8878	5644	1309	1341	342	148	94
Panel D: 3-day window: Sun midnight to COB FOMC							
All	11568	6939	1523	1883	778	275	170
Net Of duplicates	10322	6694	1467	1468	414	165	114
Net of time-non-stamped	10311	6684	1466	1468	414	165	114
Net of irrelevant stories	6971	4508	809	1070	342	148	94
Panel E: 3-day window: Sun midnight to 30-min after FOMC							
All	5774	3328	695	1055	417	165	114
Net Of duplicates	5624	3204	672	1055	414	165	114
Net of time-non-stamped	5613	3194	671	1055	414	165	114
Net of irrelevant stories	4459	2446	519	910	342	148	94

Notes: This table presents statistics of our corpus of Factiva articles for each of the six outlets in our sample: the *Associated Press* (AP), the *Financial Times* (FT), the *New York Times* (NYT), *Reuters* (RT), the *Wall Street Journal* (WSJ) (both in print and online), and the *Washington Post* (WP). Panels A through E report the number of stories used to construct SIs with various asymmetric windows around the day of the release of the FOMC statement during the week of the FOMC. The starting point of all the windows is midnight on Sunday. The end point of the windows are Friday (Panel A), Thursday (Panel B), midnight on the day of the FOMC (Panel C), close-of-business on the day of the FOMC (Panel D), and 30 minutes after the statement release on the day of the FOMC (Panel E). Each panel reports the total number of articles downloaded from Factiva and the number of stories after i) removing duplicates, ii) removing non-time-stamped stories, and iii) removing stories that have no sentences with entity or topic-keywords or correct temporal directionality. The sample period consists of the 188 scheduled FOMC meetings between the May 1999 FOMC meeting and the November 2022 FOMC meeting.
Source: Dow Jones, Factiva; authors' calculations.

Table 2: Dictionary of Entity Words

Entity Words	Count
fed	21465
federal_reserve	5715
official	2735
central_bank	2726
fomc	2452
powell	1491
committee	1019
yellen	876
policy_maker	711
greenspan	507
bernanke	266
chairman	254
policymaker	42
chair	21
federal_open_market_committee	7
federal_openmarket_committee	7
chairwoman	3

Notes: This table presents the dictionary of entity words that are used to classify the sentences, to which hawk and dove sentences are applied.
Source: Dow Jones, Factiva; authors' calculations.

Table 3: Dictionaryies of Topic Keywords

Key Words	No.	Key Words	No.	Key Words	No.
Panel A: *General* Dictionary				Panel B: *Policy Rates* Dictionary	
statement	5195			rate	14100
policy	4386			interest_rate	6910
monetary_policy	1566			target	1696
credit	1012			federal_funds_rate	764
action	861			funds_rate	487
stimulus	841			target_range	436
announcement	712			borrowing_cost	377
stance	454			target_rate	245
reserve	403			benchmark_rate	151
liquidity	269			rate_regime	1
policy_accommodation	123				
monetary_stimulus	101				
policy_stance	84				
accommodation	48				
policy_tool	33				
easy_money	30				
monetary_accommodation	16				
open_market_operations	13				
Total	16147			Total	25167
Panel C: *Asset Purchases* Dictionary				Panel D: *Forward Guidance* Dictionary	
treasury	2418	qe	67	pace	1402
bond	1356	treasury_note	27	near_zero	845
security	862	securities_holdings	26	pledge	432
balance_sheet	587	mortgage_securities	24	gradual	348
bond_purchases	503	holdings_of_securities	22	guidance	299
purchase	502	reinvestment	17	patient	284
mortgage	469	purchase_programs	16	extended_period	183
asset	460	maturing_securities	13	forward_guidance	99
portfolio	409	bond_purchase_program	11	measured_pace	98
bond_buying	343	asset_purchase_program	7	considerable_period	87
bond_buying_program	265	treasury_portfolio	7	considerable_time	84
quantitative_easing	246	buying_program	5	exceptionally_low	66
treasury_securities	212	mortgage_backed_securities	3	forward_policy_guidance	2
asset_purchases	207	mortgage_portfolio	3		
treasury_bond	183	asset_backed_securities	1		
government_bond	102	asset_purchasing_program	1		
government_debt	95	asset_purchasing_programs	1		
purchase_program	84	security_holdings	1		
Total	9555			Total	4229

Notes: This table presents the dictionary of topic keywords in four specific categories (General, Policy Rates, Asset Purchases, and Forward Guidance) in Factiva-filtered stories. Respective counts of key words in our sample are provided in the columns next to them.
Source: Dow Jones, Factiva; authors' calculations.

Table 4: Dictionaries of Keyword Modifiers

Hawkish	No.	Dovish	No.	Hawkish	No.	Dovish	No.
Panel A: *General* Dictionary				Panel B: *Policy Rates* Dictionary			
raise	1329	cut	1052	raise	5606	cut	4067
increase	731	lower	175	increase	3177	lower	925
hike	678	buy	134	hike	2884	fall	491
tighten	205	ease	127	boost	591	drop	412
boost	109	drop	118	gain	418	reduce	392
gain	91	fall	98	tighten	349	ease	300
reduce	79	reduce	97	grow	322	contract	167
firm	66	continue	94	firm	270	decrease	34
grow	57	contract	65	expand	122	loose	27
sell	54	extend	50	advance	75		
taper	54	increase	39				
expand	52	expand	34				
cut	51	grow	20				
slow	40	loose	20				
shrink	35	decrease	9				
trim	27						
advance	20						
decrease	4						
negation	19	negation	68	negation	100	negation	278

Hawkish	No.	Dovish	No.	Hawkish	No.	Dovish	No.
Panel C: *Asset Purchases* Dictionary				Panel D: *Forward Guidance* Dictionary			
raise	611	buy	745	raise	530	drop	113
increase	370	cut	423	increase	507	cut	112
reduce	352	continue	331	hike	325	continue	49
hike	327	increase	178	reduce	53	fall	47
taper	240	reduce	140	slow	53	buy	38
sell	204	lower	135	gain	52	reduce	35
cut	192	extend	129	boost	50	lower	26
slow	167	expand	108	grow	44	increase	17
shrink	153	fall	107	tighten	36	ease	15
boost	88	grow	85	expand	30	expand	14
gain	84	ease	57	taper	19	contract	9
trim	75	drop	56	firm	15	loose	6
firm	63	contract	15	cut	13	grow	5
tighten	53	decrease	7	advance	12	extend	4
expand	40	loose	3	shrink	9	decrease	1
grow	37			trim	6		
advance	12			sell	4		
decrease	11			decrease	2		
negation	26	negation	64	negation	4	negation	16

Notes: Panels A, B, C, and D of this table present the respective dictionaries and the number of (stemmed) keyword modifiers in the Factive corpus of financial media articles, in each of four topic categories: *General*, *Policy Rates*, *Asset Purchases*, and *Forward Guidance*, respectively. The sample period consists covers scheduled meetings between the May 18, 1999 and November 2, 2022 meetings, a total of 188 meetings. The bottom row in each panel reports the number of hawkish and dovish words modified by a negation in a relevant keyword dictionary.
Source: Dow Jones, Factiva; authors' calculations.

Table 5: Dictionary of Backward- and Forward-looking Words

Forward-looking words	Backward-looking words
expects	after
likely	appeared
next	seem
unlikely	last
anticipates	yesterday
possibly	been
believe	have
projecting	has
going	follow
forward	peak
outlook	record
warn	development
if	beat
see	sold
look	held
think	experience
sometime	remain
affecting	doing
attempt	already
envision	points
support	show
view	

Notes: This tables presents the dictionary of words that determine the forward- or backward-looking directionality of a sentence.
Source: Dow Jones, Factiva; authors' calculations.

Table 6: Federal Funds Futures Contracts

	FF1	FF2	FF3	FF4	FF5	FF6
Panel A: No Dummies						
SI surprise	0.003	0.003	0.005	0.007*	0.008**	0.010**
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
MP surprise	0.177***	0.389***	0.449***	0.521***	0.606***	0.671***
	(0.050)	(0.089)	(0.074)	(0.067)	(0.061)	(0.064)
Constant	−0.004*	-0.004	−0.007***	−0.007***	−0.007***	−0.010***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
R^2	0.190	0.286	0.428	0.533	0.600	0.572
Panel B: PostGFC Dummy						
SI surprise	0.003	0.003	0.005	0.007*	0.007**	0.010**
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
MP surprise	0.177***	0.388***	0.448***	0.521***	0.606***	0.672***
	(0.051)	(0.089)	(0.074)	(0.067)	(0.061)	(0.065)
PostGFC	0.003	-0.001	-0.002	0.001	0.001	0.002
	(0.003)	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)
Constant	-0.005	-0.004	-0.006	−0.008*	−0.008*	−0.011**
	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)
R^2	0.194	0.286	0.429	0.533	0.600	0.572
Panel C: ZLB Dummy						
SI surprise	0.003	0.003	0.005	0.007*	0.008**	0.010**
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
MP surprise	0.179***	0.389***	0.452***	0.525***	0.609***	0.676***
	(0.051)	(0.089)	(0.074)	(0.067)	(0.061)	(0.065)
ZLB	0.003	0.001	0.005	0.006	0.005	0.009*
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Constant	-0.005	-0.005	−0.009**	−0.009***	−0.009***	−0.013***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
R^2	0.196	0.286	0.434	0.540	0.604	0.579

Notes: This table reports regression results of the changes in the federal funds futures (FF1, FF2, ..., FF6) contracts one to six months ahead around the scheduled Federal Open Market Committee (FOMC) announcements regressed on sentiment index (SI) surprises and monetary policy (MP) surprises. The changes in the federal funds futures contracts are computed as differences in quotes 10 minutes before the FOMC statement release to 20 minutes afterwards. SI surprises are computed as differences in the average SI level of the stories within-2-days-before the FOMC statement release to within-10-hours-afterwards. The sample is from the May 1999 FOMC meeting to the November 2022 FOMC meeting, a total of 182 meetings. he Post-Global-Financial-Crisis (PostGFC) dummy is defined as one from the December 2008 FOMC meeting to the November 2022 FOMC meeting and zero otherwise. The zero-lower-bound (ZLB) dummy is defined as one from the December 2008 FOMC meeting to the October 2015 FOMC meeting and from the April 2020 FOMC meeting to the January 2022 FOMC meeting and zero otherwise. The ordinary least squares standard errors and t-statistics are provided in parentheses and the significance levels are as follows: * corresponds to $p-$values < 0.05, ** —p-values < 0.01, and *** —p-values < 0.001.
Source: Bauer and Swanson (2023) (for MP surprises), authors' calculations (for changes in federal funds futures contracts and SI surprises).

Table 7: Eurodollar Futures Contracts

	ED1	ED2	ED3	ED4
Panel A: No Dummies				
SI surprise	0.006	0.010***	0.013***	0.013***
	(0.003)	(0.002)	(0.002)	(0.003)
MP surprise	0.725***	0.901***	1.031***	1.091***
	(0.076)	(0.050)	(0.059)	(0.079)
Constant	−0.007***	−0.010***	−0.012***	−0.013***
	(0.002)	(0.002)	(0.002)	(0.002)
R^2	0.667	0.829	0.820	0.756
Panel B: PostGFC Dummy				
SI surprise	0.006*	0.010***	0.012***	0.013***
	(0.003)	(0.002)	(0.002)	(0.003)
MP surprise	0.725***	0.902***	1.032***	1.092***
	(0.076)	(0.050)	(0.059)	(0.079)
PostGFC	-0.001	0.001	0.003	0.004
	(0.004)	(0.003)	(0.004)	(0.005)
Constant	-0.006	−0.011***	−0.014***	−0.015***
	(0.003)	(0.002)	(0.003)	(0.004)
R^2	0.667	0.830	0.821	0.757
Panel C: ZLB Dummy				
SI surprise	0.006	0.010***	0.013***	0.013***
	(0.003)	(0.002)	(0.002)	(0.003)
MP surprise	0.725***	0.904***	1.035***	1.096***
	(0.076)	(0.050)	(0.059)	(0.078)
ZLB	0.001	0.004	0.007	0.009*
	(0.004)	(0.003)	(0.004)	(0.005)
Constant	−0.007**	−0.011***	−0.014***	−0.016***
	(0.002)	(0.002)	(0.002)	(0.003)
R^2	0.667	0.831	0.824	0.761

Notes: This table reports regression results of the changes in the Eurodollar (ED1, ED2, ED3, ED4) futures contracts (one to four quarters ahead) around the scheduled Federal Open Market Committee (FOMC) announcements regressed on sentiment index (SI) surprises and monetary policy (MP) surprises. The changes in the Eurodollar futures contracts are computed as differences in quotes 10 minutes before the FOMC statement release to 20 minutes afterwards. SI surprises are computed as differences in the average SI level of the stories within-2-days-before the FOMC statement release to within-10-hours-afterwards. The sample is from the May 1999 FOMC meeting to the November 2022 FOMC meeting, a total of 182 meetings. The Post-Global-Financial-Crisis (PostGFC) dummy is defined as one from the December 2008 FOMC meeting to the November 2022 FOMC meeting and zero otherwise. The zero-lower-bound (ZLB) dummy is defined as one from the December 2008 FOMC meeting to the October 2015 FOMC meeting and from the April 2020 FOMC meeting to the January 2022 FOMC meeting and zero otherwise. The ordinary least squares standard errors and t-statistics are provided in parentheses and the significance levels are as follows: * corresponds to $p-$values < 0.05, ** —p-values < 0.01, and *** —p-values < 0.001.
Source: Bauer and Swanson (2023) (for MP surprises), authors' calculations (for changes in Eurodollar futures contracts and SI surprises).

Table 8: Treasury Futures Contracts

	TNOTE02	TNOTE05	TNOTE10	TBOND
Panel A: No Dummies				
SI surprise	0.010**	0.009*	0.007*	0.004
	(0.003)	(0.003)	(0.003)	(0.003)
MP surprise	0.798***	0.724***	0.477***	0.268***
	(0.063)	(0.079)	(0.063)	(0.061)
Constant	−0.009***	−0.007*	-0.004	-0.001
	(0.002)	(0.003)	(0.003)	(0.003)
R^2	0.689	0.502	0.336	0.129
Panel B: PostGFC Dummy				
SI surprise	0.010**	0.009**	0.007*	0.004
	(0.003)	(0.003)	(0.003)	(0.003)
MP surprise	0.798***	0.723***	0.475***	0.268***
	(0.063)	(0.078)	(0.062)	(0.060)
PostGFC	-0.000	-0.005	-0.006	-0.003
	(0.004)	(0.005)	(0.005)	(0.005)
Constant	−0.009**	-0.004	-0.001	0.001
	(0.003)	(0.004)	(0.003)	(0.003)
R^2	0.689	0.504	0.341	0.130
Panel C: ZLB Dummy				
SI surprise	0.011**	0.009*	0.007*	0.004
	(0.003)	(0.004)	(0.003)	(0.003)
MP surprise	0.802***	0.727***	0.478***	0.269***
	(0.062)	(0.078)	(0.063)	(0.060)
ZLB	0.007	0.005	0.001	0.001
	(0.004)	(0.006)	(0.006)	(0.006)
Constant	−0.011***	−0.009**	−0.005*	-0.002
	(0.003)	(0.003)	(0.002)	(0.002)
R^2	0.693	0.504	0.336	0.129

Notes: This table reports regression results of the changes in the 2-year to 30-year nominal Treasury notes and bond futures around the scheduled Federal Open Market Committee (FOMC) announcements regressed on the sentiment index (SI) surprise and monetary policy (MP) shocks. The changes in the Treasury futures are computed as differences in quotes 10 minutes before the FOMC statement release to 20 minutes afterwards. SI surprises are computed as differences in the average SI level of the stories within-2-days-before the FOMC statement release to within-10-hours-afterwards. The sample is from the May 1999 FOMC meeting to the November 2022 FOMC meeting, a total of 182 meetings. The Post-Global-Financial-Crisis (PostGFC) dummy is defined as one from the December 2008 FOMC meeting to the November 2022 FOMC meeting and zero otherwise. The zero-lower-bound (ZLB) dummy is defined as one from the December 2008 FOMC meeting to the October 2015 FOMC meeting and from the April 2020 FOMC meeting to the January 2022 FOMC meeting and zero otherwise. The ordinary least squares standard errors and t-statistics are provided in parentheses and the significance levels are as follows: * corresponds to $p-$values < 0.05, ** —p-values < 0.01, and *** —p-values < 0.001.
Source: Bauer and Swanson (2023) (for MP surprises), authors' calculations (for changes in Treasury futures contracts and SI surprises).

Table 9: TIPS and Inflation Compensation

	TIPS5	TIPS10	IC5	IC10	IC5Y5F
Panel A: No Dummies					
SI surprise	0.008*	0.010**	0.013	-0.055	-0.126
	(0.004)	(0.004)	(0.012)	(0.056)	(0.129)
MP surprise	0.736***	0.540***	0.599	-1.648	-4.930
	(0.101)	(0.068)	(0.476)	(1.711)	(5.027)
Constant	−0.009*	-0.005	0.009	-0.041	-0.092
	(0.004)	(0.003)	(0.009)	(0.042)	(0.093)
Observations	143	158	143	158	143
R^2	0.370	0.326	0.042	0.023	0.028
Panel B: PostGFC Dummy					
SI surprise	0.008*	0.010**	0.013	-0.052	-0.126
	(0.004)	(0.004)	(0.012)	(0.053)	(0.129)
MP surprise	0.736***	0.540***	0.597	-1.657	-4.920
	(0.102)	(0.067)	(0.475)	(1.720)	(5.022)
PostGFC	-0.004	-0.005	0.019	-0.066	-0.167
	(0.007)	(0.006)	(0.017)	(0.068)	(0.172)
Constant	-0.006	-0.002	-0.005	0.002	0.031
	(0.005)	(0.004)	(0.007)	(0.017)	(0.062)
Observations	143	158	143	158	143
R^2	0.371	0.328	0.046	0.025	0.031
Panel C: ZLB Dummy					
SI surprise	0.009*	0.010**	0.012	-0.052	-0.111
	(0.004)	(0.004)	(0.011)	(0.053)	(0.115)
MP surprise	0.743***	0.542***	0.590	-1.607	-4.819
	(0.099)	(0.067)	(0.467)	(1.674)	(4.927)
ZLB	0.010	0.003	-0.012	0.067	0.160
	(0.007)	(0.007)	(0.016)	(0.066)	(0.162)
Constant	−0.014**	−0.006*	0.014	-0.069	-0.166
	(0.004)	(0.003)	(0.016)	(0.069)	(0.168)
Observations	143	158	143	158	143
R^2	0.379	0.327	0.044	0.025	0.031

Notes: This table reports regression results of the changes in five- and ten-year yields on Treasury Inflation-Protected Securities (TIPS) and inflation compensation measures around the scheduled Federal Open Market Committee (FOMC) announcements regressed on sentiment index (SI) surprises and monetary policy (MP) surprises. The changes in TIPS yields inflation compensation are computed as differences in quotes 10 minutes before the FOMC statement release to 20 minutes afterwards. SI surprises are computed as differences in the average SI level of the stories within-2-days-before the FOMC statement release to within-10-hours-afterwards. The sample is from the May 1999 FOMC meeting to the November 2022 FOMC meeting, a total of 182 meetings. The Post-Global-Financial-Crisis (PostGFC) dummy is defined as one from the December 2008 FOMC meeting to the November 2022 FOMC meeting and zero otherwise. The zero-lower-bound (ZLB) dummy is defined as one from the December 2008 FOMC meeting to the October 2015 FOMC meeting and from the April 2020 FOMC meeting to the January 2022 FOMC meeting and zero otherwise. The ordinary least squares standard errors and t-statistics are provided in parentheses and the significance levels are as follows: * corresponds to $p-$values < 0.05, ** —p-values < 0.01, and *** —p-values < 0.001.

Source: Bauer and Swanson (2023) (for MP surprises), authors' calculations (for changes in the TIPS yields, inflation compensation measures, and SI surprises).

Table 10: Equities and Currencies Indexes

	S&P500	NASDAQ	DXY	EURO	YEN
Panel A: No Dummies					
SI surprise	0.038	0.013	0.081^{*}	-0.055^{*}	0.044
	(0.037)	(0.038)	(0.037)	(0.025)	(0.028)
MP surprise	-6.121^{***}	-5.112^{***}	0.944	-4.652^{***}	2.887^{***}
	(0.893)	(0.975)	(0.767)	(0.568)	(0.508)
Constant	0.013	0.030	-0.068^{*}	0.044	-0.023
	(0.035)	(0.036)	(0.030)	(0.025)	(0.025)
Observations	182	161	181	182	182
R^2	0.303	0.230	0.052	0.336	0.167
Panel B: PostGFC Dummy					
SI surprise	0.024	-0.003	0.081^{*}	-0.056^{*}	0.043
	(0.035)	(0.036)	(0.036)	(0.026)	(0.028)
MP surprise	-6.050^{***}	-5.090^{***}	0.944	-4.649^{***}	2.890^{***}
	(0.889)	(0.949)	(0.763)	(0.566)	(0.506)
PostGFC	0.249^{***}	0.262^{***}	-0.004	0.010	0.011
	(0.066)	(0.070)	(0.062)	(0.051)	(0.051)
Constant	-0.131^{*}	-0.141^{*}	-0.065	0.038	-0.030
	(0.054)	(0.059)	(0.050)	(0.034)	(0.036)
Observations	182	161	181	182	182
R^2	0.354	0.290	0.052	0.336	0.167
Panel C: ZLB Dummy					
SI surprise	0.045	0.022	0.081^{*}	-0.056^{*}	0.046
	(0.037)	(0.039)	(0.038)	(0.024)	(0.028)
MP surprise	-5.999^{***}	-4.993^{***}	0.944	-4.673^{***}	2.919^{***}
	(0.870)	(0.939)	(0.761)	(0.569)	(0.504)
ZLB	0.209^{**}	0.211^{**}	-0.001	-0.036	0.055
	(0.071)	(0.074)	(0.065)	(0.057)	(0.055)
Constant	-0.063	-0.056	-0.067	0.057^{*}	-0.043
	(0.042)	(0.045)	(0.038)	(0.025)	(0.027)
Observations	182	161	181	182	182
R^2	0.337	0.271	0.052	0.338	0.172

Notes: This table reports regression results of the changes in the equity indexes and currencies around the scheduled Federal Open Market Committee (FOMC) announcements regressed on sentiment index (SI) surprises and monetary policy (MP) surprises. The changes in the equity indexes (S&P 500 and NASDAQ) and currencies indexes (DXY, Euro, and Yen) are computed as differences in quotes 10 minutes before the FOMC statement release to 20 minutes afterwards. SI surprises are computed as differences in the average SI level of the stories within-2-days-before the FOMC statement release to within-10-hours-afterwards. The changes in the S&P 500 index refer to the changes in the E-mini S&P 500 futures contract. The sample is from the May 1999 FOMC meeting to the November 2022 FOMC meeting, a total of 182 meetings. The Post-Global-Financial-Crisis (PostGFC) dummy is defined as one from the December 2008 FOMC meeting to the November 2022 FOMC meeting and zero otherwise. The zero-lower-bound (ZLB) dummy is defined as one from the December 2008 FOMC meeting to the October 2015 FOMC meeting and from the April 2020 FOMC meeting to the January 2022 FOMC meeting and zero otherwise. The ordinary least squares standard errors and t-statistics are provided in parentheses and the significance levels are as follows: * corresponds to $p-$values < 0.05, ** —p-values < 0.01, and *** —p-values < 0.001.
Source: Bauer and Swanson (2023) (for MP surprises and changes in the E-mini S&P 500 futures contract), authors' calculations (for changes currencies indexes and SI surprises).

A Appendix

This section provides historic details about the day and timing of the releases of the FOMC statements.

The day of the FOMC statement release varied in the early part of our sample that we account for when we subsequently construct the sentiment surprises. In the early part of our sample FOMC meetings were mostly held on Tuesdays with periodic two-day meetings that concluded predominantly on Wednesdays but also occasionally on Thursdays. Starting from the April 2012 FOMC meeting, the FOMC has only held scheduled two-day meetings and these typically conclude on Wednesdays, although several have also concluded on Thursdays.[25]

The timing of the FOMC statement release also varied in early part of our sample. Prior to the March 2013 FOMC meeting, the statement was typically released at or around 2:15 p.m. Since the March 2013 FOMC meeting, the release time has been consistent at 2.00 p.m. In addition to the statement release, since October 2007 the FOMC has also released the Summary of Economic Projections (SEP) at the every other meeting (March, June, September, and December meetings). Finally, since the April 2011 FOMC meeting, the FOMC Chair has held press conferences after the meetings accompanied by the SEP. Since the March 2018 FOMC meeting, the FOMC Chair has held press conferences after the conclusion of each FOMC meeting. Currently, press conferences currently start at 2:30 p.m., 30 minutes after the statement is released and typically run for about an hour.[26] We account for the variation in the date and time of the FOMC statement releases and we capture news stories in response to the suite of FOMC communications around each meeting.

[25] Among the total of 188 meetings in our sample, 57 concluded on a Tuesday, 125 on a Wednesday, and 6 on a Thursday.

[26] Until the December 2012 FOMC meeting, statements that were accompanied by the SEP have been released at 12:30 p.m., while statements of the "non-SEP" meetings have been released at 2 p.m.

B Appendix

B.1 Sentiment surprises regressions for policy sensitive rates

Turning to subsample analysis, our most intriguing result is that most of the explanatory power in Panel A appears to be driven by the pre-ZLB period (Panel B), and that in the following subperiods the sentiment surprise is almost never significant (Panels C, D, E of Table 6) never significant with the exception of post-COVID period (Panel F). This result is robust to several alternative specifications of the index.[27] We broadly attribute this robust result to the fact that monetary policy communications became increasingly more transparent with time: Since the April 2011 FOMC meeting, then-Chair of the Federal Reserve Ben S. Bernanke started holding press conferences that discussed and clarified policy actions, after every other FOMC meeting. Since the March 2018 FOMC meeting current Chair of the Federal Reserve Jerome H. Powell holds press conferences after each FOMC meeting.

Table B1 reports baseline regression results from (4) for the federal funds futures contracts one to six months ahead, FF1, FF2, ..., FF6. The left-hand side variable of the regression (4) corresponds to changes in the federal funds futures contracts 20 minutes before to 10 minutes after the release of the FOMC statement. First, as panel A shows, the response of the fed funds futures contracts reflects the surprise in sentiment; the sentiment surprise coefficient β_1 is positive and statistically significant for fed funds futures contracts four to six months out (FF4 to FF6), despite a strongly significant coefficient for monetary policy surprise at all six horizons. In other words, positive (or, hawkish) sentiment surprises are associated with positive movements in future policy-sensitive rates and negative (or, dovish) sentiment surprises are associated with negative movements in future policy-sensitive rates. Second, the response of the fed funds futures contracts to a change in media sentiment following the FOMC announcement is statistically significant at the five-percent level for FF5 and FF6 and at the ten-percent level for FF4 contracts. The MP surprise drives out significance of the sentiment surprise for the very near term contracts, namely, FF1 through FF3, but not for contracts at longer horizons. Interestingly, the explanatory power of the sentiment and monetary policy surprises increases with horizon and notably higher at longer (FF4 through FF6) than ta the shorter (FF1 through FF3) horizons. Our results suggest that MP shocks do not fully explain the change in implied rates in fed funds futures in the tight window around the FOMC announcements and that other factors are at play as well. As such, MP surprises appear to capture the surprise in the policy rate itself, while the sentiment surprise has some informational content for the "path" surprise that reflects changes in rates further out in the horizon.

B.2 Sentiment surprises regressions for other asset classes

Table B3 reports the results of regressing Treasury bills and on-the-run nominal Treasury yields of maturities ranging between 3 months and 30 years on the SI surprises. Sentiment has some informational content for the on-the-run securities in the pre-ZLB period (Panel B). Table B4 reports regression results of the one-the-run 5- and 10-year TIPS yields and inflation compensation of corresponding maturities. The last column of this table also reports regression results of the

[27] A reports regression results for a tighter time frame of collection of stories, namely, the event window closes at the COB of the FOMC statement release day.

five-year, five-year-forward inflation compensation. Sentiment appears to explain movements in 10-year TIPS rates in the full sample (Panel A), and in 10-year TIPS rates and 10-year inflation compensation in the post-ZLB period (Panel D). This arguably makes sense as discussions related to inflation in policy communications are apparently dominant during this period, given the focus on inflation in the current macroeconomic environment.

Table B5 reports regression results of the effect that SI surprises have on changes in the S&P 500 and NASDAQ equity indexes as well as on the changes in the currency indexes DXY, EURO, and YEN. The surprises in SI explain changes in DXY (with positive sign) and in EURO (with negative sign) in the full sample period (see Panel A). The SI surprise also appears to be explaining movements in the S&P500 prices in the pre-ZLB period (see Panel B). This means that a hawkish surprise is associated with the increases in equity prices. In contrast, a positive $MP1$ shock is associated with the declines in equity prices. This finding is interesting because it contrasts with the findings in Tables B1 and B3, where sentiment surprise and monetary policy shock affect policy rates and nominal Treasury yields in the same direction. Our findings regarding the MP regressor are directionally consistent with Bernanke and Kuttner (2005) who show that the unanticipated tightening (or easing) in monetary policy is associated with a decline (or increase) in broad stock indexes.

Table B1: Federal Funds Futures Contracts

	FF1	FF2	FF3	FF4	FF5	FF6	FF1	FF2	FF3	FF4	FF5	FF6
	Panel A: Full Sample: May 1999 to November 2022						Panel B: Pre-ZLB Period: May 1999 to December 2008					
SI surprise	0.003	0.003	0.005	0.007*	0.008**	0.010**	0.005	0.007	0.011***	0.013***	0.013***	0.017***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
MP surprise	0.177***	0.389***	0.449***	0.521***	0.606***	0.671***	0.241***	0.522***	0.575***	0.633***	0.707***	0.771***
	(0.050)	(0.089)	(0.074)	(0.067)	(0.061)	(0.064)	(0.067)	(0.111)	(0.087)	(0.082)	(0.074)	(0.073)
Constant	−0.004*	−0.004	−0.007***	−0.007***	−0.007***	−0.010***	−0.006	−0.005	−0.007*	−0.008*	−0.009*	−0.011**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)
Observations	182	182	182	182	182	182	78	78	78	78	78	78
R^2	0.190	0.286	0.428	0.533	0.600	0.572	0.268	0.420	0.590	0.669	0.714	0.706
	Panel C: ZLB period: January 2009 to November 2015						Panel D: Post-ZLB period: December 2015 to January 2020					
SI surprise	−0.001	−0.000	0.001	0.002	0.002	0.002	0.000	−0.006	−0.003	−0.003	−0.002	−0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.001)	(0.003)	(0.004)	(0.004)	(0.004)	(0.006)
MP surprise	0.039	0.107*	0.183***	0.207***	0.249***	0.342***	0.058	0.180	0.322**	0.500***	0.605***	0.726***
	(0.022)	(0.052)	(0.044)	(0.048)	(0.049)	(0.055)	(0.049)	(0.103)	(0.097)	(0.050)	(0.045)	(0.111)
Constant	−0.001	−0.001	−0.002	−0.001	−0.003*	−0.004**	−0.001	0.002	−0.005	−0.004	−0.004	−0.008
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.004)	(0.003)	(0.003)	(0.003)	(0.005)
Observations	55	55	55	55	55	55	34	34	34	34	34	34
R^2	0.073	0.115	0.330	0.343	0.424	0.514	0.071	0.226	0.390	0.671	0.763	0.628
	Panel E: COVID period: February 2020 to December 2021						Panel F: Post-COVID period: January 2022 to November 2022					
SI surprise	0.003	0.010	0.007	0.015*	0.016*	0.017*	0.004	0.020	0.030*	0.042*	0.044	0.094
	(0.006)	(0.010)	(0.006)	(0.004)	(0.005)	(0.006)	(0.009)	(0.012)	(0.007)	(0.014)	(0.030)	(0.037)
MP surprise	−0.027	0.011	0.023	0.231**	0.387**	0.433*	0.009	0.018	0.082	0.217	0.409	0.384
	(0.052)	(0.119)	(0.095)	(0.046)	(0.082)	(0.108)	(0.066)	(0.128)	(0.064)	(0.138)	(0.306)	(0.394)
Constant	0.001	0.000	−0.001	−0.002	−0.002	−0.001	−0.009	−0.041	−0.065***	−0.071*	−0.069	−0.131
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.011)	(0.016)	(0.004)	(0.019)	(0.040)	(0.050)
Observations	8	8	8	8	8	8	7	7	7	7	7	7
R^2	0.210	0.329	0.383	0.745	0.772	0.724	0.032	0.180	0.620	0.614	0.428	0.474

Notes: This table reports regression results of the changes in the federal funds futures (FF1, FF2, ..., FF6) contracts one to six months ahead around the scheduled Federal Open Market Committee (FOMC) announcements regressed on the sentiment index (SI) surprises and monetary policy (MP) surprises. The changes in the federal funds futures contracts are computed as differences in quotes 10 minutes before the FOMC statement release to 20 minutes afterwards. SI surprises are computed as differences in the average SI level of the stories within-2-days-before the FOMC statement release to within-10-hours-afterwards. The sample period is from the May 1999 FOMC meeting to the November 2022 FOMC meeting, a total of 182 meetings. The ordinary least squares standard errors and t-statistics are provided in parentheses and the significance levels are as follows: * corresponds to $p-$values < 0.05, ** —p-values < 0.01, and *** —p-values < 0.001.
Source: Bauer and Swanson (2023) (for MP surprises), authors' calculations (for changes in federal funds futures contracts and SI surprises).

Table B2: Eurodollar Futures Contracts

	ED1	ED2	ED3	ED4	ED1	ED2	ED3	ED4
	Panel A: Full Sample: May 1999 to November 2022				Panel B: Pre-ZLB Period: May 1999 to December 2008			
SI surprise	0.006	0.010***	0.013***	0.013***	0.008	0.013***	0.018***	0.019***
	(0.003)	(0.002)	(0.002)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
MP surprise	0.725***	0.901***	1.031***	1.091***	0.797***	0.942***	1.041***	1.089***
	(0.076)	(0.050)	(0.059)	(0.079)	(0.105)	(0.066)	(0.079)	(0.106)
Constant	−0.007***	−0.010***	−0.012***	−0.013***	−0.008*	−0.012***	−0.014***	−0.015***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)	(0.003)	(0.004)
Observations	182	182	182	182	78	78	78	78
R^2	0.667	0.829	0.820	0.756	0.681	0.868	0.853	0.783
	Panel C: ZLB period: January 2009 to November 2015				Panel D: Post-ZLB period: December 2015 to January 2020			
SI surprise	0.004	0.001	−0.004	−0.007	0.000	0.001	0.003	0.004
	(0.003)	(0.004)	(0.005)	(0.005)	(0.001)	(0.002)	(0.002)	(0.003)
MP surprise	0.393***	0.702***	0.970***	1.168***	0.602***	0.835***	1.016***	1.127***
	(0.072)	(0.092)	(0.079)	(0.071)	(0.034)	(0.055)	(0.086)	(0.104)
Constant	−0.003	−0.006**	−0.008***	−0.009**	−0.008***	−0.012***	−0.016***	−0.017***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.001)	(0.002)	(0.003)	(0.003)
Observations	55	55	55	55	34	34	34	34
R^2	0.490	0.666	0.754	0.739	0.892	0.892	0.848	0.805
	Panel E: COVID period: February 2020 to December 2021				Panel F: Post-COVID period: January 2022 to November 2022			
SI surprise	0.006	0.010***	0.013***	0.013***	0.008	0.013***	0.018***	0.019***
	(0.003)	(0.002)	(0.002)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
MP surprise	0.725***	0.901***	1.031***	1.091***	0.797***	0.942***	1.041***	1.089***
	(0.076)	(0.050)	(0.059)	(0.079)	(0.105)	(0.066)	(0.079)	(0.106)
Constant	−0.007***	−0.010***	−0.012***	−0.013***	−0.008*	−0.012***	−0.014***	−0.015***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)	(0.003)	(0.004)
Observations	182	182	182	182	78	78	78	78
R^2	0.667	0.829	0.820	0.756	0.681	0.868	0.853	0.783

Notes: This table reports regression results of the changes in the Eurodollar (ED1, ED2, ED3, and ED4) futures contracts one to four quarters ahead around the scheduled Federal Open Market Committee (FOMC) announcements regressed on sentiment index (SI) surprises and monetary policy (MP) surprises. The changes in the Eurodollar futures contracts are computed as differences in quotes 10 minutes before the FOMC statement release to 20 minutes afterwards. SI surprises are computed as differences in the average SI level of the stories within-2-days-before the FOMC statement release to within-10-hours-afterwards. The sample is from the May 1999 FOMC meeting to the November 2022 FOMC meeting, a total of 182 meetings. The ordinary least squares standard errors and t-statistics are provided in parentheses and the significance levels are as follows: * corresponds to $p-$values < 0.05, ** —p-values < 0.01, and *** —p-values < 0.001.
Source: Bauer and Swanson (2023) (for MP surprises), authors' calculations (for the changes in the Eurodollar futures contracts and SI surprises).

Table B3: Treasury Futures Contracts

	TNOTE02	TNOTE05	TNOTE10	TBOND	TNOTE02	TNOTE05	TNOTE10	TBOND
	Panel A: Full Sample: May 1999 to November 2022				Panel B: Pre-ZLB Period: May 1999 to December 2008			
SI surprise	0.010**	0.009*	0.007*	0.004	0.016***	0.013**	0.008*	0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.004)	(0.003)
MP surprise	0.798***	0.724***	0.477***	0.268***	0.762***	0.664***	0.435***	0.276***
	(0.063)	(0.079)	(0.063)	(0.061)	(0.083)	(0.105)	(0.081)	(0.074)
Constant	−0.009***	−0.007*	−0.004	−0.001	−0.008*	−0.004	−0.001	0.000
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
Observations	182	182	182	182	78	78	78	78
R^2	0.689	0.502	0.336	0.129	0.729	0.596	0.489	0.287
	Panel C: ZLB period: January 2009 to November 2015				Panel D: Post-ZLB period: December 2015 to January 2020			
SI surprise	−0.003	0.005	0.015	0.017	0.002	0.002	0.002	0.002
	(0.006)	(0.012)	(0.018)	(0.021)	(0.002)	(0.003)	(0.002)	(0.002)
MP surprise	0.927***	1.141***	0.830***	0.445	0.971***	0.938***	0.605***	0.228*
	(0.068)	(0.136)	(0.188)	(0.243)	(0.099)	(0.128)	(0.103)	(0.092)
Constant	−0.007*	−0.005	−0.004	−0.000	−0.016***	−0.016***	−0.011***	−0.005*
	(0.003)	(0.006)	(0.005)	(0.006)	(0.003)	(0.003)	(0.003)	(0.002)
Observations	55	55	55	55	34	34	34	34
R^2	0.613	0.416	0.243	0.088	0.754	0.672	0.573	0.204
	Panel E: COVID period: February 2020 to December 2021				Panel F: Post-COVID period: January 2022 to November 2022			
SI surprise	0.022	0.034	0.024	0.009	0.020	0.022	0.017	0.025
	(0.014)	(0.034)	(0.023)	(0.021)	(0.027)	(0.019)	(0.016)	(0.018)
MP surprise	0.402	0.288	0.189	0.011	0.948**	0.684**	0.371*	0.058
	(0.160)	(0.236)	(0.146)	(0.214)	(0.135)	(0.126)	(0.109)	(0.095)
Constant	0.003	0.007	0.006	0.008	−0.026	−0.033	−0.023	−0.025
	(0.005)	(0.010)	(0.007)	(0.009)	(0.032)	(0.021)	(0.019)	(0.022)
Observations	8	8	8	8	7	7	7	7
R^2	0.292	0.130	0.169	0.067	0.920	0.913	0.827	0.499

Notes: This table reports regression results of the changes in the 2-year to 30-year nominal Treasury note and bond futures around the scheduled Federal Open Market Committee (FOMC) announcements regressed on sentiment index (SI) surprises and monetary policy (MP) surprises. The changes in the Treasury futures are computed as differences in quotes 10 minutes before the FOMC statement release to 20 minutes afterwards. SI surprises are computed as differences in the average SI level of the stories within-2-days-before the FOMC statement release to within-10-hours-afterwards. The full sample is from the May 1999 FOMC meeting to the November 2022 FOMC meeting, a total of 182 meetings. The ordinary least squares standard errors and t-statistics are provided in parentheses and the significance levels are as follows: * corresponds to $p-$values < 0.05, ** —p-values < 0.01, and *** —p-values < 0.001.
Source: Bauer and Swanson (2023) (for MP surprises), authors' calculations (for changes in Treasury futures contracts and SI surprises).

Table B4: TIPS and Inflation Compensation

	TIPS5	TIPS10	IC5	IC10	IC5Y5F	TIPS5	TIPS10	IC5	IC10	IC5Y5F
	Panel A: Full Sample: May 1999 to November 2022					Panel B: Pre-ZLB Period: May 1999 to December 2008				
SI surprise	0.008*	0.010**	0.013	−0.055	−0.126	0.010	0.008	−0.002	0.000	0.006**
	(0.004)	(0.004)	(0.012)	(0.056)	(0.129)	(0.005)	(0.004)	(0.003)	(0.002)	(0.002)
MP surprise	0.736***	0.540***	0.599	−1.648	−4.930	0.553***	0.477***	0.039	0.024	0.168***
	(0.101)	(0.068)	(0.476)	(1.711)	(5.027)	(0.102)	(0.089)	(0.082)	(0.042)	(0.045)
Constant	−0.009*	−0.005	0.009	−0.041	−0.092	−0.007	−0.003	−0.000	0.000	0.001
	(0.004)	(0.003)	(0.009)	(0.042)	(0.093)	(0.005)	(0.004)	(0.003)	(0.002)	(0.003)
Observations	143	158	143	158	143	39	54	39	54	39
R^2	0.370	0.326	0.042	0.023	0.028	0.615	0.553	0.049	0.013	0.392
	Panel C: ZLB period: January 2009 to November 2015					Panel D: Post-ZLB period: December 2015 to January 2020				
SI surprise	0.012	0.022	0.003	−0.003	−0.008	0.004	0.006*	0.002	0.003*	0.003*
	(0.012)	(0.021)	(0.005)	(0.008)	(0.012)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)
MP surprise	1.234***	0.840***	0.110	0.045	−0.020	1.139***	0.687***	0.211***	0.167**	0.122
	(0.229)	(0.229)	(0.151)	(0.107)	(0.144)	(0.121)	(0.111)	(0.057)	(0.058)	(0.074)
Constant	−0.004	−0.001	0.002	0.002	0.003	−0.019***	−0.013***	−0.003*	−0.003	−0.002
	(0.006)	(0.006)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)
Observations	55	55	55	55	55	34	34	34	34	34
R^2	0.418	0.215	0.036	0.008	0.019	0.715	0.596	0.461	0.444	0.320
	Panel E: COVID period: February 2020 to December 2021					Panel F: Post-COVID period: January 2022 to November 2022				
SI surprise	0.071	0.048	0.032	0.026	0.021	0.025	0.022	−0.075	0.347	0.769
	(0.061)	(0.043)	(0.035)	(0.030)	(0.026)	(0.066)	(0.029)	(0.355)	(1.786)	(3.928)
MP surprise	0.536	0.333	0.203	0.208	0.213	0.731	0.558*	3.495	−14.403	−32.301
	(0.366)	(0.225)	(0.298)	(0.281)	(0.267)	(0.547)	(0.124)	(3.881)	(19.033)	(41.947)
Constant	0.002	0.001	−0.006	−0.006	−0.007	−0.051	−0.019	0.263	−1.232	−2.727
	(0.019)	(0.012)	(0.013)	(0.012)	(0.011)	(0.082)	(0.036)	(0.490)	(2.434)	(5.358)
Observations	8	8	8	8	8	7	7	7	7	7
R^2	0.197	0.205	0.168	0.148	0.120	0.298	0.830	0.164	0.121	0.125

Notes: This table reports regression results of the changes in 5- and 10-year Treasury Inflation-Protected Securities (TIPS) and inflation compensation measures around the scheduled Federal Open Market Committee (FOMC) announcements regressed on sentiment index (SI) surprises and monetary policy (MP) surprises. The changes in inflation compensation are computed as differences in quotes 10 minutes before the FOMC statement release to 20 minutes afterwards. SI surprises are computed as differences in the average SI level of the stories within-2-days-before the FOMC statement release to within-10-hours-afterwards. The sample period is from the May 1999 FOMC meeting to the November 2022 FOMC meeting, a total of 182 meetings. The ordinary least squares standard errors and t-statistics are provided in parentheses and the significance levels are as follows: * corresponds to $p-$values < 0.05, ** —p-values < 0.01, and *** —p-values < 0.001.

Source: Bauer and Swanson (2023) (for MP surprises), authors' calculations (for changes in TIPS, inflation compensation measures, and SI surprises).

Table B5: Equities and Currencies Indexes

	S&P500	NASDAQ	DXY	EURO	YEN	S&P500	NASDAQ	DXY	EURO	YEN
	Panel A: Full Sample: May 1999 to November 2022					Panel B: Pre-ZLB Period: May 1999 to December 2008				
SI surprise	0.038	0.013	0.081*	−0.055*	0.044	0.101*	0.068	0.090	−0.057*	0.057
	(0.037)	(0.038)	(0.037)	(0.025)	(0.028)	(0.049)	(0.058)	(0.051)	(0.028)	(0.033)
MP surprise	−6.121***	−5.112***	0.944	−4.652***	2.887***	−6.172***	−4.863***	−0.329	−3.575***	1.645**
	(0.893)	(0.975)	(0.767)	(0.568)	(0.508)	(1.179)	(1.269)	(0.971)	(0.663)	(0.570)
Constant	0.013	0.030	−0.068*	0.044	−0.023	−0.105	−0.110	−0.067	0.042	−0.029
	(0.035)	(0.036)	(0.030)	(0.025)	(0.025)	(0.054)	(0.057)	(0.048)	(0.035)	(0.035)
Observations	182	161	181	182	182	78	57	77	78	78
R^2	0.303	0.230	0.052	0.336	0.167	0.408	0.333	0.052	0.394	0.137
	Panel C: ZLB period: January 2009 to November 2015					Panel D: Post-ZLB period: December 2015 to January 2020				
SI surprise	−0.200	−0.151	0.174	−0.207	0.085	−0.030	−0.007	−0.000	0.001	−0.001
	(0.118)	(0.100)	(0.098)	(0.131)	(0.149)	(0.028)	(0.035)	(0.027)	(0.028)	(0.026)
MP surprise	−7.776***	−6.384***	2.494	−10.775***	7.681***	−4.198**	−4.668*	7.680***	−8.012***	7.201***
	(1.913)	(1.652)	(2.195)	(1.916)	(1.473)	(1.504)	(2.071)	(0.895)	(0.950)	(1.065)
Constant	0.109	0.115*	−0.055	−0.001	0.017	0.115**	0.104*	−0.075*	0.076*	−0.066
	(0.055)	(0.052)	(0.058)	(0.049)	(0.046)	(0.040)	(0.047)	(0.034)	(0.037)	(0.035)
Observations	55	55	55	55	55	34	34	34	34	34
R^2	0.279	0.241	0.077	0.456	0.268	0.275	0.225	0.643	0.620	0.568
	Panel E: COVID period: February 2020 to December 2021					Panel F: Post-COVID period: January 2022 to November 2022				
SI surprise	0.037	0.205	0.295	−0.442	0.254	0.455	0.518	−0.143	0.171*	−0.063
	(0.381)	(0.571)	(0.240)	(0.288)	(0.212)	(0.223)	(0.367)	(0.064)	(0.059)	(0.119)
MP surprise	5.952	13.400*	3.664*	−4.767*	3.294	−7.080*	−8.901*	4.040**	−4.068**	4.049**
	(3.994)	(4.999)	(1.367)	(1.410)	(1.383)	(2.102)	(2.602)	(0.533)	(0.573)	(0.753)
Constant	0.084	0.114	−0.058	0.053	0.020	−0.626	−0.679	0.065	−0.095	−0.034
	(0.134)	(0.177)	(0.073)	(0.083)	(0.063)	(0.290)	(0.440)	(0.065)	(0.061)	(0.145)
Observations	8	8	8	8	8	7	7	7	7	7
R^2	0.191	0.322	0.175	0.264	0.180	0.735	0.711	0.924	0.917	0.895

Notes: This table reports regression results of the changes in the equity indexes and currencies indexes around the scheduled Federal Open Market Committee (FOMC) announcements regressed on sentiment index (SI) surprises and monetary policy (MP) surprises. The changes in the equity indexes (S&P 500 and NASDAQ) and currencies indexes (DXY, Euro, and Yen) are computed as differences in quotes 10 minutes before the FOMC statement release to 20 minutes afterwards. SI surprises are computed as differences in the average SI level of the stories within-2-days-before the FOMC statement release to within-10-hours-afterwards. Changes in the S&P 500 index refer to changes in the E-mini S&P 500 futures contract. The sample period is from the May 1999 FOMC meeting to the November 2022 FOMC meeting, a total of 182 meetings. The ordinary least squares standard errors and t-statistics are provided in parentheses and the significance levels are as follows: * corresponds to $p-$values < 0.05, ** —p-values < 0.01, and *** —p-values < 0.001.
Source: Bauer and Swanson (2023) (for MP surprises and changes in the E-mini S&P 500 futures contract), authors' calculations (for changes in the NASDAQ index, currencies indexes, and SI surprises).

C Appendix

In this appendix, we present a brief overview of five alternative methodologies developed by researchers in various central banks and report results of regression (4) based on SI construction following each of the five methodologies.

C.1 Alternative methodologies

Lucca-Trebbi index: developed by Lucca and Trebbi (2009). This methodology also starts with the Factiva database search and look for the articles in the three-day window around FOMC announcements (i.e., the day before, the day of, and the day after the FOMC) with words "Federal Reserve, Fed, FOMC". The authors filter out stories on the day of the FOMC with no time stamps. Subsequently, in those articles, the authors use only *relevant* sentences, that is, the sentences that include words "Rates, Policies, policies, statement, announcement, Fed, FOMC, Federal Reserve". In those sentences, they look for hawkish words (hawkish, tighten, hike, raise, increase, boost) and dovish words (dovish, ease, cut, lower, decrease, loose). They subsequently compute a Factiva Semantic Orientation (FSO) score, similar to a computation in eqution (1). Direct negations in the methodology are handled by switching hawkish into dovish words and vice verse if these words are preceded by "not". While not made explicit in the LT paper/appendices, we assume that LT include "n't" contractions as well (e.g. didn't). In addition, the authors remove all past tense verbs so they can only capture the future policy actions.

Cannon index: Cannon (2015) looks at positive and negative words in the FOMC meeting transcripts. At the text processing level the author eliminates stop words, convert letters to lower case, remove numbers, and remove punctuation. The negation is accounted for by checking polarity of word directly preceding positive or negative (in our case, hawkish or dovish) words using two sentiment dictionaries, either Loughran and McDonald (2011) or Hu-Liu dictionary for product reviews. Finally, she defines the tone of a particular communication as: the ratio of the difference between positive and negative words to the sum of positive and negative words.

Carvalho, Hsu, and Nechio index: Carvalho et al. (2016) use the Lucca and Trebbi (2009) approach but count in the articles only the number of the word "hawkish" or the word "dovish" and construct the words in the FSO similar to Lucca and Trebbi (2009) and our sentiment index (1).

Apel and Grimaldi index: Apel and Grimaldi (2012) apply their methodology to the Riskbank communications released in Swedish. The authors look at combinations of words to determine if a statement is dovish or hawkish. They use a prespecified list of seven nouns (i.e., inflation, cyclical position, growth, price, wages, oil price, development) and a set of either dovish adjectives (decreasing, slower, weaker, lower) or hawkish adjectives (increasing, faster, stronger, and higher) determining if the adjective-noun combination is hawkish or dovish. The adjectives used include all forms (stemmer) of a particular adjective (e.g., fast, faster, and fastest). Then they define the four indexes using the count of hawk and dove adjective-noun combinations:

- Net Hawkish Index = [(hawk/(hawk+dove)) - (dove/(hawk + dove))] + 1;
- Net Dovish Index = [(dove/(hawk + dove)) - (hawk/(hawk+dove))] + 1;
- Hawkish Index = (hawk/(hawk+dove));
- Dovish Index = (dove/(hawk + dove)).

Nyman, Kapadia, Tuckett, Gregory, Ormerod, and Smith index: The Nyman et al. (2018) methodology counts the number of excitement and anxiety words in the financial market text-based data. The authors use Loughran and McDonald (2011) dictionary to determine the presence of negation. If a negative word occurs within three words of a hawk/dove word then the hawk/dove word is counted as the opposite. The set of negative words used is {no, not, none, neither, never, nobody}. The sentiment is defined as the difference between the number of hawkish and dovish words in a particular text scaled by the size of the text.

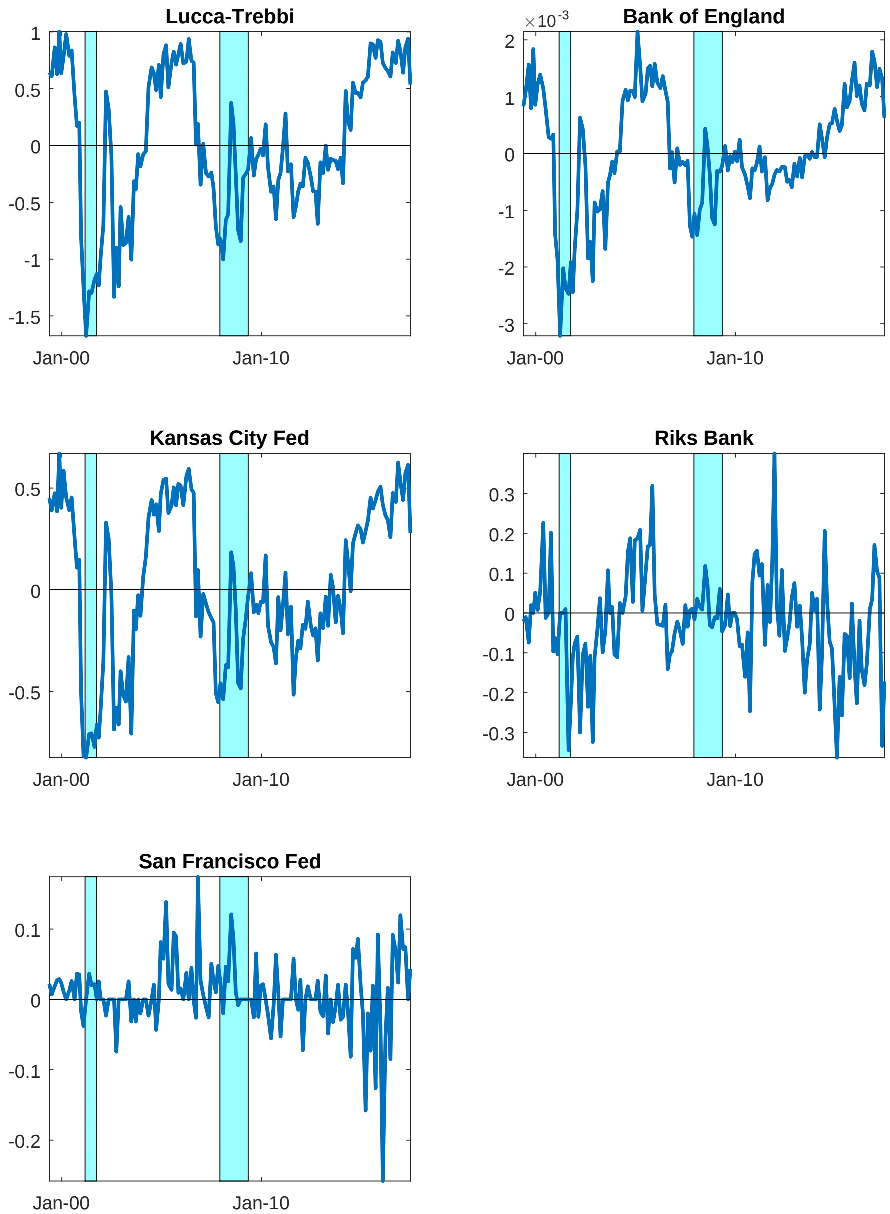
C.2 Regression results

Tables C1 through C5 show regression results that for the full sample period for five alternative methodologies described above for the SI construction.[28] Table C1 presents results for the Lucca and Trebbi (2009) index for the full sample period. As the table shows, their index surprise is almost never significant except a few occurrences: the FF3 and FF4 contracts, 10-year TIPS yield and the EURO index (Panel C). Table C2 presents the results for the Carvalho et al. (2016) index. This index has more significant loadings, for example, it is significant in explaining changes in TIPS yields, equity indexes, and currency indexes. Interestingly, this index appears to become more dovish as other indexes indexes become more hawkish during the economic upturn and at the start of the late 2015 Fed tightening cycle, according to Figure C1. Turning to Cannon (2015) index, surprises in this index appear to have little explanatory power for changes in asset prices except for a couple of fed funds futures contracts, FF4 and FF5. Apel and Grimaldi (2012) methodology yields a few mildly significant results, according to table C4, but overall, changes in asset prices are relatively mute to SI surprises constructed using this methodology.[29] Finally, table C5 reports results based on the Nyman et al. (2018) methodology and has only two significant loadings: the FF1 contract and the DXY currency index. Note that the Nyman et al. (2018) methodology is based on extracting semantic content from financial-market text-based data. It is not necessarily directly related to BoE communications. We nevertheless apply the index to the corpus of our Factiva stories. Overall, none of these indexes appears to have results comparable and consistent across several asset classes and, most importantly, consistent across horizons. One explanation could be is that these methodologies are not designed to capture economic environment marked by unconventional monetary policies, when different sets of dictionaries are needed,as we argue in the paper.

[28] Results for the pre- and post-GFC periods for these alternative indexes are not presented in the paper but available upon request.

[29] For Riksbank index, we report results based on one out of their four variations of the index, namely, the Net Hawkish Index. Results for the other three variations are available upon request.

Figure C1: Sentiment Index: Alternative Methodologies



This figure shows the sentiment index (SI) of the Federal Open Market Committee (FOMC) monetary policy communications constructed following five alternative methodologies of Lucca and Trebbi (2009) (LSI), Cannon (2015) (Kansas City Fed), Nyman et al. (2018) (Bank of England), Apel and Grimaldi (2012) (Riksbank), and Carvalho et al. (2016) (San Francisco Fed) methodologies. The SIs are computed for the period of 36 hours before the FOMC statement release to 36 hours afterwards. The sample period consists of 146 scheduled FOMC meetings, between the May 1999 FOMC meeting to the June 2017 FOMC meeting. The frequency is FOMC. The blue-shaded bars indicate the National Bureau of Economic Research recessions. Source: Dow Jones, Factiva; authors' calculations.

Table C1: Lucca and Trebbi (2009) methodology

Panel A: Federal Fund Futures	FF1	FF2	FF3	FF4	FF5	FF6				
SI surprise	0.007	0.002	0.011*	0.017*	0.014	0.014				
	(1.81)	(0.61)	(2.09)	(2.42)	(1.57)	(1.25)				
MP surprise	0.483***	0.899***	0.761***	0.725***	0.718***	0.771***				
	(7.40)	(20.51)	(11.27)	(8.19)	(7.36)	(8.95)				
Constant	-0.001	0.001	-0.002	-0.003	-0.003	-0.005				
	(-1.71)	(1.02)	(-1.10)	(-1.34)	(-1.32)	(-1.56)				
Observations	146	146	146	146	146	146				
R^2	0.7957	0.9442	0.7480	0.6320	0.5394	0.4889				
Panel B: On-the-run Nominal Treasury Yields										
	ONRUN3M	ONRUN6M	ONRUN2Y	ONRUN5Y	ONRUN10Y	ONRUN30Y				
SI surprise	0.008	0.011	0.025	0.029	0.022	0.018				
	(1.31)	(1.40)	(1.68)	(1.90)	(1.97)	(1.88)				
MP surprise	0.496***	0.536***	0.482***	0.330***	0.163	-0.047				
	(5.75)	(7.43)	(5.53)	(3.75)	(1.88)	(-0.73)				
Constant	-0.003	-0.004	-0.006	-0.004	-0.004	-0.002				
	(-1.74)	(-1.85)	(-1.40)	(-0.89)	(-0.80)	(-0.49)				
Observations	146	146	146	146	146	146				
R^2	0.5737	0.4916	0.1753	0.0833	0.0286	0.0111				
Panel C: Inflation Compensation, Equities, and Currencies										
	TIPS5Y	TIPS10Y	IC5Y	IC10Y	IC5Y5F	SP500	NASDAQ	DXY	EURO	YEN
SI surprise	0.020	0.025*	-0.008	-0.005	-0.000	0.118	0.090	0.141	-0.276*	0.152
	(1.06)	(1.99)	(-1.05)	(-1.10)	(-0.02)	(0.67)	(0.49)	(1.22)	(-2.02)	(1.67)
MP surprise	0.522***	0.323**	0.128	0.134**	0.248***	-4.489**	-3.918	0.760	-2.478***	1.651*
	(5.51)	(3.33)	(1.31)	(3.36)	(3.52)	(-2.66)	(-1.85)	(0.87)	(-3.71)	(2.41)
Constant	-0.004	-0.003	0.002	0.002	0.004	-0.045	-0.022	-0.073*	0.027	-0.013
	(-0.73)	(-0.63)	(1.13)	(1.41)	(1.48)	(-1.01)	(-0.53)	(-1.98)	(0.78)	(-0.38)
Observations	107	122	107	122	107	146	125	146	146	146
R^2	0.1210	0.0785	0.0642	0.0876	0.0955	0.1102	0.0934	0.0134	0.0955	0.0462

Notes: This table reports regression results of asset price changes around the scheduled Federal Open Market Committee (FOMC) meeting announcements regressed on the changes in the sentiment index (SI) surprises and MP surprises. SI and MP surprises are constructed following methodologies in Lucca and Trebbi (2009, LT) and Gurkaynak et al. (2005), respectively. MP surprises and asset prices changes in the regressions are computed as differences in quotes 10 minutes before the FOMC statement release to 20 minutes afterwards. SI surprises are computed as the difference in the average SI level of the stories within-36-hours-before the FOMC statement release to within-36-hours-afterwards. The ordinary least squares standard errors and t-statistics are provided in parentheses and the significance levels are as follows: * corresponds to $p-$values < 0.05, ** —p-values < 0.01, and *** —p-values < 0.001. The results are reported for the sample period of the May 1999 FOMC meeting to the June 2017 FOMC meeting, a total of 146 observations, with the exception of Treasury Inflation-Protected Securities (TIPS) and inflation compensation series when the number of observations is fewer due to unavailability of the TIPS securities early in the sample period.
Source: Authors' calculations.

Table C2: Carvalho et al. (2016) methodology

Panel A: Federal Funds Futures	FF1	FF2	FF3	FF4	FF5	FF6
SI surprise	0.006	0.002	0.030*	0.035	0.054*	0.064*
	(0.64)	(0.30)	(2.02)	(1.72)	(2.28)	(2.15)
MP surprise	0.488***	0.900***	0.767***	0.735***	0.724***	0.775***
	(7.26)	(20.26)	(11.14)	(8.06)	(7.18)	(8.79)
Constant	-0.001	0.001	-0.001	-0.002	-0.003	-0.004
	(-1.43)	(1.21)	(-0.90)	(-1.06)	(-1.17)	(-1.47)
Observations	146	146	146	146	146	146
R^2	0.7903	0.9441	0.7455	0.6241	0.5408	0.4934

Panel B: On-the-run Nominal Treasury Yields	ONRUN3M	ONRUN6M	ONRUN2Y	ONRUN5Y	ONRUN10Y	ONRUN30Y
SI surprise	0.022	0.047*	0.093	0.094	0.056	0.006
	(1.48)	(2.17)	(1.95)	(1.68)	(1.49)	(0.17)
MP surprise	0.500***	0.539***	0.492***	0.342***	0.174	-0.035
	(5.67)	(7.21)	(5.31)	(3.54)	(1.91)	(-0.53)
Constant	-0.002	-0.003	-0.005	-0.003	-0.003	-0.001
	(-1.64)	(-1.81)	(-1.22)	(-0.67)	(-0.63)	(-0.28)
Observations	146	146	146	146	146	146
R^2	0.5716	0.4959	0.1779	0.0813	0.0237	0.0012

Panel C: Inflation Compensation, Equities, and Currencies	TIPS5Y	TIPS10Y	IC5Y	IC10Y	IC5Y5F	SP500	NASDAQ	DXY	EURO	YEN
SI surprise	0.141*	0.088*	0.031	0.023	0.012	-1.141*	-1.076*	0.710	-1.180**	0.482
	(2.51)	(2.26)	(1.47)	(1.40)	(0.62)	(-2.36)	(-2.26)	(1.66)	(-2.95)	(1.45)
MP surprise	0.521***	0.333**	0.120	0.132**	0.247***	-4.314*	-3.853	0.803	-2.578***	1.719*
	(4.96)	(3.20)	(1.15)	(3.16)	(3.52)	(-2.55)	(-1.79)	(0.92)	(-3.59)	(2.43)
Constant	-0.003	-0.002	0.001	0.002	0.004	-0.036	-0.016	-0.069	0.018	-0.007
	(-0.66)	(-0.47)	(0.93)	(1.30)	(1.53)	(-0.86)	(-0.40)	(-1.91)	(0.52)	(-0.22)
Observations	107	122	107	122	107	146	125	146	146	146
R^2	0.1589	0.0811	0.0713	0.0932	0.0968	0.1289	0.1195	0.0205	0.1089	0.0444

Notes: This table reports regression results of asset price changes around the scheduled Federal Open Market Committee (FOMC) meeting announcements regressed on the changes in the sentiment index (SI) surprises and MP surprises. SI and MP surprises are constructed following methodologies in Carvalho et al. (2016) and Gurkaynak et al. (2005), respectively. MP surprises and asset prices changes in the regressions are computed as differences in quotes 10 minutes before the FOMC statement release to 20 minutes afterwards. SI surprises are computed as the difference in the average SI level of the stories within-36-hours-before the FOMC statement release to within-36-hours-afterwards. The ordinary least squares standard errors and t-statistics are provided in parentheses and the significance levels are as follows: * corresponds to $p-$values < 0.05, ** —p-values < 0.01, and *** —p-values < 0.001. The results are reported for the sample period of the May 1999 FOMC meeting to the June 2017 FOMC meeting, a total of 146 observations, with the exception of Treasury Inflation-Protected Securities (TIPS) and inflation compensation series when the number of observations is fewer due to unavailability of the TIPS securities early in the sample period.
Source: Authors' calculations.

Table C3: Cannon (2015) methodology

Panel A: Federal Funds Futures

	FF1	FF2	FF3	FF4	FF5	FF6
SI surprise	0.008*	0.003	0.017	0.024*	0.027*	0.027
	(2.27)	(0.77)	(1.97)	(2.23)	(2.21)	(1.83)
MP surprise	0.487***	0.900***	0.766***	0.733***	0.723***	0.775***
	(7.38)	(20.51)	(11.59)	(8.44)	(7.56)	(9.38)
Constant	-0.001	0.001	-0.002	-0.003	-0.003	-0.005
	(-1.64)	(1.00)	(-1.11)	(-1.31)	(-1.40)	(-1.62)
Observations	146	146	146	146	146	146
R^2	0.7949	0.9444	0.7507	0.6344	0.5481	0.4966

Panel B: On-the-run Nominal Treasury Yields

	ONRUN3M	ONRUN6M	ONRUN2Y	ONRUN5Y	ONRUN10Y	ONRUN30Y
SI surprise	0.007	0.009	0.015	0.013	0.018	0.019
	(0.84)	(0.85)	(0.70)	(0.59)	(1.03)	(1.33)
MP surprise	0.500***	0.541***	0.496***	0.347***	0.175*	-0.039
	(5.73)	(7.53)	(5.63)	(3.75)	(1.99)	(-0.59)
Constant	-0.002	-0.004	-0.005	-0.003	-0.003	-0.002
	(-1.66)	(-1.79)	(-1.25)	(-0.68)	(-0.69)	(-0.42)
Observations	146	146	146	146	146	146
R^2	0.5706	0.4877	0.1641	0.0688	0.0225	0.0085

Panel C: Inflation Compensation, Equities, and Currencies

	TIPS5Y	TIPS10Y	IC5Y	IC10Y	IC5Y5F	SP500	NASDAQ	DXY	EURO	YEN
SI surprise	-0.006	0.014	-0.009	-0.006	0.001	0.154	0.037	0.195	-0.180	0.089
	(-0.27)	(0.77)	(-1.03)	(-1.08)	(0.10)	(0.76)	(0.19)	(1.16)	(-1.13)	(0.69)
MP surprise	0.537***	0.332**	0.127	0.133**	0.248***	-4.437**	-3.880	0.821	-2.637***	1.740*
	(5.12)	(3.31)	(1.28)	(3.28)	(3.51)	(-2.62)	(-1.82)	(0.96)	(-3.88)	(2.51)
Constant	-0.002	-0.002	0.002	0.002	0.004	-0.045	-0.020	-0.072	0.019	-0.008
	(-0.46)	(-0.51)	(1.15)	(1.41)	(1.38)	(-1.00)	(-0.47)	(-1.91)	(0.55)	(-0.24)
Observations	107	122	107	122	107	146	125	146	146	146
R^2	0.1128	0.0669	0.0629	0.0880	0.0956	0.1103	0.0917	0.0145	0.0758	0.0384

Notes: This table reports regression results of asset price changes around the scheduled Federal Open Market Committee (FOMC) announcements regressed on the changes in sentiment index (SI) surprises and monetary policy (MP) surprises. SI and MP surprises are computed following methodologies in Cannon (2015) and Gurkaynak et al. (2005), respectively. MP surprises and asset prices changes in the regressions are computed as differences in quotes 10 minutes before the FOMC statement release to 20 minutes afterwards. SI surprises are computed as the difference in the average SI level of the stories within-36-hours-before the FOMC statement release to within-36-hours-afterwards. The ordinary least squares standard errors and t-statistics are provided in parentheses and the significance levels are as follows: * corresponds to $p-$values < 0.05, ** —p-values < 0.01, and *** —p-values < 0.001. The results are reported for the sample period of the May 1999 FOMC meeting to the June 2017 FOMC meeting, a total of 146 observations, with the exception of Treasury Inflation-Protected Securities (TIPS) and inflation compensation series when the number of observations is fewer due to unavailability of the TIPS securities early in the sample period.
Source: Authors' calculations.

Table C4: Apel and Grimaldi (2012) methodology

Panel A: Federal Funds Futures

	FF1	FF2	FF3	FF4	FF5	FF6
SI surprise	0.015*	-0.001	0.009	0.010	0.007	0.032*
	(2.11)	(-0.15)	(0.93)	(0.77)	(0.51)	(2.06)
MP surprise	0.485***	0.901***	0.768***	0.736***	0.727***	0.774***
	(7.86)	(20.42)	(10.95)	(7.99)	(7.20)	(8.68)
Constant	-0.001	0.001	-0.001	-0.002	-0.003	-0.004
	(-1.35)	(1.21)	(-0.83)	(-1.00)	(-1.09)	(-1.38)
Observations	146	146	146	146	146	146
R^2	0.8010	0.9441	0.7437	0.6216	0.5328	0.4961

Panel B: On-the-run Nominal Treasury Yields

	ONRUN3M	ONRUN6M	ONRUN2Y	ONRUN5Y	ONRUN10Y	ONRUN30Y
SI surprise	0.021*	0.027*	0.021	0.019	0.021	0.034*
	(2.02)	(2.47)	(0.91)	(0.82)	(1.11)	(2.25)
MP surprise	0.498***	0.538***	0.495***	0.346***	0.175	-0.041
	(6.04)	(7.59)	(5.17)	(3.52)	(1.92)	(-0.65)
Constant	-0.002	-0.003	-0.004	-0.003	-0.003	-0.001
	(-1.52)	(-1.70)	(-1.12)	(-0.58)	(-0.57)	(-0.24)
Observations	146	146	146	146	146	146
R^2	0.5832	0.5031	0.1652	0.0697	0.0221	0.0162

Panel C: TIPS, Inflation Compensation, Equities, and Currencies

	TIPS5Y	TIPS10Y	IC5Y	IC10Y	IC5Y5F	SP500	NASDAQ	DXY	EURO	YEN
SI surprise	-0.032	0.008	-0.020	-0.019*	-0.003	0.297	0.342	-0.267	-0.101	-0.109
	(-1.17)	(0.44)	(-1.68)	(-2.41)	(-0.27)	(1.13)	(1.30)	(-1.34)	(-0.53)	(-0.76)
MP surprise	0.529***	0.332**	0.120	0.138***	0.247***	-4.462**	-3.966*	0.911	-2.654***	1.779*
	(5.34)	(3.14)	(1.15)	(3.77)	(3.54)	(-2.82)	(-2.02)	(1.05)	(-3.66)	(2.54)
Constant	-0.003	-0.002	0.002	0.002	0.004	-0.039	-0.019	-0.067	0.014	-0.006
	(-0.53)	(-0.41)	(1.02)	(1.36)	(1.55)	(-0.91)	(-0.48)	(-1.86)	(0.40)	(-0.19)
Observations	107	122	107	122	107	146	125	146	146	146
R^2	0.1207	0.0643	0.0799	0.1152	0.0958	0.1148	0.1049	0.0166	0.0704	0.0384

Notes: This table reports regression results of asset price changes around the scheduled Federal Open Market Committee (FOMC) meeting announcements regressed on the changes in the sentiment index (SI) surprises and MP surprises. SI and MP surprises are constructed following methodologies in Apel and Grimaldi (2012) and Gurkaynak et al. (2005), respectively. MP surprises and asset prices changes in the regressions are computed as differences in quotes 10 minutes before the FOMC statement release to 20 minutes afterwards. SI surprises are computed as the difference in the average SI level of the stories within-36-hours-before the FOMC statement release to within-36-hours-afterwards. The ordinary least squares standard errors and t-statistics are provided in parentheses and the significance levels are as follows: * corresponds to $p-$values < 0.05, ** —p-values < 0.01, and *** —p-values < 0.001. The results are reported for the sample period of the May 1999 FOMC meeting to the June 2017 FOMC meeting, a total of 146 observations, with the exception of Treasury Inflation-Protected Securities (TIPS) and inflation compensation series when the number of observations is fewer due to unavailability of the TIPS securities early in the sample period.

Source: Authors' calculations.

Table C5: Nyman et al. (2018) methodology

Panel A: Federal Funds Futures

	FF1	FF2	FF3	FF4	FF5	FF6
SI surprise	3.679*	0.260	4.149	5.512	6.829	7.673
	(2.11)	(0.13)	(1.02)	(1.21)	(1.34)	(1.19)
MP surprise	0.483***	0.900***	0.763***	0.729***	0.717***	0.769***
	(7.45)	(20.80)	(11.70)	(8.41)	(7.51)	(9.33)
Constant	-0.001	0.001	-0.002	-0.003	-0.003	-0.005
	(-1.73)	(1.15)	(-1.22)	(-1.38)	(-1.47)	(-1.74)
Observations	146	146	146	146	146	146
R^2	0.7978	0.9441	0.7460	0.6260	0.5403	0.4919

Panel B: On-the-Run Nominal Treasury Yields

	ONRUN3M	ONRUN6M	ONRUN2Y	ONRUN5Y	ONRUN10Y	ONRUN30Y
SI surprise	3.179	3.496	9.745	9.430	7.203	3.851
	(1.09)	(1.09)	(1.52)	(1.41)	(1.37)	(0.98)
MP surprise	0.497***	0.538***	0.484***	0.335***	0.167	-0.041
	(5.74)	(7.45)	(5.59)	(3.77)	(1.93)	(-0.62)
Constant	-0.003	-0.004	-0.006	-0.004	-0.004	-0.001
	(-1.66)	(-1.88)	(-1.39)	(-0.82)	(-0.74)	(-0.38)
Observations	146	146	146	146	146	146
R^2	0.5723	0.4884	0.1719	0.0754	0.0236	0.0034

Panel C: Inflation Compensation, Equities, and Currencies

	TIPS5Y	TIPS10Y	IC5Y	IC10Y	IC5Y5F	SP500	NASDAQ	DXY	EURO	YEN
SI surprise	8.062	9.568	-0.458	0.166	0.342	52.404	51.772	123.477*	-98.584	89.456
	(0.75)	(1.33)	(-0.12)	(0.07)	(0.09)	(0.70)	(0.59)	(2.15)	(-1.66)	(1.77)
MP surprise	0.516***	0.325***	0.124	0.132**	0.247***	-4.488**	-3.923	0.666	-2.518***	1.618*
	(5.28)	(3.38)	(1.25)	(3.23)	(3.40)	(-2.66)	(-1.85)	(0.80)	(-3.89)	(2.42)
Constant	-0.004	-0.003	0.002	0.002	0.004	-0.046	-0.024	-0.081*	0.026	-0.016
	(-0.69)	(-0.61)	(0.88)	(1.23)	(1.30)	(-1.01)	(-0.55)	(-2.13)	(0.74)	(-0.48)
Observations	107	122	107	122	107	146	125	146	146	146
R^2	0.1177	0.0725	0.0523	0.0829	0.0956	0.1101	0.0942	0.0314	0.0854	0.0529

Notes: This table reports regression results of asset price changes around the scheduled Federal Open Market Committee (FOMC) meeting announcements regressed on the changes in the sentiment index (SI) surprises and MP surprises. SI and MP surprises are constructed following methodologies in Nyman et al. (2018) and Gurkaynak et al. (2005), respectively. MP surprises and asset prices changes in the regressions are computed as differences in quotes 10 minutes before the FOMC statement release to 20 minutes afterwards. SI surprises are computed as the difference in the average SI level of the stories within-36-hours-before the FOMC statement release to within-36-hours-afterwards. The ordinary least squares standard errors and t-statistics are provided in parentheses and the significance levels are as follows: * corresponds to $p-$values < 0.05, ** —p-values < 0.01, and *** —p-values < 0.001. The results are reported for the sample period of the May 1999 FOMC meeting to the June 2017 FOMC meeting, a total of 146 observations, with the exception of Treasury Inflation-Protected Securities (TIPS) and inflation compensation series when the number of observations is fewer due to unavailability of the TIPS securities early in the sample period.
Source: Authors' calculations.