Journal of Financial Economics 143 (2022) 993–1025

Contents lists available at ScienceDirect

Journal of Financial Economics

journal homepage: www.elsevier.com/locate/jfec

Real-time price discovery via verbal communication: Method and application to Fedspeak☆

Roberto Gómez-Cram, Marco Grotteria*

London Business School, Regent's Park, Sussex Place, London, NW1 4SA, United Kingdom

ARTICLE INFO

Article history:
Received 12 October 2021
Revised 13 December 2021
Accepted 13 December 2021
Available online 2 January 2022

JEL classification:
C55
E40
E52
E58

Keywords:
Price discovery
Monetary policy
Federal reserve
FOMC
Video data

ABSTRACT

We study the price discovery process on FOMC days. For several asset classes, we find that price movements around the post-meeting statement release are strong predictors of price movements around the subsequent press conference. The correlation is 58% for medium-term Eurodollar futures and 44% for the S&P500 index. We then time-stamp the words pronounced in press conference videos and align these words with high-frequency financial data. Minutes in which the chairman discusses changes in the newly issued policy statement underlie the positive correlation. We discuss potential explanations and consider the implications of our findings for asset pricing and monetary economics.

1. Introduction

When policy analysis ignores the role of investor expectations and how investor expectations evolve over time, policy conclusions can be misleading (Lucas, 1972; 1973; 1976). As a result, today's central bankers place a high priority on communications with financial markets in an attempt to manage the public's expectations. It is often argued that communication has to be clear and credible to be effective, which has historically led to a difficult trade-off between clarity and time consistency (Kydland and Prescott, 1977; Calvo, 1978; Barro and Gordon, 1983a, 1983b; Cukierman and Meltzer, 1986; Stein, 1989). Yet, little is known about how investors form their expectations in response to central bank communications. In this paper, we aim to answer this question by identifying news or shocks to investors' information sets. To do this, we use high-frequency asset price data, high-frequency communication data, and textual analysis techniques to probe the workings of the marketplace in new and powerful ways, focusing on episodes in which the source of price movements is well identified and tracing investors' reaction to a specific sentence communicated by the central bank.

This paper makes two contributions to the literature. The first is empirical and the second methodological. For

☆ We thank William Schwert and Nikolai Roussanov (the editors) and an anonymous referee for their valuable feedback. We also thank Jules van Binsbergen, Anna Cieslak, João Cocco, Max Croce, Kent Daniel, James Dow, Itamar Drechsler, Francisco Gomes, João Gomes, Christopher Hennessy, Ralph Koijen, John C.F. Kuong, Matteo Leombroni, Michael McMahon, Emanuel Moench, Stefan Nagel, Emi Nakamura, Stephen Schaepher, Jesse Shapiro, Jessica Wachter, Paul Whelan, and Amir Yaron for helpful discussions and/or comments. We thank the AQR Asset Management Institute for generous financial support. Yutong Hu, Oksana Smirnova, and Tianhao Yin provided excellent research assistantship.

* Corresponding author.
E-mail addresses: rgomezcram@london.edu (R. Gómez-Cram), mgrotteria@london.edu (M. Grotteria).

https://doi.org/10.1016/j.jfineco.2021.12.004
0304-405X/

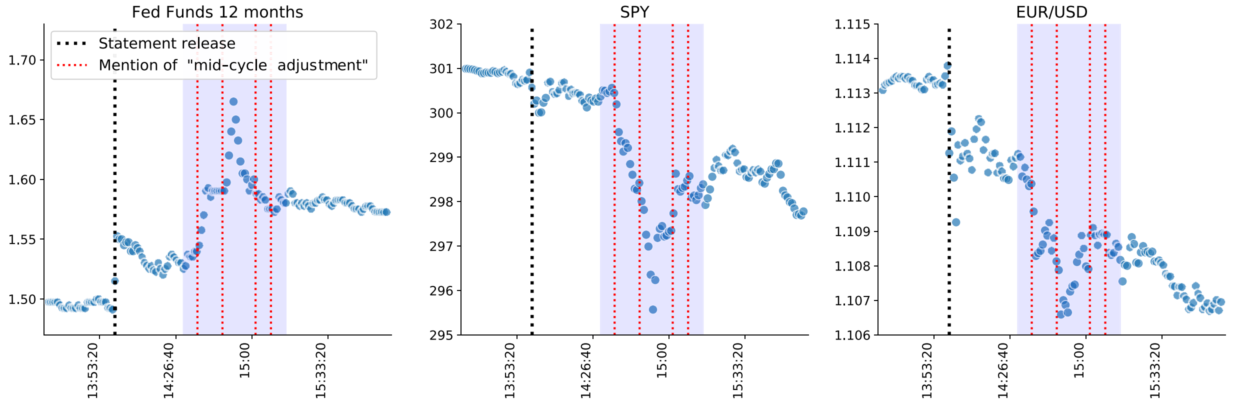


Fig. 1. The figure shows the intraday evolution of the implied rate from the 12-month federal funds futures, the SPY price level, and the EUR/USD exchange rate on July 31, 2019. The black dashed vertical line represents the release time (14:00) of the FOMC statement. The shaded area represents the FOMC press conference. The conference started at 14:30 and lasted for about 45 min. The red dotted lines highlight the times at which the Chairman mentioned a "mid-cycle adjustment to policy." (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the days on which the Federal Open Market Committee (FOMC) has a scheduled meeting, we document, for a wide range of financial assets, a strong, positive correlation between price changes in a narrow window around the statement release and those during the subsequent press conference. This correlation is as high as 58% for 60-month Eurodollar futures and 44% for the S&P 500 index. These values are large given that price changes are computed over two nonoverlapping, nonconsecutive windows. Moreover, the relation is strong and stable enough that a simple strategy that trades on this empirical pattern becomes highly profitable.

We then introduce a new method that allows us to identify the specific message contained in the press conference that induces this correlation. We first scrape the videos of the Fed chairman's post-meeting press conference. Then we convert the audio into interpretable text and time-stamp it at one-second intervals. Next, we align high-frequency financial data with the exact words pronounced in each moment. This approach allows us to match a specific message with the market's response. Our setting offers a natural way to study how market participants' beliefs adapt to central banks' messages because such high-frequency shocks to prices are nearly ideal measures of unexpected movements in investors' expectations (Cochrane and Piazzesi, 2002; Nakamura and Steinsson, 2018). This method allows us to show that the largest asset price changes occur during the minutes in which the chairman clarifies the information added to the newly issued policy statement and in which the chairman discusses forward guidance. In those minutes, trading volume increases significantly, and asset prices move on average in the same direction as they did around the policy statement release. These minutes lie behind the strong positive correlation mentioned above.

The example of the FOMC meeting on July 31, 2019, provides the intuition underlying our findings. Three related signals lie behind the movements in asset prices between 14:00 and 15:30 that day. First, before the conclusion of the FOMC meeting, markets expected a reduction of a quarter point in the target federal funds rate, with some possibility for a half-point cut, averaging 35 bps. The actual rate cut was 25 bps, less than what the markets expected, and market prices adjusted accordingly. Second, while investors still expected future easing, the statement included a new sentence adding uncertainty: "the Committee contemplates the future path of the target range for the federal funds rate." Third, when the press conference Q&A started, Powell was assaulted by questions about the meaning of this change in the statement. He answered "we're contemplating the future path of the target range for the federal funds rate. [...] The Committee is really thinking of this [current change] as a mid-cycle adjustment to policy." The "*mid-cycle adjustment* comment signaled there was no plan for a series of rate cuts."[1]

Figure 1 plots the intraday evolution of the interest rate implied by the 12-month federal funds futures; the price level of SPY, the exchange-traded fund that tracks the performance of the S&P 500; and the EUR/USD exchange rate on July 31, 2019. Every reference to the *mid-cycle adjustment* sentence in the post-meeting statement induced some investors to trade and market prices to adjust, on average, in the same direction as they did when the statement was released.

To measure the effect of words on financial asset prices, we must grapple with two methodological challenges. First, we need to convert the post-meeting press conference audio into interpretable text and time-stamp the words. We split the audio into smaller frames of around three seconds, which we then convert into readable text using an end-to-end deep learning algorithm for probabilistic character modeling (Hannun et al., 2014). Second, we identify statement news by tracking the words changed (added or removed) between two consecutive FOMC policy statements. We use automated textual analysis to capture those sentences in the press conference text. Such a

[1] Andrew Cinko, editor of U.S. Markets, Princeton, is the author of this sentence, which has been reported by Bloomberg on its live blog of FOMC events.

link does not exploit any information from asset prices; it only reflects the linguistic link between the policy statement news and the press conference.

We find that investors closely scrutinize statement changes for insights into what the changes imply for future policy rates. In the first few questions, financial reporters ask for a clarification of the statement changes and for more details about the context of the current decision, while Fed officials, for their part, anticipate the confusion caused by the statement.[2,3] When Fed officials speak about statement changes (henceforth statement-related minutes), we find the average absolute variation in financial asset prices is larger than in the rest of the conference, trading volume goes up significantly, and, more importantly, prices move on average in the same direction as their initial reaction around the statement release.

That our findings are stronger for longer-maturity interest rate derivatives, stocks, and exchange rates highlights the link between expectations formation and forward guidance. Consistent with this hypothesis, we identify the different language patterns and styles that characterize the minutes in which the chairman discusses the statement. We show that those sentences tend to discuss the long-term future and adopt a more clarifying language as defined by Pennebaker et al. (2015). In particular, the sentences related to the largest asset price movements are those in which the chairman discusses the future, while talking about changes in the statement text. The time orientation of the talk subsumes part of the effect we have identified in statement-related minutes.

To extend our linguistic analysis of the press conference and our study of the link between words pronounced and asset price movements, we employ alternative off-the-shelf textual analysis techniques in our new environment with time-stamped text. We search for "hawkish" or "dovish" terms following (Neuhierl and Weber, 2019). We analyze the sentiment behind the speech using the dictionary proposed by Loughran and Mc Donald (2011); the dictionary uses financial documents. In both cases, and unlike the results on the time orientation of the talk, we find that the identified words are important, but their relation to the asset price variation does not subsume the relation captured by the statement-related minutes.

Collectively, our findings suggest that the chairman's discussion of statement news (i.e., the linguistic changes to the policy statement) provides useful information to market participants about the future path of monetary policy decisions, that is, forward guidance. We then ask to what extent this information reduces investors' uncertainty about future monetary policy decisions. Using the implied volatility from options on Eurodollar futures, we measure investors' uncertainty about interest rates and document that, while the policy statement helps significantly reduce interest rate uncertainty for the closest maturities, the information conveyed in the press conference is responsible for the larger drops in uncertainty in interest rates over the longer term. More importantly, the largest reductions in implied volatility indeed occur in statement-related minutes.

In Section 5, we evaluate eight possible mechanisms and characterize them on the basis of whether they can be reconciled with our findings. Our results provide direct evidence against models in which traders are endowed with full-information rational expectations (FIRE). This is important because almost every central bank today uses FIRE-based models to guide their monetary policy (Coibion et al., 2018). Market prices are forward looking and should already incorporate all information available to the public. So, especially at such a high frequency, they should be close to unpredictable. In addition, our findings present a puzzle to frictionless models of rational economic agents with Bayesian updating, that is, standard learning frameworks with parameter uncertainty (Lewellen and Shanken, 2002). For these models to explain our findings, they would require either implausible assumptions about investors' priors or a counterfactual positive price drift coming from a decline in estimation risk. We also show that our results are inconsistent with theories of the *Fed put*, microstructure effects, or liquidity, as well as with the idea that the positive autocorrelation of price changes is a continuation of the Lucca and Moench (2015) preannouncement drift.

On the contrary, our results are consistent with models that explicitly feature traders' differential interpretation of public signals (Banerjee et al., 2009; Banerjee and Kremer, 2010). These frameworks naturally generate a positive autocorrelation in price changes. Prices are endogenous, and the positive autocorrelation is an outcome of equilibrium in which investors receive sequential signals. We extend our results and test some additional predictions of these frameworks, finding further supportive evidence. On days in which preannouncement uncertainty is larger, we document (1) a larger price drift; (2) a larger trading volume; (3) a larger realized price volatility; and (4) a stronger relation between the trading volumes during the press conference and around the statement.

Our manuscript makes a methodological contribution to the economics literature by combining video analysis with time-stamped high-frequency financial asset prices. The approach we develop contributes to an extant literature that uses textual analysis methods across different fields of economics (see, for instance, Tetlock, 2007; Lucca and Trebbi, 2009; Gentzkow and Shapiro, 2010; Loughran and Mc Donald, 2011; Born et al., 2014; Hansen and Mc Mahon, 2016; Hansen et al., 2017; Gentzkow et al., 2019a; Gentzkow et al., 2019b; Hassan et al., 2019; Handlan, 2020; Gardner et al., 2021). Unlike these works, we are able to look at the exact moment at which each word has been pronounced. This avoids jointly gathering multiple updates

[2] A key goal of post-FOMC press conferences is to clarify the decision and the related changes in the statement: "If we don't hold a press conference [...] there's a decent chance that market participants will be quite confused," Jeffrey M. Lacker, President of the Federal Reserve Bank of Richmond, said during the FOMC meeting in July 2013.

[3] The press conference helps clarify the underlying motivation for the policy decision, and thereby provides news to asset holders. To generate movements in asset prices, the information communicated in the press conference has to be new to at least some investors. Teaching may be the best analogy: the instructor repeats the same concepts a few times using (slightly) different words, provides more context, and tries to respond to questions from students so that eventually the concept is clear to everybody.

together, and for our purposes, it eases the understanding of which news or word the market is responding to. Our approach not only improves on the identification of the effect of words on financial investors' beliefs but also extends the set of questions that can be asked. The recipe we develop can be applied in numerous settings in which someone wants to bridge linguistics with economics using market prices, such as the field of mass communication.

Our work is also linked to a fast-growing literature at the intersection of monetary policy, information transmission, and asset pricing (Gürkaynak et al., 2005; Swanson, 2017; Mueller et al., 2017; Neuhierl and Weber, 2019; Jarociński and Karadi, 2020; Cieslak and Schrimpf, 2019; Swanson, 2020). We add to this literature by documenting evidence consistent with theories positing that investors differently interpret the signals coming from the Federal Reserve. Moreover, the predictability results we document are consistent with recent works that show substantial predictability in investors' expectations about short-term interest rates (Cieslak, 2018) and monetary policy surprises (Bauer and Swanson, 2020). They argue that this predictability is due to markets underestimating the Fed's responsiveness to the state of the economy, or more generally, the "Fed response to news" channel, not a risk premium.

A recent body of literature has focused on the European Central Bank (ECB) and, similar to our work, has analyzed press conferences separately from the statement releases (see, for instance, Altavilla et al., 2019, 2020; Leombroni et al., 2020). Relative to these works, we have an exact match between the words spoken by the Central Bank chairman in each given minute and the price of financial assets at the same minute. This improves on the identification of which specific message the market reacted to and of the "communication surprises" in the press conference. Our methodology permits us also to identify the close connection between statement news and press conference news and to document the key role of clarification of statement news within the context of the press conference.

Finally, the literature on the signaling effects of monetary policy is among the largest in economics. Seminal contributions include Cukierman and Meltzer (1986) and Ellingsen and Soderstrom (2001). Recent contributions include Berkelmans (2011), Melosi (2016), and Nakamura and Steinsson (2018). We contribute to this literature by showing the link between statement and press conference news to financial investors and the relation between messages sent and signals received. We show how the messages communicated during the post-FOMC press conference help form investors' expectations and document the importance of those moments in which the Fed chairman answers questions related to the interpretation of the post-meeting statement.

2. Data

Our data come from multiple sources, and their nature is twofold. On the one hand, we propose a novel way to generate and use time-stamped text as data. We apply our method to post-FOMC-meeting press conferences, which are key events for financial investors worldwide. On the other hand, we have high-frequency quote-level prices for a wide range of financial assets. To the best of our knowledge, we are the first in economics to use videos by linking time-stamped words with high-frequency financial asset prices.

2.1. FOMC meetings

Given their importance to financial investors, FOMC meetings are an ideal laboratory in which to study real-time price discovery. Every year, committee members hold eight regularly scheduled meetings, during which they set the current monetary policy actions and discuss the likely future course of monetary policy. Starting in 1994, the decisions have been announced to the public via the release of a policy statement, usually at 14:00 Eastern Time (ET). In April 2011, then-chairman Ben Bernanke began the practice of holding a post-meeting press conference four times a year.[4] Since 2019, a press conference has followed all FOMC meetings. The overall goal of the statement and the following press conference is to increase the transparency of the Fed's actions and reduce market reactions and surprises.[5]

2.1.1. Time-stamped FOMC press conferences

The first source of our information is the audio of post-FOMC-meeting press conferences.[6] To generate this new data set, we (a) convert the audio into an interpretable text and (b) record the exact time at which each word was pronounced.

We convert a sequence of audio, X, into a sequence of words, W. Let $p(W|X)$ denote the probability of a word sequence given the audio. We obtain W^* by maximizing $p(W|X)$ over the set of all possible word sequences $\mathcal{V}$, that is,

$$W^* = \arg\max_{W \in \mathcal{V}} p(W|X). \tag{1}$$

To obtain an estimate of W^*, we proceed in four steps. First, we split the audio into smaller frames of around three seconds each and preprocess the audio clips into spectrograms. Second, we use the end-to-end deep learning algorithm developed by Hannun et al. (2014) to optimize $p(W|X)$ directly.[7] In particular, we use recurrent

[4] The introduction of post-FOMC-meeting press conferences in the United States was a response to the 2007–2008 financial crisis. In fact, clear communication is especially important when economic conditions require additional policy stimulus but the policy rate is already at its effective lower bound. The great public interest in the Federal Reserve's communication during this period makes our sample ideal to study the connection between the Fed chairman's words and movements in investors' beliefs. Additionally, the post-FOMC-meeting press conferences are the perfect laboratory to analyze real-time price discovery.

[5] Janet Yellen was in charge of the subcommittee studying the rationale for moving ahead with press conferences. During the March 2011 FOMC meeting, she said: "a crucial element of our mission was to consider approaches for ensuring that the public understands both the consensus of the Committee and the diversity of views among individual participants.... the purpose is to allow any news to be digested into market prices."

[6] The original video files can be found at https://www.federalreserve.gov/monetarypolicy/fomccalendars.htm.

[7] Alternatively, we could have applied Bayes' theorem to obtain $p(W|X) \propto p(X|W)p(W)$ and then optimized the conditional distribution,

Table 1
Example of Time-Stamped Transcription.

Start	End	Text
14:36:34.096	14:36:37.906	In terms of the rest of your question,
14:36:38.356	14:36:42.416	the Committee is really thinking of this as a way
14:36:42.416	14:36:43.526	of adjusting policy
14:36:43.526	14:36:45.576	to a somewhat more accommodative stance
14:36:46.046	14:36:48.596	to further the three objectives that I mentioned:
14:36:49.296	14:36:53.786	to insure against downside risks, to provide support
14:36:53.786	14:36:59.726	to the economy, that those factors are-where factors are
14:36:59.726	14:37:02.756	pushing down on economic growth, and then to support inflation.
14:37:02.756	14:37:05.586	So we do think it will serve all of those goals, but again,
14:37:05.586	14:37:07.696	we're thinking of it as essentially in the nature
14:37:07.696	14:37:09.526	of a mid-cycle adjustment to policy.

The table reports an example of transcribed text from a press conference on July 31, 2019. Starting and ending times (in hours, minutes, seconds, milliseconds) are given.

neural networks to convert the spectrograms into a sequence of characters, c, and all corresponding probabilities.[8] Conditional on c, we use the Connectionist Temporal Classification (CTC) algorithm of Graves et al. (2006) to draw a sequence of readable text transcriptions, W. Third, once we are able to evaluate $p(W|X)$, we follow Hannun et al. (2014) and use a beam-search algorithm to estimate W^* in (1). Fourth, we leverage the specific structure of our application and align our estimate of W^* with the text in the press conference transcripts, published by the FOMC. This approach allows us to create a perfect match between the audio and the text transcription using a combination of manual and automated procedures.

Next, we time-stamp the text of each three-second audio frame.[9] For each press conference, we append the three-second text and align the beginning and the end of the press conference with the times published by *Bloomberg*. Table 1 shows an example of a time-stamped transcription and highlights the precision with which we identify the time of each word pronounced during the press conference.

Let $\mathbf{W_j}$ be a matrix summarizing the press conference on date j. The columns correspond to the words contained in the text of the press conference, while the rows are the three-second time windows. The matrix elements are equal to one if a certain word was mentioned in a three-second window and zero otherwise. Before creating this matrix, we preprocess the raw text with these steps: (1) lowercasing the words; (2) removing punctuation, including hyphens and apostrophes; (3) removing words specific to the speech-to-audio translation, such as noise coming from the acoustic environment and spontaneous speech; (4) removing a list of very common English words (e.g., stop words);[10] and (5) reducing the remaining words to their root based on the Porter (1980) stemmer algorithm. Finally, for each press conference, we further record the start and the end of the question and answer section, together with the time in which each question was asked, the name of the reporter, and their affiliation.

Overall, we consider all 41 press conferences, covering a sample period from April 2011 to January 2020. On average, the duration of each press conference is 54 min and 47 s, with the first 10 min and 17 s corresponding to the opening statement made by the chair of the FOMC. The rest of the conference corresponds to the question and answer section, which contains on average 23 different questions. After preprocessing the text, we are left with an overall vocabulary comprising 7580 unique words pronounced a total of 156,767 times; each word is mentioned on average 20 times.

2.1.2. Extracting news from the FOMC meeting statement

Our second source of information is the news contained in FOMC statements. We identify this news by tracking the sentences and/or words added or removed relative to the previous statement. Indeed, Fed watchers have the common practice of parsing those changes to infer any new guidance on rates or variation in the economic outlook.[11]

For each press conference, j, we append the changes and build a vector, $\mathbf{s_j}$. On average, each policy statement contains changes in 3.8 sentences. The average length of the changes is seven words. Appendix A provides two examples of statement news: one with a large number of changes relative to the previous statement, and one with only a few variations in the text. In Section 4.1, we show that the audience directly asks about the statement news, a component that allows us to link $\mathbf{s_j}$ and $\mathbf{W_j}$.

$p(X|W)$, for a given language model, $p(W)$. However, as explained in Hannun et al. (2014) and Amodei et al. (2016), estimating $p(X|W)$ separately can lead to suboptimal results because of the lack of error propagation between the probability densities. In contrast, end-to-end methods that optimize $p(W|X)$ directly allow the model to learn from the data conditional on a sufficiently large training data set.

[8] The output of an RNN will have different lengths, for instance, depending on the speaking rate of the speaker, their pronunciation, the acoustic environment, or their spontaneous speech (e.g., "um" or "uh"). Therefore, we need an additional step that maps the neural network's output into a readable transcription. To address this issue, we use the Connectionist Temporal Classification (CTC), a state-of-the-art algorithm.

[9] We can increase or decrease the length of the audio frame by modifying the length of the audio clips input into (1).

[10] The list of stop words that we remove come from the Python Natural Language Toolkit.

[11] For instance, the *Wall Street Journal* publishes the changes between consecutive statements a couple of minutes after the statement release. For an example, see https://www.wsj.com/articles/parsing-the-fed-how-the-november-statement-changed-from-september-01604603089.

Table 2
Summary Statistics for the Changes in Prices for Different Asset Classes around FOMC Post-Meeting Statement Release and Press Conference.

		Fed funds futures		Eurodollar futures		Stocks	Forex
Δp	Event	1m–6m	9m–15m	6m–12m	24m–70m		
Average	ST	0.19	0.97	0.68	0.67	17.35	5.78
	PC	0.08	0.01	0.07	0.08	2.99	−3.68
Standard deviation	ST	2.00	3.92	3.73	6.03	46.32	39.75
	PC	1.08	2.92	2.24	4.57	50.97	30.21
Average absolute value	ST	1.30	2.94	2.70	4.32	36.31	30.69
	PC	0.56	1.95	1.42	3.24	37.42	23.76

For a wide range of financial assets, the table reports the average value, standard deviation, and average absolute value for price changes around the times of the post-FOMC-meeting statement release (ST) and press conference (PC). On FOMC days with press conferences, the change in price around the statement is equal to the change in price from 10 min before the statement to 20 min after. The change in price around the press conference equals the change in price from the beginning to the end of the post-meeting press conference held by the fed chairman, for example, starting at 14:30. All values in the table are in basis points.

2.2. High-frequency asset prices.

After constructing a second-level time-stamped text data set, we use high-frequency financial data to characterize the real-time price discovery. In this regard, our financial data come from three different sources.

First, we use best of book (BBO) trade and quote data for federal funds futures and Eurodollar futures from the Chicago Board of Trade and the Chicago Mercantile Exchange, respectively. Federal funds futures contracts are offered with an expiration of up to two years, while Eurodollar futures span a longer horizon of up to seven years. At each point in time, we have over 20 different maturities for federal funds futures and over 30 different maturities for Eurodollar futures. The advantage of using these contracts is that their prices are closely linked to investors' expectations of monetary policy actions, and they target federal funds rates.

For both products, our data set contains the bid and ask prices, the traded price, and the trading volume. Prices are reported according to the International Monetary Market Index quote convention, that is, 100 minus the rate. For the case of federal funds futures, the rate is an arithmetic average of the daily effective rate during the contract expiration month, so a price quote of $94.25 would imply an average daily rate of 5.75% per annum. As to Eurodollar futures, the implied rate is the three-month London interbank offered rate for spot settlement on the third Wednesday of the contract expiration month. For every minute and futures maturity, we compute the implied rate estimates using mid prices.

Second, we use the trades and quote (TAQ) database for the intraday behavior of the S&P 500 index, as well as its constituents, during FOMC days. We form industry portfolios by combining the high-frequency prices of individual S&P 500 stock constituents with the Fama-French definition of 30 sectors. We require that at least 10 stocks are present in each portfolio each day. At 10:00 am ET of the FOMC day, we invest one dollar in each stock in the portfolio. We look at the portfolio performance during that day. The TAQ database offers a complete history of trades and quotes within the U.S. National Market System; it contains the bid and ask prices and is time-stamped at the millisecond level. Within each minute, we take the median of millisecond mid prices.

Third, and finally, we use spot exchange rate quotes on seven currencies against the U.S. dollar: Australian dollar, euro, British pound, New Zealand dollar, Swiss franc, Japanese yen, and Canadian dollar. All quotes are from Dukascopy, which offers historical tick-by-tick market data for dealable interbank foreign exchange rates for each millisecond. Again, within each minute, we take the median of millisecond mid prices.

3. Statement and press conference news

We compute changes in asset prices around two separate, nonconsecutive time windows. The first is a 30-minute window around the FOMC announcement, which usually occurs at 14:00 ET. Following, among others, Gürkaynak, Sack and Swanson (2005), Fleming and Piazzesi (2005), and Nakamura and Steinsson (2018), we use the exact time of the announcement as reported by *Bloomberg* and compute the price changes from 10 min before the statement to 20 min after the statement. The second is the press conference window: it generally starts at 14:30 ET and lasts on average 55 min. We use the exact start and end times. The two windows do not overlap in time at all.

Table 2 shows the average value, standard deviation, and mean absolute value for each asset class in our study around both the statement release and the press conference. We group all assets into different buckets: short- and medium-term federal funds futures (1–6 and 9–15 months, respectively), short- and medium-term Eurodollar futures (6–12 and 24–70 months, respectively), stocks, and exchange rates. For each asset, we compute the summary statistics and then report the bucket mean value in the table. The average value of both shocks is close to zero. Moreover, the variations of the statement and the press conference shocks are rather similar. Both the standard deviation and the mean absolute value for press conference shocks are comparable to the ones for the statement.

Table 3
Press conference shocks against statement shocks.

	Fed funds futures		Eurodollar futures		Stocks	Forex
	1m–6m	9m–15m	6m–12m	24m–70m		
a	0.05	−0.16	0.03	−0.14	−4.30	−5.18
	[0.41]	[−0.54]	[0.11]	[−0.28]	[−0.51]	[−1.51]
b	0.17	0.17	0.19	0.33	0.41	0.25
	[1.99]	[1.47]	[3.87]	[2.77]	[2.59]	[3.10]
R^2	8.53	5.50	8.43	20.21	14.10	11.20

For each asset bucket k, the table reports the regression estimates for the following equation:

$$\underbrace{\Delta p_{it,PC}}_{\Delta\text{p at press conference: e.g., 14:30-15:30}} = a_k + b_k \underbrace{\Delta p_{it,ST}}_{\Delta\text{p around statement: 13:50-14:20}} + \epsilon_{it},$$

where $\Delta p_{it,PC}$ is the change in asset i's price during the date-t press conference, $\Delta p_{it,ST}$ is the change in asset i's price around the date-t FOMC statement release, and asset i belongs to bucket k. The two price changes (in basis points) are computed over two nonoverlapping, nonconsecutive time intervals. The times (13:50–14:20, 14:30–15:30) are only examples. We always use the price change from 10 min before the statement to 20 min after the statement, as well as the price change during the press conference. t-statistics are in brackets. Standard errors are double clustered at the date-asset level. R^2 statistics are expressed as a percentage.

Hence, price changes around the press conference are of similar magnitude as those around the statement.[12]

3.1. Persistence in price shocks around FOMC events

Figure 2 examines the relation between price changes around the press conference and those around the statement release for federal funds and Eurodollar futures. Each dot corresponds to an FOMC day. The line represents the regression line from a univariate linear regression model. The relation is positive across all subplots, and the slope increases with asset maturity.

To test the significance of the positive correlation between the two price changes, we run a pooled ordinary least squares (OLS) regression, where we group all assets into different buckets as before. For each asset bucket k, we estimate the following equation:

$$\Delta p_{it,PC} = a_k + b_k\,\Delta p_{it,ST} + \epsilon_{it}, \tag{2}$$

where $\Delta p_{it,PC}$ is the change in asset i's price during the date-t press conference, $\Delta p_{it,ST}$ is the change in asset i's price around the date-t FOMC statement release, and asset i belongs to bucket k. We double cluster the standard errors at the date-asset level.[13]

Table 3 reports the regression results. The point estimates confirm the evidence from the scatterplots of a strong and statistically significant positive relation between the two shocks. For all asset classes, except for federal funds futures, the results are highly significant. The slope coefficient estimates are similar across all asset classes, ranging from 0.2 to 0.4.[14]

In Table 4, we repeat the analysis for federal funds futures, Eurodollar futures, foreign exchange rates, and the S&P 500 ETF (SPY) for a "placebo" event period.[15] We use FOMC days without a press conference and compute price changes around the statement release and around an alternative window that mimics the average press conference time (from 14:30 to 15:24 ET). We do not find any evidence of a positive autocorrelation of price changes on days without a press conference.[16] Figure E.1 in the appendix offers a graphical representation of this result.

3.2. Additional results and robustness

Additional results in Appendix D describe when the strong autocorrelation just documented is more likely to happen. We find that the positive correlation is concentrated (a) in those FOMC events with a larger premeeting dispersion of analysts' forecasts about the policy rate decision and (b) in those FOMC events with a premeeting VIX above the historical average. Conversely, we do not find any statistical difference between days with more and fewer changes to the text of the post-FOMC statement. Finally, we separate the press conference into two parts, the introductory statement by the chairman and the Q&A. The idea is that the introductory statement is a closer repetition of the post-FOMC statement, while in the Q&A session, it is difficult to follow a script. We ask whether our results

[12] In Appendix C, we compute the coefficient of variation for minute-level changes in the price of federal funds and Eurodollar futures. We report its distribution for separate maturities and four nonoverlapping subperiods during FOMC days. We document a large variation in these prices around the statement release, as well as during the press conference. In contrast, there is almost no variation in prices before the statement and after the press conference. Appendix C provides further details on the exercise.

[13] We allow observation (i, t) to be correlated with observation (i, s) for time $s \neq t$ and with observation (j, t) for asset $j \neq i$.

[14] The R^2 in Table 3 suggests that the correlation is of the same magnitude as the slope coefficient in the regression (because the two shocks have similar volatilities). For instance, the correlation between price changes is 40% for medium-term Eurodollar futures, but it goes as high as 58% for the 60-month maturity. Similarly, the average correlation for all stock portfolios is 33% and reaches 44% for SPY.

[15] For data availability reasons, we use only SPY to represent movements in the stock market. In Table E.2 we document that the results of Table 3 hold strongly for SPY with a slope coefficient of 0.515 (t-stat of 3.09) and an R^2 of about 20%.

[16] Notably, the intercept for fed funds futures, especially short-term ones, is significantly negative suggesting that those meetings without an accompanying press conference might be different. Yet, the effect appears concentrated in the years before the Fed introduced regular press conferences. If one excludes those years, the intercepts would be −0.042 (t-stat of −1.06) and −0.046 (t-stat −1.00) for short- and medium-term fed funds futures, respectively.

Table 4
FOMC Days without a Press Conference.

	Federal funds futures		Eurodollar futures		SPY	Forex
	1m–6m	9m–15m	6m–12m	24m–70m		
a	−0.16	−0.15	0.04	0.18	−4.28	−1.59
	[−2.17]	[−2.15]	[0.16]	[0.70]	[−0.47]	[−0.87]
b	0.08	0.05	0.01	0.04	−0.21	−0.01
	[1.49]	[1.19]	[0.16]	[0.33]	[−1.11]	[−0.05]
R^2	0.35	1.30	0.01	0.55	0.51	0.30

In this table, we repeat the analysis from Table 3, except we add a "placebo" event period: we use FOMC days without a press conference and compute price changes around the statement release and around an alternative window that mimics the average press conference time (from 14:30 to 15:24 ET). The columns in the table report the estimates of the following equation for each asset bucket k:

$$\underbrace{\Delta p_{it,AW}}_{\Delta\text{p in alternative window}} = a_k + b_k \underbrace{\Delta p_{it,ST}}_{\Delta\text{p around statement: 13:50-14:20}} + \epsilon_{it},$$

where $\Delta p_{it,AW}$ is the change in asset i's price during the date-t alternative window mimicking the press conference time, and $\Delta p_{it,ST}$ is the change in asset i's price around the date-t FOMC statement release. The two price changes are computed over two nonoverlapping, nonconsecutive time intervals. t-statistics are in brackets. Standard errors are double clustered at the date-asset level. R^2 statistics are expressed as a percentage.

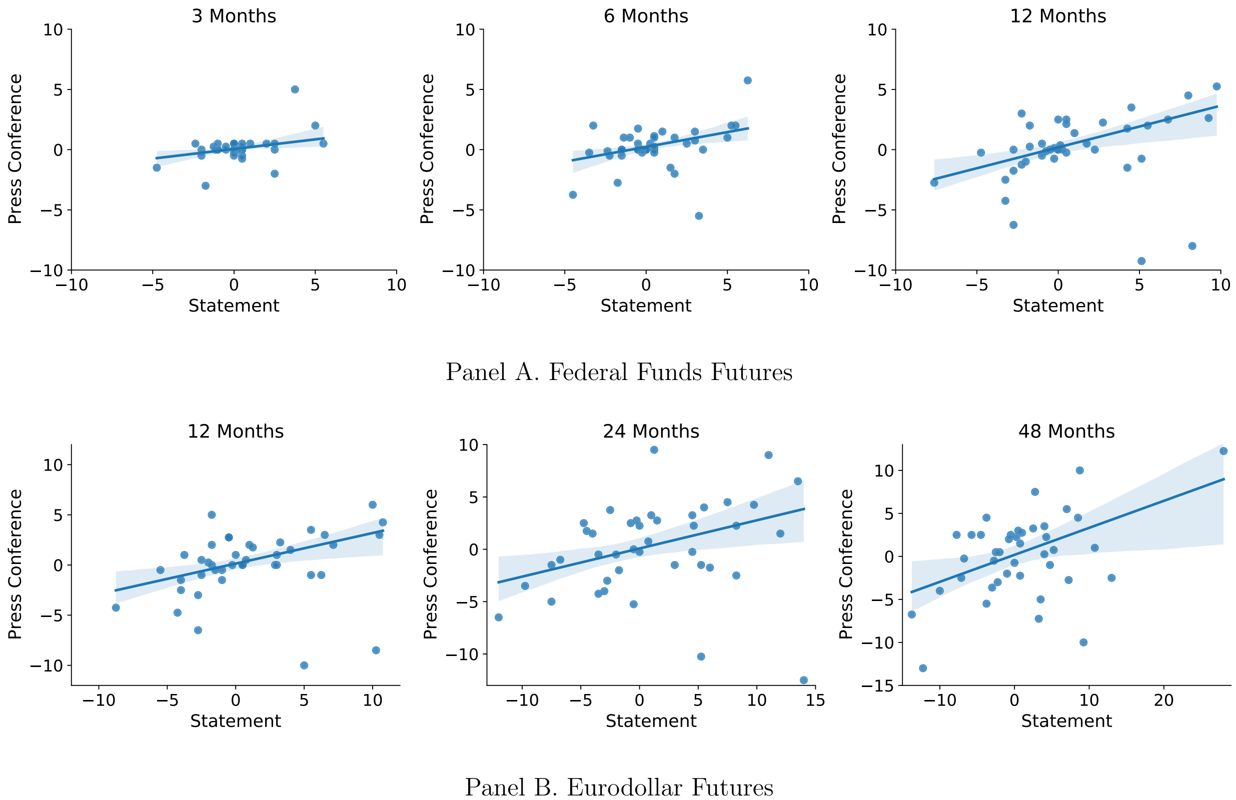


Fig. 2. The figure shows the statement shocks on the x-axis and the press conference shocks on the y-axis for the 30-day federal funds futures expiring in 3, 6, and 12 months (Panel A) and Eurodollar futures expiring in 12, 24, and 48 months (Panel B). The shocks are in basis points. The straight line represents the regression fit line, and the dashed area around the line represents the 95% confidence interval band.

are stronger or weaker when the information in the statement and in the press conference is more similar. We find that the chairman's statement is a close repetition of the post-meeting release, while the Q&A adds informational range, so we compute asset price changes around those two windows and find that the correlation we document is realized only during the Q&A session.

In Appendix E, we run several robustness tests. Tables E.1 and E.2 report the regression estimates of Eq. (2) for each asset separately. Finally, in Table E.3, we use all data, both FOMC and non-FOMC days, and run

$$\Delta p_{it,PC} = a_k + b_k \Delta p_{it,ST} + c_k \; \Delta p_{it,ST} \; \mathbb{1}_{PC} + \epsilon_{it}, \tag{3}$$

Table 5
Economic Significance.

	Fed funds futures		Eurodollar futures		Stocks	Forex
	1m–6m	9m–15m	6m–12m	24m–70m		
α	0.37	0.40	1.16	1.02	12.66	8.14
	[1.27]	[1.65]	[2.80]	[2.11]	[2.30]	[2.57]
β	0.54	0.33	0.32	0.08	−0.13	0.18
	[2.40]	[2.53]	[2.68]	[0.42]	[−0.61]	[1.12]
R^2	9.84	17.79	4.38	0.89	1.69	3.39

The table reports statistics from a regression evaluating the economic significance of a market-timing strategy that exploits the information released around the FOMC announcement. We take a long position in the asset at the beginning of the press conference if its price went up when the statement was released and a short position otherwise. We close the position at the end of the press conference. We compare this strategy with a simple buy-and-hold strategy. For each asset bucket k, we regress the returns of the market-timing strategy onto the ones from the buy-and-hold strategy:

$$\mathrm{r}_{it,MT} = \alpha_k + \beta_k \mathrm{r}_{it,B} + \epsilon_{it},$$

where $\mathrm{r}_{it,MT}$ are the returns from a market-timing strategy involving asset i, $\mathrm{r}_{it,B}$ are the returns from a passive buy-and-hold strategy, and asset i belongs to bucket k. t-statistics are in brackets. Standard errors are double clustered at the date-asset level. The α coefficients are in basis points. R^2 statistics are expressed as a percentage.

where $\Delta p_{it,PC}$ and $\Delta p_{it,ST}$ denote price changes, and $\mathbb{1}_{PC}$ is an indicator variable that takes a value of one on FOMC days that contain a press conference and zero otherwise. On FOMC days, $\Delta p_{it,PC}$ denotes price changes during the date-t press conference, and $\Delta p_{it,ST}$ is the change in asset i's price around the date-t FOMC statement release. On non-FOMC days, the price changes are computed using the same time as in the previous FOMC meeting day. Because of a lack of data, we run the regression only for federal funds futures and Eurodollar futures. The table shows that $b_k + c_k$ has a similar magnitude as in Table 3, but b_k is insignificant and close to zero. In sum, the interesting pattern we document for FOMC days with a press conference is not shared by other days.

3.3. Economic significance of the persistence in price shocks

To measure the economic value of our empirical pattern, we implement a simple trading strategy. For each asset class, we use the half-hour returns around the FOMC statement release as a trading signal. For every asset, we take a long position at the beginning of the press conference if its price went up when the statement was released and a short position otherwise. We close the position at the end of the press conference. This strategy does not require any parameter estimation.

We compare the results of our trading strategy with a buy-and-hold strategy in which we buy the assets regardless of the information received at the statement release. For each asset bucket k, we run the following regression:

$$\mathrm{r}_{it,MT} = \alpha_k + \beta_k \mathrm{r}_{it,B} + \epsilon_{it}, \quad (4)$$

where $\mathrm{r}_{it,MT}$ is the returns from the active strategy involving asset i in the FOMC date t, and $\mathrm{r}_{it,B}$ is the returns from a passive buy-and-hold strategy. Asset i belongs to bucket k. A positive intercept, α, is necessary for the active strategy to have a higher Sharpe ratio relative to the passive buy-and-hold approach, that is, a higher average return scaled by the return volatility.[17]

Table 5 reports the regression results, where we double cluster the standard errors at the date-asset level. A timing strategy that exploits the information coming from the statement substantially outperforms the passive strategy. The numbers reported are not converted to reflect a lower frequency; for example, they are not annualized. The intercepts are positive and statistically significant. They imply a large increase in Sharpe ratios. For instance, a timing strategy that exploits the information in the statement applied to 60-month Eurodollar futures will have a Sharpe ratio increase of 25% relative to a buy-and-hold strategy. For SPY, the Sharpe ratio goes up by 34%.

Figure 3 shows the mean pointwise cumulative intraday return of the active trading strategy compared to a buy-and-hold strategy. We report results for three different assets: 60-month Eurodollar futures, SPY, and the EUR/USD exchange rate. The x-axis represents the minutes since the press conference started. The solid line represents the returns from the market timing strategy, while the dotted line represents the returns from the passive buy-and-hold strategy. For all three assets, the overperformance starts from minute 10 when the Q&A session starts. The SPY seems to react rapidly: after 20 min into the Q&A session, the cumulative returns stabilize. For the other two assets, the cumulative returns show a steadily growing pattern all the way from minute 10 to the end.

[17] Specifically, let the Sharpe ratio for asset j be $\frac{E(r_j)-r_f}{\sigma_j}$, where r_f is the risk-free rate and σ_j the volatility of asset j's returns. The relation between the Sharpe ratio and alpha is

$$\frac{E(r_j)-r_f}{\sigma_j} = \frac{\alpha_j}{\sigma_j} + \rho_{j,B}\frac{E(r_B)-r_f}{\sigma_B},$$

where $\rho_{j,B}$ denotes the correlation parameter between r_j and r_B given by $\sqrt{R^2}$.

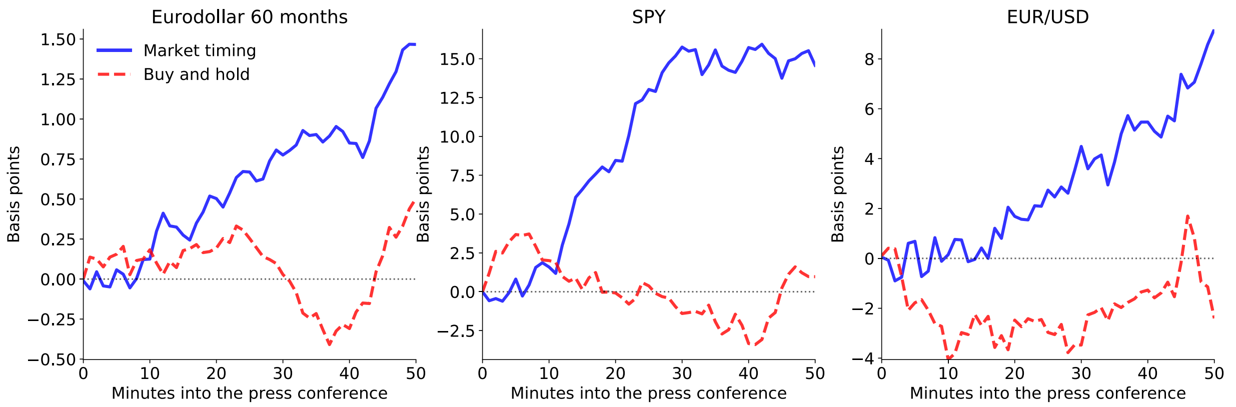


Fig. 3. The figure shows the intraday evolution of the average cumulative performance (in basis points) for market timing and passive buy-and-hold strategies. Both strategies are implemented on 60-month Eurodollar futures (left panel), SPY (middle panel), and the EUR/USD exchange rate (right panel). The market-timing strategy exploits the information released around the FOMC announcement. We take a long position in the asset at the beginning of the press conference if its price went up when the statement was released and a short position otherwise. We close the position at the end of the press conference. We compare this strategy with a simple buy-and-hold strategy, which always goes long the asset. Both strategies are implemented from the beginning to the end of the press conference.

3.4. Informational content of the press conferences

Our previous results document a strong serial autocorrelation in asset prices in a tight window around the statement release and the subsequent press conference. An important related question is whether information is more efficiently incorporated into asset prices with or without a press conference. So, we test whether market participants are better at predicting future monetary policy decisions with or without the press conference.

We estimate the following equation:

$$|\Delta \mathrm{FE(ff)}_{it}| = b_k^{ST} \cdot I_{ST} + b_k^{ST-PC} \cdot I_{ST-PC} + \epsilon_{it}, \tag{5}$$

where $\Delta \mathrm{FE(ff)}_{it}$ denotes the daily difference in the ex post forecast error implied by federal funds futures. To compute the forecast error, we calculate for each contract the difference between the federal funds futures closing rate and the arithmetic average of daily effective federal funds rates during the contract month rounded to the nearest one-tenth of 1 bps. When the futures contract expires, the forecast error is zero. We scale this difference by the average daily effective federal funds rate for the delivery month. The regressors in (5) are dummy variables. The dummy variable I_{ST} takes a value of one on FOMC days on which the committee published a policy statement but did not hold a post-meeting press conference, and zero otherwise. I_{ST-PC} takes a value of one on FOMC days on which the committee published a policy statement and subsequently held a press conference, and zero otherwise. The parameters of interest, b_k^{ST-PC} and b_k^{ST}, measure the average change in monetary policy forecasting errors on FOMC days with or without the press conference.

Table 6 presents the results. From 2008 (the start of our data set) to 2010, during which no press conferences were held, we always find a reduction in forecast errors following an FOMC day. The bottom panel of Table 6 reports the results. More interesting is the top panel covering the years between 2011 and 2018. In those years, we have two types of meetings: (1) the ones followed by a statement release only and (2) the ones followed by both a statement release and a press conference. We find reductions in pricing errors that are both larger in magnitude and more significant following FOMC days in which the chairman holds a press conference. Smaller or insignificant reductions are visible for FOMC days without a press conference. Overall, the lower forecasting error suggests that press conferences are useful for information to be more efficiently incorporated into asset prices.[18]

The approach followed in this section is simple, yet it provides evidence of a tight link between statement and press conference news. In the next section, we take the analysis a step further. We combine the exact words pronounced in each given minute of the press conference with higher-frequency returns and show that the minutes in which the Fed chairman discusses the statement news lie behind the positive autocorrelation in price changes documented so far.

4. Within-press-conference analysis

We now introduce time-stamped text and use our new method to understand which moments the autocorrelation of price changes described above are realized in.

4.1. Variable construction: Linking statements with press conference news

We link the statement news $\mathbf{s_j}$ computed in Section 2.1.2 with the press conference word matrix, $\mathbf{W_j}$, described in Section 2.1.1. Our approach proceeds in four steps: First, we aggregate the three-second-level text in $\mathbf{W_j}$ to a one-minute frequency. Heuristically, we observe that one minute is an adequate amount of time

[18] This is in line with the view stated by Janet Yellen during a March 2011 FOMC meeting, where she spoke about the benefits of post-meeting press conferences are “an important and effective communications tool… to allow any news to be digested into market prices.”

Table 6
Change in Forecast Errors around FOMC Days.

Coef.	Variable	Time to maturity (in months) 0m–2m (1)	2m–6m (2)	6m–12m (3)
Time period: January 2011 to December 2018				
b_k^{ST}	I_{ST}	0.164	−1.218	0.369
		[0.402]	[−3.974]	[0.780]
b_k^{ST-PC}	I_{ST-PC}	−1.698	−1.407	−1.506
		[−2.441]	[−1.852]	[−1.722]
Time period: January 2008 to December 2010				
b_k^{ST}	I_{ST}	−4.421	−7.308	−10.985
		[−1.906]	[−3.209]	[−4.155]

For each maturity bucket k, the table reports the regression estimates for the following equation:

$$|\Delta \text{FE(ff)}_{it}| = b_k^{ST} \cdot I_{ST} + b_k^{ST-PC} \cdot I_{ST-PC} + \epsilon_{it},$$

where $\Delta \text{FE(ff)}_{it}$ denotes the daily difference in the ex post forecast error and the regressors are dummy variables. To compute the forecast error, we calculate for each contract the difference between the federal funds futures closing rate and the arithmetic average of daily effective federal funds rates during the contract month rounded to the nearest one-tenth of one basis point. We scale this difference in rates by the average daily effective federal funds rate for the delivery month. The dummy variable I_{ST} takes a value of one on FOMC days in which the committee published a policy statement but did not hold a post-meeting press conference, and zero otherwise. I_{ST-PC} takes a value of one on FOMC days in which the committee published a policy statement and subsequently held a press conference, and zero otherwise. t-statistics are in brackets. Standard errors are double clustered at the date-asset level. Coefficient estimates are in percentage.

to capture the asset price response to words.[19] Second, we run a part-of-speech analysis of the sentences identified in $\mathbf{s_j}$. This means deconstructing those sentences into parts of speech: nouns, adjectives, verbs, etc. Third, within the press conference text, we search for all combinations that include those nouns and verbs from $\mathbf{s_j}$. We also take their synonyms, which are reported for convenience in Table B.1 in the appendix. To make sure that our words actually capture the link with the statement, we add the requirement that the word “statement” should appear in the same sentence.[20] Fourth, and finally, we create a minute-level dummy variable, D_t, equal to one when that combination is identified in a given minute of the press conference.

Our minute-level statement-related dummy only captures the linguistic connection between the press conference discussion and the news first presented to the public with the statement released earlier in the same day. Our construction of the dummy does not exploit any asset price information. Taking note of this is important because the construction of our dummy allows us to test whether the positive autocorrelation in asset prices documented above is indeed coming from the similarity of information between the statement and press conference.

Overall, statement-related minutes account for 7.5% of press conference minutes; however, they are not uniformly distributed. Figure 4 shows the average values of the dummy across different moments of the press conference. We separate the press conference into the opening statement and questions, grouping the latter by their order. We document a strong connection between the average values of the dummy and the press conference’s progress. About 18% of the opening statement is devoted to statement news. During the opening statement, the chairman describes the policy statement in detail: only a few words or topics are actual news; the rest refers to aspects of the economic outlook or policy that have not changed relative to the previous FOMC meeting.

The figure also illustrates a close link between the question order and statement news. This link fades as time passes and more questions arrive. Fed watchers try to infer large changes in the Fed’s policy from small changes in the statement’s wording.[21] So they ask in the first few questions whether the chairman could provide additional information about the changes in the statement.[22]

[19] The Fed video feed requires more bandwidth and lags the audio feed by approximately three seconds. From the way we time-stamp the text, we implicitly assume that investors listen to the audio and react to it. Aggregating the text at a one-minute frequency helps reduce any noise potentially coming from a three-second difference with which different investors receive the same information. In an unreported robustness test, we also shifted the text by three seconds, aggregated it again at the one-minute frequency, and reran our analysis. Results were unaffected. Therefore, we can conclude that the three-second lag between the video and audio feeds is immaterial to our results.

[20] The combination of the word “statement” and “statement news” is necessary to avoid false positives, such as “the New York Fed’s website contains a statement” or “Milton Friedman’s statement.”

[21] Fed watchers “try to make a living out of parsing these statements” (Peter Barnes, Fox News, April 2012).

[22] Our identifying assumption is that no other shocks influence the explanatory variable during these one-minute windows. Such an assumption is common in the literature on high-frequency identification of monetary policy or other macroeconomic announcements. However, unlike us, previous studies have used longer windows: for instance, Cook and Hahn (1989), Kuttner (2001), Cochrane and Piazzesi (2002), Bernanke and Kuttner (2005) use a one- or two-day window around FOMC announcements; Nakamura and Steinsson (2018) use a 30-minute window; and

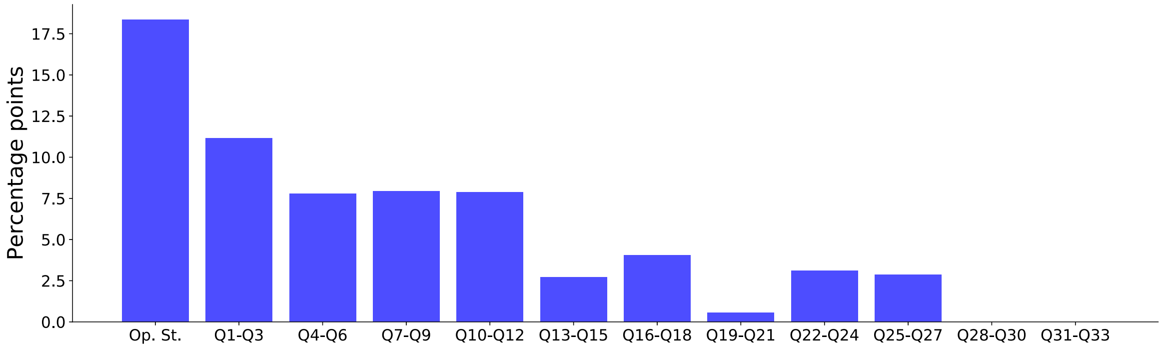


Fig. 4. The figure shows the average value of the dummy, D_t, capturing statement-related minutes during different phases of the press conference. We separate the press conference into the opening statement and the questions (Q1–Q33), the latter being grouped by their order.

We further analyze directly the linguistics of the messages to identify the different language patterns and styles that characterize the minutes in which the chairman talks about the statement.[23] We report the results in Appendix E, but we will briefly describe them here. Minutes in which the chairman talks about the statement news are characterized by a larger use of future tense, relative to present or past tense; they tend to involve more insight words, such as "think" or "consider," and more relative words to qualify the statement, such as "during" and "when"; and finally, they feature more comparison words, "than" or "as," as well as numbers, which tend to be used almost 20% more frequently than during non-statement-related minutes. Overall, this suggests that messages in statement-related minutes are more specific and informative than messages in other minutes (Pennebaker, Boyd, Jordan and Blackburn, 2015).

4.2. How the chairman's message induces variation in investors' beliefs

We run three simple regressions that make use of the minute-level dummy variable, D_t, constructed in 4.1, to quantify the average absolute price variation, trading volume, and mean returns in statement-related minutes. Our identifying assumption is that unexpected changes in statement-related minutes for both asset prices and trading volume arise from the message communicated in that minute.

4.2.1. Absolute variation

The first regression we estimate serves to assess the average absolute variation in minute-level returns for statement-related minutes. We group all assets described in Section 2 into different buckets and run a pooled OLS regression. Let $|r_{it}|$ be the absolute value of the financial returns of asset i between minutes $t-1$ and t, and let D be the dummy variable. For each asset bucket, we estimate the following equation:

$$|r_{it}| = a_k + b_k D_{t-1} + \epsilon_{it}, \tag{6}$$

where asset i belongs to bucket k.

A positive slope coefficient, b_k, associated with the dummy variable implies that statement-related minutes are more relevant to forming investors' expectations. However, if the chairman merely repeats some sentences in statement-related minutes, a negative slope coefficient should be observed.

Table 7 reports the results. News related to the information previously released in the statement affects prices, and the effect is generally statistically significant. The slope coefficient in the regression is positive and economically large. For medium-term Eurodollars, stocks, and forex, the slope coefficient implies that the average price variation when the chairman discusses the policy statement news is about 14% larger than for other minutes. These results do not necessarily imply that other nonstatement minutes do not matter, but on average they move prices less than statement-related minutes. The effect of statement-related minutes for shorter-maturity assets, both federal funds and Eurodollar futures, is instead close to zero and insignificant. Consistent with the findings in Section 3, these results suggest that investors update their beliefs in statement-related minutes mostly for the longer-term horizon.

4.2.2. Trading volume

A large literature has already documented that both trading volume and market depth increase during FOMC announcement days and in particular in the minutes surrounding the statement release (Fleming and Piazzesi, 2005). Nevertheless, not much is known about their behavior during the chairman's post-meeting press conference. Figure 5 shows the average trading volume for federal funds futures in FOMC days with a press conference and compares it with the average trading volume in non-FOMC days, as well as FOMC days without a press conference (all dates starting from 2011). We plot these values from one hour before the statement release to two and a half hours after for shorter-term (left panel) and medium-term (right panel) federal funds futures. The definition of

Andersen et al. (2003) use a five-minute return series around the announcement. Recent papers, such as Bianchi et al. (2019) and Arteaga-Garavito et al. (2021), focus on high-frequency asset price responses to news in tweets.

[23] We use a rather standard word-count strategy. The search words are categorized into language categories following the Linguistic Inquiry and Word Count (LIWC) by Pennebaker et al. (2015).

Table 7
Absolute Price Variation.

	Fed funds futures		Eurodollar futures		Stocks	Forex
	1m–6m	9m–15m	6m–12m	24m–70m		
a	0.08	0.15	0.17	0.26	3.73	2.58
	[4.54]	[19.61]	[12.08]	[35.99]	[17.36]	[13.82]
b	−0.01	0.01	0.00	0.04	0.49	0.36
	[−1.30]	[0.35]	[0.02]	[2.10]	[1.94]	[2.12]

The table reports the statistics from a regression comparing the average absolute price variation in statement-related minutes to all other minutes of the press conference. For each asset bucket k, we estimate the following equation:

$$|r_{it}| = a_k + b_k D_{t-1} + \epsilon_{it},$$

where r_{it} is the minute-level returns (in basis points) of asset i belonging to bucket k and D is the dummy variable constructed as in Section 4.1. t-statistics are in brackets. Standard errors are double clustered at the date-asset level.

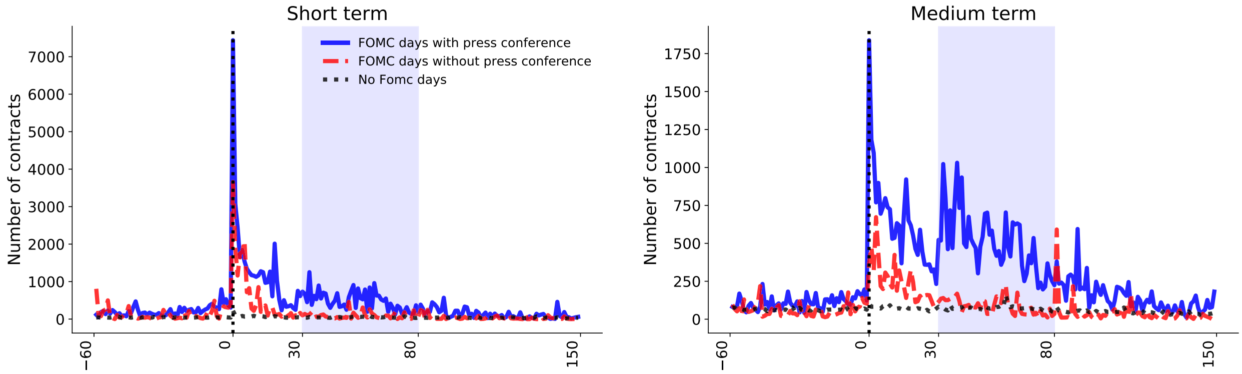


Fig. 5. The figure shows the average trading volume (the number of traded contracts) for the 30-day federal funds futures for three different groups of dates. The notional amount of each contract is given by the product of the price of the futures contract times a multiplier of $4,167. The solid blue line depicts the average volume for FOMC days with a press conference, the dashed red line for FOMC days without a press conference, and the dotted black line for non-FOMC days. The left panel shows results for federal funds futures maturing before 9 months, while the right panel shows results for contracts with maturities above 9 months. The dashed vertical line highlights the time in which the FOMC statement is released. The shaded area represents the FOMC press conference. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

short and medium terms is the same as in Table 3. The basic finding is that the volume jumps at the announcement and steadily decreases for shorter-term assets. In contrast, for medium-term assets, the steady decrease is interrupted by the press conference, when a second jump in trading volume occurs. On average, the total volume during the press conference is of the same magnitude if not higher than that around the FOMC statement release. Figure E.2 in the appendix shows this result for federal funds and Eurodollar futures.

We then study the dynamics of the trading volume during the press conference. We scale the minute-level volume of each asset i by the total volume of the same asset during the press conference, that is, $\frac{\text{Vol}_{ijt}}{\sum_{t\in T_j}\text{Vol}_{ijt}}$, where i refers to the asset, t to the minute, j to the day, and T_j to the set of minutes on day j. For each asset bucket k, we estimate the following equation:

$$\frac{\text{Vol}_{ijt}}{\sum_{t\in T_j}\text{Vol}_{ijt}} = a_k + b_k D_t + \epsilon_{it}. \tag{7}$$

Given that the regression is estimated on press conference days only, the intercept represents the percentage of trading occurring in non-statement-related minutes during the press conference. The slope coefficient associated with the dummy is the additional average trading volume in statement-related minutes as a percentage of the total.

Table 8 reports the regression estimates. Statement-related minutes exhibit a larger trading volume, which is both statistically and economically significant. The relation is stronger at longer maturities. Trading volume for Eurodollar futures between 24 and 70 months is 17% (= 0.30/1.78) larger in minutes mentioning the statement, while for federal funds futures with a maturity above 9 months the difference is almost 50% (= 0.86/1.75) larger. These values are highly economically significant given that FOMC days have been shown to be among the days with the largest trading activity across several financial markets, a point reinforced by Fig. 5.

4.2.3. Mean returns

Finally, in this section, we analyze the direction of price shocks in statement-related minutes. We test whether in those minutes prices move in the same direction as they did around the statement. In addition, we quantify how much of the correlation documented in Section 3 is due to a discussion of the post-meeting statement news.

Table 8
Trading Volume.

	Fed funds futures		Eurodollar futures	
	1m–6m	9m–15m	6m–12m	24m–70m
a	1.77	1.75	1.80	1.78
	[42.46]	[39.75]	[54.84]	[64.45]
b	0.48	0.86	0.04	0.30
	[1.31]	[4.96]	[0.31]	[2.57]

For each asset bucket k, the table reports the regression statistics to compare the average trading volume in statement-related minutes to all other minutes of the press conference. We estimate the following equation:

$$\frac{\text{Vol}_{ijt}}{\sum_{t\in j}\text{Vol}_{ijt}} = a_k + b_k D_t + \epsilon_{it},$$

where $\frac{\text{Vol}_{ijt}}{\sum_{t\in j}\text{Vol}_{ijt}}$ is the trading volume of asset i in minute t of day j scaled by the total trading volume of asset i during the press conference in date j, and D is the dummy variable constructed as in Section 4.1. Asset i belongs to bucket k. t-statistics are in brackets. Standard errors are double clustered at the date-asset level.

For each asset bucket k, we estimate the following equation:

$$r_{it} = \begin{cases} a_k^- + b_k^- D_{t-1} + \epsilon_{it}, & \text{if } \Delta p_{ij,ST} < 0; \\ a_k^+ + b_k^+ D_{t-1} + \epsilon_{it}, & \text{if } \Delta p_{ij,ST} > 0, \end{cases} \tag{8}$$

where r_{it} is the minute-level returns in basis points of asset i belonging to bucket k, D is the dummy variable constructed as in Section 4.1, and $\Delta p_{ij,ST}$ is the price shock around the statement release on date j.

Table 9 reports the estimates. The slope coefficient is of the same sign as in the initial price reaction. The average price movement for Eurodollars futures contracts between 24 and 70 months is −0.1 bps in statement-related minutes and only −0.02 bps in the rest of the conference. The same holds for stocks and forex, where the variation is about 8 and 4 times larger in statement-related minutes, respectively. Moreover, statement-related minutes are only 7.5% of the overall minutes, yet they account for a large portion of the positive correlation in Section 3. For instance, when the initial price response around the statement was negative, 40% of the total price change over the press conference for stocks and 30% for medium-term Eurodollars futures took place during statement-related minutes.

4.3. Linguistic analysis of the press conference

Our methodology has several applications stemming from simple extensions of off-the-shelf textual analysis techniques to our new environment using time-stamped text. We will explore some of these next. Our results of a strong and positive autocorrelation for medium-term assets and of the absence of such for short-term assets hint at an important role of forward guidance in explaining our findings. So we now study the relation between the time orientation of the talk and the movements of asset prices. Our conjecture is that when the chairman overly discusses the future, for example, by providing signals about what the committee intends to do and under what conditions, financial investors are more likely to react. In contrast, when the language is more oriented toward the present or the past, messages will be less likely to generate a market reaction.

For each minute, we compute the percentage of words that falls into one of the following three categories, defined by LIWC2015: focuspast, focuspresent, or focusfuture. We take the top 10% of observations and construct a dummy variable equal to one if that minute falls into the specified category. We then run the following regression:

$$|r_{it}| = a_k + b_{S,k} \cdot I_{S,t-1} + \epsilon_{it}, \tag{9}$$

where r_{it} denotes the minute-level returns in basis points of asset i belonging to bucket k, and $I_{S,t-1}$ is the indicator variable that takes the value of one when the sentiment measure $S \in$ {focuspast, focuspresent, focusfuture} is in the top 10% of observations, and zero otherwise. The 90th percentile is used to approximately match the sample size in

Table 9
Return Variation Conditioning on Statement News.

	Fed funds futures		Eurodollar futures		Stocks	Forex
	1m–6m	9m–15m	6m–12m	24m–70m		
Days when statement shock was negative						
a^-	−0.01	−0.01	−0.01	−0.02	−0.27	−0.17
	[−2.24]	[−0.98]	[−1.37]	[−2.52]	[−1.54]	[−1.89]
b^-	0.00	−0.03	−0.02	−0.08	−1.82	−0.55
	[0.22]	[−1.31]	[−0.52]	[−2.17]	[−2.80]	[−1.86]
Days when statement shock was positive						
a^+	0.00	0.00	0.00	0.02	0.27	0.08
	[0.43]	[0.80]	[0.15]	[1.84]	[3.31]	[0.94]
b^+	−0.00	0.01	0.05	0.04	0.58	0.22
	[−0.12]	[0.53]	[2.26]	[1.04]	[1.92]	[0.56]

For each asset bucket k, the table reports the regression statistics to quantify how much of the correlation documented in Section 3 derives from a discussion of statement-related news. We estimate the following equation:

$$r_{it} = \begin{cases} a_k^- + b_k^- D_{t-1} + \epsilon_{it}, & \text{if } \Delta p_{ij,ST} < 0; \\ a_k^+ + b_k^+ D_{t-1} + \epsilon_{it}, & \text{if } \Delta p_{ij,ST} > 0, \end{cases}$$

where r_{it} are the minute-level returns in basis points of asset i belonging to bucket k, D is the dummy variable constructed as in Section 4.1, and $\Delta p_{ij,ST}$ is the price shock around the statement release on date j. t-statistics are in brackets. Standard errors are double clustered at the date-asset level.

Table 10
The Effect of Words on Asset Prices.

	Fed funds futures				Eurodollar futures							
	1m–6m		9m–15m		9m–15m		24m–70m		Stocks		Forex	
Coef.	Language Category: Future											
a	0.06	0.06	0.15	0.16	0.17	0.18	0.27	0.27	4.25	4.21	2.70	2.68
	[3.85]	[3.92]	[10.40]	[10.85]	[36.85]	[99.50]	[27.32]	[31.10]	[13.93]	[14.29]	[14.73]	[15.33]
b_S	0.00	0.00	0.04	0.03	0.04	0.02	0.04	0.02	0.52	0.42	0.43	0.36
	[0.44]	[0.47]	[2.31]	[5.36]	[2.27]	[9.06]	[1.66]	[2.17]	[1.97]	[12.48]	[2.35]	[5.41]
b_D	–	−0.02	–	−0.01	–	−0.02	–	0.00	–	0.40	–	0.23
	–	[−7.05]	–	[−1.86]	–	[−1.05]	–	[0.08]	–	[5.20]	–	[3.00]
b_{S-D}	–	0.01	–	0.03	–	0.22	–	0.12	–	0.72	–	0.51
	–	[2.23]	–	[1.99]	–	[3.25]	–	[3.68]	–	[3.85]	–	[2.73]
	Language Category: Present											
a	0.06	0.06	0.16	0.16	0.18	0.18	0.28	0.28	4.33	4.30	2.78	2.76
	3.72	3.79	10.91	11.52	40.44	589.49	30.29	34.03	13.90	14.35	14.43	14.99
	[3.72]	[3.79]	[10.91]	[11.52]	[40.44]	[589.49]	[30.29]	[34.03]	[13.90]	[14.35]	[14.43]	[14.99]
b_S	−0.01	−0.00	−0.02	−0.02	−0.01	−0.01	−0.03	−0.03	−0.31	−0.40	−0.37	−0.43
	[−1.29]	[−1.04]	[−2.18]	[−5.25]	[−0.65]	[−0.47]	[−2.40]	[−16.78]	[−1.40]	[−7.08]	[−2.78]	[−5.50]
b_D	–	−0.01	–	−0.00	–	0.02	–	0.02	–	0.38	–	0.24
	–	[−5.89]	–	[−0.54]	–	[0.53]	–	[2.10]	–	[6.39]	–	[3.75]
b_{S-D}	–	−0.03	–	−0.03	–	−0.03	–	0.01	–	1.59	–	0.91
	–	[−17.74]	–	[−8.51]	–	[−0.44]	–	[1.79]	–	[9.28]	–	[4.25]
	Language Category: Past											
a	0.06	0.06	0.16	0.16	0.18	0.18	0.28	0.27	4.31	4.27	2.77	2.73
	[3.86]	[3.94]	[10.46]	[10.98]	[30.70]	[59.76]	[32.65]	[37.52]	[14.24]	[14.71]	[14.99]	[15.79]
b_S	0.00	−0.00	−0.01	−0.01	−0.02	−0.02	−0.01	−0.00	−0.18	−0.12	−0.29	−0.22
	[0.07]	[−0.12]	[−0.92]	[−4.10]	[−1.64]	[−1.61]	[−0.30]	[−0.13]	[−0.67]	[−1.85]	[−1.95]	[−4.43]
b_D	–	−0.02	–	−0.00	–	0.01	–	0.02	–	0.58	–	0.39
	–	[−6.30]	–	[−0.56]	–	[0.63]	–	[2.99]	–	[9.40]	–	[5.53]
b_{S-D}	–	0.01	–	−0.03	–	0.02	–	−0.06	–	−0.78	–	−0.87
	–	[1.62]	–	[−3.13]	–	[0.35]	–	[−5.68]	–	[−3.10]	–	[−2.58]

For each asset bucket k, we estimate the following equation:

$$|r_{it}| = a_k + b_{S,k} \cdot I_{S,t-1} + b_{D,k} \cdot D_{t-1} + b_{S-D,k} \cdot I_{S,t-1} \cdot D_{t-1} + \epsilon_{it},$$

where r_{it} denotes the minute-level returns in basis points of asset i belonging to bucket k, D is the dummy variable constructed as in Section 4.1, and $I_{S,t-1}$ is an indicator variable that takes the value of one whenever sentiment measure S is above its 90th percentile. We consider three different measures of linguistic information: *past, present*, and *future*. To compute these linguistic measures, for each minute in press conference i, we count the number of *past, present*, and *future* words using the language categories of the Linguistic Inquiry and Word Count provided by Pennebaker et al. (2015). We scale this minute-level measure, s_t^i, by the total number of words in that minute. t-statistics are in brackets. Standard errors are double clustered at the date-asset level.

which the statement-related dummy takes a value of one. To assess for an additional relation between asset price movements and language beyond what is already captured by the statement dummy, we also estimate

$$|r_{it}| = a_k + b_{S,k} \cdot I_{S,t-1} + b_{D,k} \cdot D_{t-1} + b_{S-D,k} \cdot I_{S,t-1} \cdot D_{t-1} + \epsilon_{it}, \tag{10}$$

with D_{t-1} being the statement-related minute dummy variable constructed as in Section 4.1. Table 10 presents the results.

The top panel shows that the minutes in which the Fed chairman focuses the most on the future are responsible for the larger variation in asset prices, and the effect increases with contract maturity. Moreover, this subsumes most of the effect we have identified with our statement-related dummy: the strong relation we document between asset price variation and statement-related minutes is concentrated in those minutes that highly focus on the future. On the other hand, we find that minutes relatively more focused on the past and present exhibit lower variation in asset prices, and the coefficient associated with the interaction with the statement-related dummy is also negative.

In separate tests, we investigate whether other popular text sentiment measures are also linked to larger asset price reactions. Specifically, we search for "hawkish" or "dovish" terms in our minute-level text using the bag of words compiled by Neuhierl and Weber (2019). Hawkish and dovish are probably the most common categories used to describe FOMC members and their words. We create a dummy variable by assigning a value of one to the minutes in which a hawkish or dovish word was pronounced and zero to all other minutes. We test whether asset prices move more when a sentence pronounced by the chairman contains a hawkish or a dovish word.

Our specification is the same as (10), except we substitute the time focus variable with the new dummy capturing the hawkish or dovish words. We test whether $b_{S,k}$ in such a specification can be positive. Table E.6 in the appendix shows that the variable is indeed positive. Notably, however, the coefficient associated with the statement-related minutes alone is significantly larger than the one associated with hawkish and dovish terms alone, and we do not find a stronger effect if these terms are pronounced during statement-related minutes (i.e., the interaction of the two dummy variables is negative and not significant using standard confidence levels).

We extend the textual analysis even further. We count the fraction of words in our statement-related minutes that fall into categories, such as "positive," "negative," "uncertainty," "litigious," "strongModal," "weakModal," and "constraining," as proposed by Loughran and Mc Donald (2011). We construct a dummy variable with the same procedure as we did for the analysis of the time orientation of the talk. We do not observe any larger asset price reaction in the minutes in which these words are pronounced than what is already captured by the statement-related dummy (Table E.6).

4.4. Uncertainty reduction about forward guidance

The findings described so far suggest that the chairman's discussion of what we called statement news (i.e., the linguistic changes to the policy statement) provides useful information to market participants about the future path of monetary policy decisions, that is, forward guidance. The next question asks to what extent this information indeed reduces investor uncertainty about future monetary policies.[24]

For this exercise, we use options on Eurodollar futures, which are among the most actively traded exchange-listed interest rate options in the world, which traded, for instance, over 1.4 million contracts a day on average in 2018. From the tick-by-tick best-of-book trade and quote data, we compute two measures of implied volatility for each option contract in our sample (i.e., for each minute of trading, strike, maturity, and option type, whether call or put). The first measure of implied volatility is commonly used for these contracts and employs the model proposed by Black (1976). This treats options as if they were European, even though these are all American options; however, the pricing error is tiny, as shown by Bikbov and Chernov (2009), Choi et al. (2017), and Lakdawala et al. (2019). The second measure we use instead corrects for the early exercise embedded in the American options and employs the Barone-Adesi and Whaley (1987) approximation of American option values. We consider only at-the-money options, where "at-the-money" is defined as the absolute difference between the value of the underlying futures in a given minute and the strike being lower than 5% of the strike value. Following van Binsbergen et al. (2021), we use a minute-by-minute interest rate series that comes from the high-frequency estimation of put-call parity for European options on the S&P 500. For each minute, strike, and maturity, we then compute the weighted average of the implied volatilities of the put and call, weighting them by their market price (similar to the VIX's computation).

Figure 6 shows the average change in the implied volatility around the policy statement release and the subsequent press conference. The top subplot shows the results using the implied volatility from the Black model, whereas the bottom one uses the Barone-Adesi and Whaley model. The blue bars represent the average change in the implied volatility from 10 min before the statement to 20 min after the statement. The gray bars represent the average change from the start to the end of the press conference. Changes are expressed in basis points. To correctly interpret the magnitude, it is worth noting that before the statement release the average volatility from the Black model is 31.84 bps for contracts with expiration below 6 months, 42.02 bps for contracts with expiration between 6 and 12 months, 72.28 bps for contracts with expiration between 12 and 24 months, and 98.01 bps for contracts with expiration above 24 months. Similar magnitudes are observed for the volatility from the Barone-Adesi and Whaley model. Standard errors are double clustered at the date-maturity level. t-statistics are in brackets (on top of the bars).

The figure shows that the release of the policy statement substantially decreases investor uncertainty about monetary policy for the short term only. Relative to the average value before the press conference, the implied volatility for short-term contracts drops by about 7.5% (t-statistic $= -3.78$). We do not find evidence of an average reduction in implied volatility around the statement for maturities above six months. On the other hand, we observe the press conference is successful at reducing monetary policy uncertainty for all maturities (even if the results are not always statistically significant). For longer maturities above 24 months, we find the largest average drops in implied volatility (drops of about 2%) significant at standard confidence levels (t-statistic $= -2.46$).

In sum, while the policy statement helps significantly reduce investors' interest rate uncertainty for the closest maturities, the information conveyed in the press conference is responsible for the larger drops in investor uncertainty in interest rates for the longer term. Moreover, given that the implied volatility does not seem to be reduced during the statement for such longer-term contracts, we test whether the minutes in the press conference in which the chairman discusses the statement can explain the reduction in uncertainty visible during the press conference for the same assets. Table 11 reports the results. We indeed find that, regardless of the implied volatility measure we use and regardless of the contract's maturity, the statement-related minutes we defined in Section 4.1 are also the minutes in the press conference in which the largest reductions in the implied volatility occur. This provides strong evidence supporting the hypothesis that the minutes in which the chairman discusses the statement news are also those in which investors make the most updates about the Fed's forward guidance regarding interest rates.

5. Potential explanations

A number of possible mechanisms link central bank communication with financial asset prices. In this section, and in light of our results, we will discuss eight of these mechanisms and assess their plausibility as potential explanations.

[24] We thank an anonymous referee for suggesting this test.

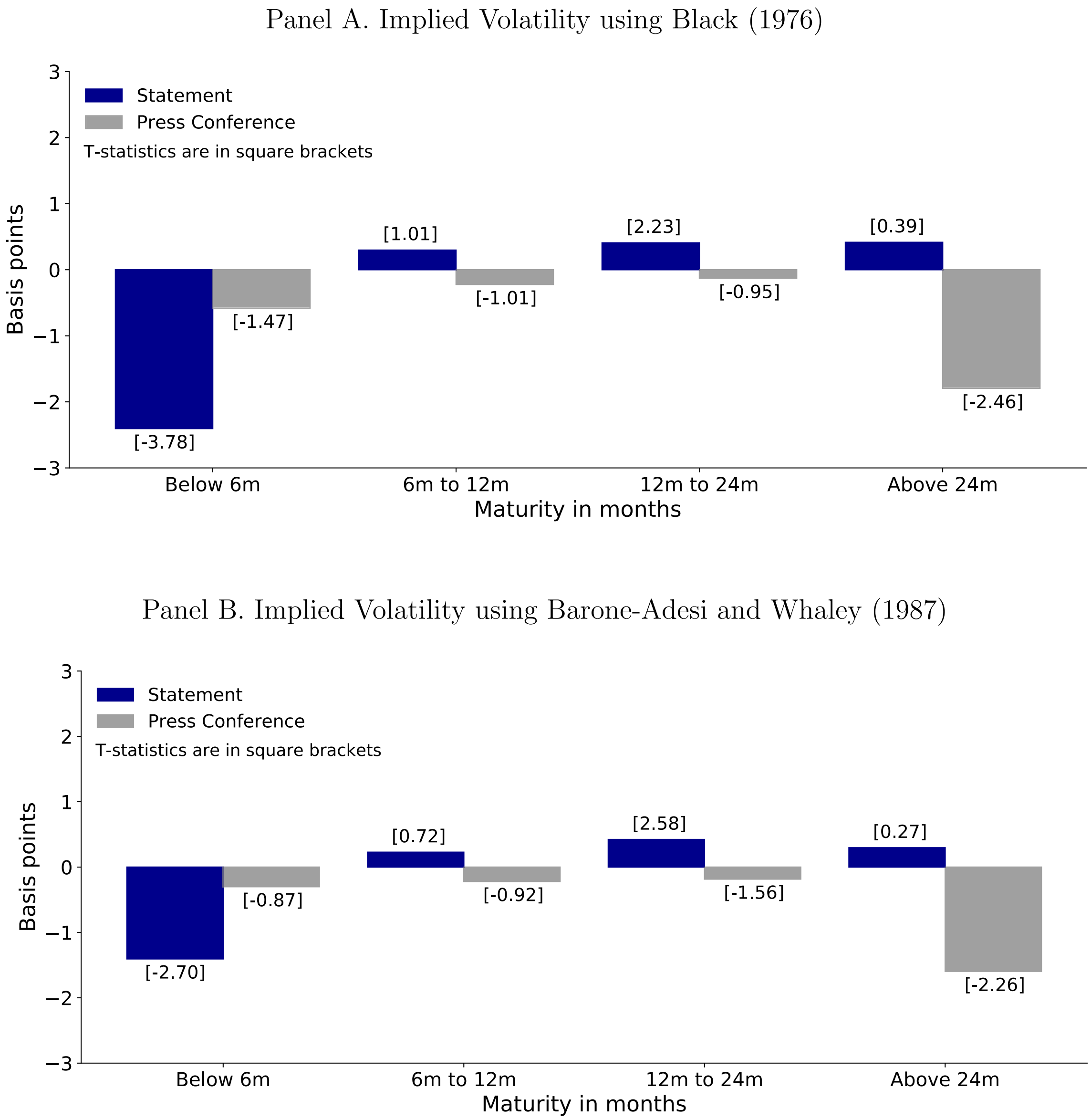


Fig. 6. The figure shows the average reduction in the implied volatility from options on Eurodollar futures around the policy statement release and the subsequent press conference. The blue bars represent the average change in the implied volatility from 10 min before the statement to 20 min after the statement. The gray bars represent the average change from the start to the end of the press conference. Changes are expressed in basis points. *t*-statistics are in brackets. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

5.1. Differences in higher-order beliefs

The models most directly consistent with the facts documented so far are those that explicitly feature traders' differential interpretation of public signals. For our discussion, we follow the frameworks proposed by Banerjee et al. (2009) and Banerjee and Kremer (2010).[25]

Banerjee et al. (2009) show that in the presence of uncertainty about other agents' opinions, difference-of-opinion models naturally generate a drift in prices even in dynamic settings in which investors are allowed to

[25] The assumption that traders interpret words by the chairman or the committee in different ways is realistic. Some fed officials anticipate investor confusion in the interpretation or a lack of clarity in the FOMC statement itself. For instance, from the transcripts of FOMC meetings (which are released to the public five years after each meeting), we have sentences such as “I think the document has made vagueness a virtue to an excessive degree, and there's a nontrivial risk that what comes out of this will actually be more of a cacophony than a clarification” (Daniel K. Tarullo, former member of the Board of Governors of the Fed, talking about the post-meeting policy statement, transcript of the January 2012 FOMC meeting) or “if we don't hold a press conference [...] there's a decent chance that market participants will be quite confused” (Jeffrey M. Lacker, President of the Federal Reserve Bank of Richmond, during the FOMC meeting of July 2013).

Table 11
Changes in Implied Volatility from Options on Eurodollar Futures.

Panel A. Implied Volatility Using Black (1976)

	Maturity in months			
	Below 6m	6m to 12m	12m to 24m	Above 24m
Statement-related minutes	−0.105	−0.008	−0.113	−0.061
	[−2.341]	[−0.313]	[−2.267]	[−2.354]
Other minutes	−0.013	−0.001	−0.012	−0.003
	[−1.185]	[−0.166]	[−1.001]	[−0.319]

Panel B. Implied Volatility Using Barone-Adesi and Whaley (1987)

	Maturity in months			
	Below 6m	6m to 12m	12m to 24m	Above 24m
Statement-related minutes	−0.074	−0.018	−0.127	−0.063
	[−1.247]	[−0.654]	[−2.364]	[−2.001]
Other minutes	−0.004	−0.001	−0.011	0.002
	[−0.291]	[−0.095]	[−0.889]	[0.158]

The table shows the average reduction in implied volatility from options on Eurodollar futures within the press conference. For the computation of the implied volatility, Panel A uses the model proposed by Black (1976), while Panel B employs the approximation for American option values proposed by Barone-Adesi and Whaley (1987). For both of these methods, we report the average change in implied volatility in statement-related minutes and in other minutes during the press conference. See Section 4.1 for a detailed description of the computation of the statement-related minutes. Standard errors are double clustered at the date-maturity level. t-statistics are in brackets. The values for the implied volatility are in basis points.

learn from prices (as in rational expectations equilibrium models). Price drift is an outcome of the slow aggregation of heterogeneous beliefs. On the other hand, standard difference-of-opinion models, which make the strong and unnatural assumption that investors, while having heterogeneous beliefs, are certain about other agents' opinions (i.e., different views are common knowledge), are unable to generate price drifts in multiperiod frameworks.[26]

The Banerjee et al. (2009) model makes the additional prediction that stronger price drifts should coincide with higher uncertainty. So, we now test it to provide further suggestive evidence in favor of this explanation. Following our results in Section 4.4, we use as a measure of interest rate uncertainty the implied volatility from options on Eurodollar futures, a commonly used measure of the uncertainty associated with FOMC events (e.g., Ederington and Lee, 1996; Lakdawala et al., 2019). We use the implied volatility for the six-month maturity options computed two hours before the statement release. We then calculate the median value of this implied volatility by the Chair of the Federal Reserve and construct a dummy variable equal to one if the implied volatility is above this median and zero otherwise. We add the I_t dummy variable to specification (2), which allows us to assess the extent to which price drifts differ across low- and high-uncertainty periods:

$$\Delta p_{it,PC} = a_k + b_k \, \Delta p_{it,ST} + c_k \, \Delta p_{it,ST} \, I_t + \epsilon_{it}. \tag{11}$$

Table 12 presents the results. Across the different assets, the estimated c_k's are positive and highly statistically significant. Notably, R^2 in the regressions also increase considerably. For instance, for stocks, R^2 increases from 14% to 18%. Overall, this result implies that the strong positive relation that we document between $\Delta p_{it,PC}$ and $\Delta p_{it,ST}$ is concentrated in periods of high interest rate uncertainty.

Banerjee and Kremer (2010) extend these ideas and show how a dynamic model in which investors disagree about the interpretations of public information also generates a positive relation between disagreement, return volatility, and trading volume. Periods of high disagreement are associated with periods of high volatility and high trading volume.

The model's first prediction is about the relation of disagreement and realized volatility. So, for each asset i and FOMC day t, we compute the intradaily realized return volatility from 10 min before the statement to the end of the day using minute-level returns, and denote it by $\sigma_{i,t}$. We estimate the following equation:

$$\sigma_{i,t} = a_k + b_k \cdot I_t + \epsilon_{it}, \tag{12}$$

where $\sigma_{i,t}$ is in basis points, I_t is the same dummy variable as above, and asset i belongs to bucket k. Table 13 reports the results. We find that FOMC days preceded by larger interest rate uncertainty indeed experience a larger intradaily realized volatility. The increases in intradaily realized volatility range from about 15% for medium-term Eurodollar futures to 57% for short-term fed funds futures.

We perform a similar exercise to test the second key prediction: whether periods of high uncertainty are also associated with high trading volume. We estimate the following equation:

$$V_{it} = a_k + b_k \cdot I_t + \epsilon_{it}. \tag{13}$$

The trading volume of asset i during FOMC day t (V_{it}) is expressed as the percentage change relative to the trading volume in the previous business day to adjust for the up-

[26] In a previous version of this paper, we discussed a model of noisy signals as described by Coibion and Gorodnichenko (2012, 2015). That model can be thought of as a one-period model in which traders feature a differential interpretation of public signals. However, the framework we discuss now by Banerjee et al. (2009) is a much more general version of that model, again, extending it to multiperiod frameworks and allowing investors to learn from prices.

Table 12
Press Conference Shocks against Statement Shocks.

	Fed funds futures		Eurodollar futures		Stocks	Forex
	1m–6m	9m–15m	6m–12m	24m–70m		
a	0.02	0.20	0.12	0.22	−2.42	−5.31
	[0.22]	[0.90]	[0.40]	[0.71]	[−0.55]	[−1.87]
b	−0.29	−0.25	−0.14	0.17	0.17	0.04
	[−1.28]	[−1.63]	[−2.69]	[1.33]	[6.52]	[0.51]
c	0.69	0.73	0.56	0.35	0.45	0.36
	[2.14]	[3.57]	[12.62]	[4.71]	[2.15]	[3.60]
R^2	32.63	30.70	26.20	25.60	18.37	16.83

For each asset bucket k, the table reports the regression estimates for the following equation:

$$\Delta p_{it,PC} = a_k + b_k \Delta p_{it,ST} + c_k \ \Delta p_{it,ST} \cdot I_t + \epsilon_{it},$$

where $\Delta p_{it,PC}$ is the change in asset i's price during the date-t press conference, $\Delta p_{it,ST}$ is the change in asset i's price around the date-t FOMC statement release, and asset i belongs to bucket k. I_t is an indicator variable that takes the value of one when the implied volatility from options on Eurodollar futures is above its median value computed separately for each Chair of the Federal Reserve. The price changes, $\Delta p_{it,PC}$ and $\Delta p_{it,ST}$, are in basis points and are computed over two nonoverlapping, nonconsecutive time intervals. t-statistics are in brackets. Standard errors are double clustered at the date-asset level. R^2 statistics are expressed as a percentage.

Table 13
Volatility during FOMC Days.

	Fed funds futures		Eurodollar futures		Stocks	Forex
	1m–6m	9m–15m	6m–12m	24m–70m		
a	0.0296	0.0798	0.1419	0.1627	2.7392	1.6377
	[6.4614]	[7.9110]	[11.471]	[9.6253]	[11.081]	[12.312]
b	0.0170	0.0204	0.0531	0.0244	0.8125	0.2618
	[1.8637]	[1.1661]	[2.2174]	[4.6862]	[2.1728]	[2.1896]

For each asset bucket k, the table reports the regression estimates for the following equation:

$$\sigma_{i,t} = a_k + b_k \cdot I_t + \epsilon_{it},$$

where $\sigma_{i,t}$ denotes the realized volatility on FOMC day t (in basis points) of asset i; asset i belongs to bucket k. I_t is an indicator variable that takes the value of one when the implied volatility from options on Eurodollar futures is above its median value; computed separately for each chair of the Federal Reserve. t-statistics are in brackets. Standard errors are double clustered at the date-asset level.

Table 14
Trading Volume during FOMC Days.

	Fed funds futures		Eurodollar futures	
	1m–6m	9m–15m	6m–12m	24m–70m
a	5.4423	2.8518	2.0039	2.4371
	[7.4578]	[8.4383]	[8.6530]	[8.8983]
b	1.1541	0.3180	1.2837	0.5865
	[0.7922]	[0.4963]	[2.6802]	[1.8292]

For each asset bucket k, the table reports the regression estimates for the following equation:

$$V_{it} = a_k + b_k \cdot I_t + \epsilon_{it},$$

where V_{it} denotes the trading volume during FOMC day t expressed as the percentage change relative to the trading volume from the previous business day. I_t is an indicator variable that takes the value of one when the implied volatility from options on Eurodollar futures is above its median value computed separately for each Chair of the Federal Reserve. Standard errors are double clustered at the date-asset level. t-statistics are in brackets.

ward trend in volume over the years of our sample (from 2011 to 2020). As before, I_t is the dummy variable, and asset i belongs to bucket k. Table 14 reports the results. We find that FOMC days preceded by larger interest rate uncertainty also experience a much larger trading volume. This is especially true for Eurodollar futures contracts between 6 and 12 months, where the trading volume on high-uncertainty FOMC days is 64% larger than the volume on low uncertainty FOMC days.

Moreover, these models also predict that the volume should exhibit a larger positive autocorrelation around larger uncertainty periods. So, we test this hypothesis as well. Table 15 shows that periods with larger preannouncement uncertainty indeed exhibit a stronger relation between the trading volume in the press conference and around the statement. For each asset bucket k, the table reports the regression estimates for the following equation:

$$V_{it,PC} = (a_k + b_k \cdot I_t) \cdot V_{it,ST} + \epsilon_{it}, \tag{14}$$

where $V_{it,PC}$ denotes the trading volume during the press conference, $V_{it,ST}$ denotes the trading volume around the statement release, and asset i belongs to bucket k. Especially for longer-maturity fed funds futures and Eurodollar futures, we find that the trading volume during the press conference is as large as, if not larger than, the trading volume around the statement during high-disagreement

Table 15
Trading Volume around the Statement and Press Conference.

	Fed funds futures		Eurodollar futures	
	1m–6m	9m–15m	6m–12m	24m–70m
a	0.519	0.6464	0.8767	0.8701
	[5.371]	[5.2059]	[9.4302]	[10.104]
b	0.026	1.3061	0.2359	0.2090
	[0.186]	[7.3632]	[2.1118]	[3.3044]
R^2	59.06	76.94	82.06	82.11

For each asset bucket k, the table reports the regression estimates for the following equation:

$$V_{it,PC} = (a_k + b_k \cdot I_t) \cdot V_{it,ST} + \epsilon_{it},$$

where $V_{it,PC}$ denotes the trading volume during the press conference (e.g., 14:30–15:30), $V_{it,ST}$ denotes the trading volume around the statement release (e.g., 13:50–14:20), and asset i belongs to bucket k. We always use the price change from 10 min before the statement to 20 min after the statement, as well as the price change during the press conference. I_t is an indicator variable that takes the value of one when the implied volatility from options on Eurodollar futures is above its median value computed separately for each Chair of the Federal Reserve. Standard errors are double clustered at the date-asset level. t-statistics are in brackets.

FOMC days, while it is less than the statement's volume on low-disagreement days.

5.2. Alternative explanations

What other models could explain our results? We now evaluate seven alternative frameworks that could also ideally describe these events and our results.

First, regarding the Fed put, the idea that the Federal Reserve's actions are excessively driven by considerations about financial markets' reactions (Cieslak et al., 2019; Cieslak and Vissing-Jorgensen, 2020), we find the opposite of what a theory based on it would predict. When the stock market collapses around the statement release, the negative trend continues during the press conference. The chairman's words reinforce the original reaction to the statement no matter what direction it took.

Second, our results are inconsistent with the hypothesis that illiquidity or some microstructure effects underlie our findings. As evidence against this hypothesis, we see no relation between price changes around the statement release and price changes in the time window between the statement release and the press conference or in the 30-minute window immediately after the press conference. Table 16 reports the results.

We estimate Eq. (2) by modifying our dependent variable to be the price change during each of the corresponding time windows. For both intervals, the slope coefficient is small and not statistically different from zero, and R^2 is close to zero. The presence of such "quiet periods" provides strong evidence against the hypothesis that our results are a mere consequence of microstructure effects.[27] Only during the press conference does the trend we document after the statement release happen. This is why tick-by-tick financial data are so important, as is connecting them to the words pronounced in that moment.

Third, we are able to reject the hypothesis that the positive autocorrelation in price changes documented in this paper is a continuation of the Lucca and Moench (2015) preannouncement drift. We observe that when the stock market collapses around the statement release, such a negative trend continues during the press conference. This is the opposite of what the continuation of the preannouncement drift of Lucca and Moench (2015) would imply. Moreover, again this correlation is realized only in the press conference window, and outside that window we see no relation with the price change around the statement.[28]

Fourth, the results in this paper provide direct evidence against frictionless models of rational economic agents with full information. Market prices are forward looking and should already incorporate all information available to the public. So, especially at such a high frequency, they should be close to unpredictable. Imagine that investors were aware of the Federal Reserve's communication strategy, which says that, during the press conference, the chairman should confirm and reinforce the market interpretation of the statement. This behavior can be anticipated and exploited right away: under this framework there should be no positive autocorrelation in price changes.

Fifth, some colleagues let us notice that our findings could be generated by a model in which investors learn about the chairman's communication strategy, political independence, policy preferences, etc. Such a model would imply that estimation risk gets reduced over time as the chairman holds more press conferences; that is, within a chairman's term our results should get weaker as time passes. We propose the following test.[29] For each chairman in our sample—Bernanke, Yellen, and Powell—we split the sample into two halves. The first half covers the first 50% of FOMC press conferences that chairman held, while the second half covers the remaining 50%. For each asset bucket k, we estimate the following equation:

$$\Delta p_{it,PC} = a_k + b_{1k}\, \mathbb{1}_{\text{1st half}}\, \Delta p_{it,ST} + b_{2k}\, \mathbb{1}_{\text{2nd half}}\, \Delta p_{it,ST} + \epsilon_{it}, \tag{15}$$

where $\Delta p_{it,PC}$ is the change in asset i's price during the date-t press conference, $\Delta p_{it,ST}$ is the change in asset i's price around the date-t FOMC statement release, and asset i belongs to bucket k. We double cluster the standard errors at the date-asset level. The dummy variable $\mathbb{1}_{\text{1st half}}$ is equal to one if the press conference belongs to the first

[27] Trading activity is at the highest on FOMC days (some people compare them to the final of the World Cup, see for instance, Fig. 5), and the assets we study are among the most liquid assets in the entire financial world. So, we believe that an illiquidity story would be a very difficult stretch.

[28] This is the reason our findings cannot be explained by the post-FOMC announcement drift in the U.S. bond markets documented by Brooks et al. (2018). Unlike us, they study the daily response of fixed-income prices for the 100 days following the FOMC announcement, and they document that Treasury yields initially respond sluggishly to fed funds rate surprises, and only does the response peak after 50 days before reverting back. We focus on the intraday variation in asset prices within FOMC days, and our results are realized only within the very short press conference window.

[29] We thank Stefan Nagel for suggesting this test.

Table 16
Press Conference Shocks against Statement Shocks.

	Fed funds futures		Eurodollar futures		Stocks	Forex
	1m–6m	9m–15m	6m–12m	24m–70m		
Quiet Period 1: Time Window between Statement Release and Press Conference						
a	−0.07	−0.04	−0.03	0.32	3.14	2.87
	[−1.42]	[−0.30]	[−0.21]	[0.88]	[0.77]	[1.56]
b	0.02	0.01	0.01	−0.04	0.06	0.08
	[1.01]	[0.39]	[0.41]	[−0.52]	[0.59]	[1.62]
R^2	1.24	0.21	0.08	0.74	0.84	4.12
Quiet Period 2: 30-Minute Time Window after the Press Conference						
a	0.05	0.15	0.17	0.05	−4.11	2.72
	[1.12]	[1.35]	[1.93]	[0.25]	[−1.52]	[1.32]
b	0.03	0.03	0.01	−0.02	0.02	0.08
	[1.74]	[1.33]	[0.65]	[−0.39]	[0.42]	[0.91]
R^2	1.98	2.34	0.17	0.71	0.17	2.48

For each asset bucket k, the table reports the regression estimates for the following equation:

$$\underbrace{\Delta p_{it,\text{quiet}}}_{\Delta\text{p - quiet period}} = a_k + b_k \underbrace{\Delta p_{it,ST}}_{\Delta\text{p around statement}} + \epsilon_{it},$$

where $\Delta p_{it,\text{quiet}}$ is the change in asset i's price during the selected date-t quiet period (between either the statement and the press conference windows or the 30-minute window right after the press conference), $\Delta p_{it,ST}$ is the change in asset i's price around the date-t FOMC statement release, and asset i belongs to bucket k. The two price changes (in basis points) are computed over two nonoverlapping, nonconsecutive time intervals. t-statistics are in brackets. Standard errors are double clustered at the date-asset level. R^2 statistics are expressed as a percentage.

Table 17
Press Conference Shocks against Statement Shocks.

	Fed funds futures		Eurodollar futures		Stocks	Forex
	1m–6m	9m–15m	6m–12m	24m–70m		
a	0.04	−0.15	0.04	−0.16	−3.81	−5.17
	[−0.39]	[0.50]	[−0.15]	[0.30]	[−0.47]	[−1.52]
b_{1st}	0.15	0.10	0.09	0.17	0.51	0.25
	[2.19]	[0.41]	[1.20]	[0.90]	[2.54]	[1.71]
b_{2nd}	0.26	0.22	0.26	0.41	0.28	0.26
	[2.88]	[1.76]	[4.61]	[3.17]	[1.82]	[3.02]
R^2	14.60	6.24	10.23	22.59	15.35	11.21

For each asset bucket k, the table reports the regression estimates for the following equation:

$$\Delta p_{it,PC} = a_k + b_{1k}\, \mathbb{1}_{\text{1st half}}\, \Delta p_{it,ST} + b_{2k}\, \mathbb{1}_{\text{2nd half}}\, \Delta p_{it,ST} + \epsilon_{it},$$

where $\Delta p_{it,PC}$ is the change in asset i's price during the date-t press conference, $\Delta p_{it,ST}$ is the change in asset i's price around the date-t FOMC statement release, and asset i belongs to bucket k. We double cluster the standard errors at the date-asset level. The dummy variable $\mathbb{1}_{\text{1st half}}$ is equal to one in the first half of the sample for each chairman, and zero otherwise, while $\mathbb{1}_{\text{2nd half}}$ is defined in opposite terms. The two price changes (in basis points) are computed over two nonoverlapping, nonconsecutive time intervals. t-statistics are in brackets. Standard errors are double clustered at the date-asset level. R^2 statistics are expressed as a percentage.

half of a chairman's press conferences and zero otherwise, while $\mathbb{1}_{\text{2nd half}}$ is defined oppositely.

Table 17 reports the regression results. For all asset classes, except stocks, the coefficient we estimate for the chairman's second subsample is larger than for the first half. This is inconsistent with a model in which traders learn about the chairman's type. The slow reaction we have documented does not disappear as the chairman holds more conferences. In fact, it persists strongly. This is surprising given that the entire objective of post-FOMC meeting press conferences is the facilitation of rapid and clear communication to investors.

Sixth, we explore a standard Bayesian learning model with parameter uncertainty, à la Lewellen and Shanken (2002). Given that the hypothesis of learning across FOMC meetings about the chairman's communication strategy, political independence, and policy preference is inconsistent with our findings, here we hypothesize that every meeting is separate from the others, and investor learning happens only within a single FOMC day. Suppose we are in the world sketched by Lewellen and Shanken (2002). For better correspondence, we use the same notation they used, which means that we will describe only how learning affects stock prices, but the discussion can be easily generalized.

A riskless asset pays a real rate r, and one risky security pays a real dividend d_t i.i.d. over time and drawn from a normal distribution with mean δ and variance σ^2. Investors know the variance, but they don't know the mean of the dividend distribution. They have some prior beliefs centered on some δ^* with variance σ^2/h, where h is a measure of prior information (equivalent to a sample of h dividends). They update their beliefs using Bayes' rule, incorporating the information in observed dividends. With this prior, the investor's belief at time t about dividends at time $t+1$ is

$$d_{t+1} \sim \mathcal{N}\left(\frac{t}{t+h}\bar{d}_t + \frac{h}{t+h}\delta^*, \frac{t+h+1}{t+h}\sigma^2\right), \tag{16}$$

where $\bar{d}_t$ is the average dividend observed up to t. Investors are born with a constant absolute risk-aversion utility with risk-aversion parameter $\gamma \geq 0$. Under the true distribution, the price of the risky asset can be shown to be

$$p_t = \frac{1}{r}\left(\frac{t}{t+h}\bar{d}_t + \frac{h}{t+h}\delta^*\right) - 2\gamma f(t+h)\sigma^2, \tag{17}$$

where $f(t)$ is a deterministic function of time. The function $f(t)$ decreases as t passes and converges to $1/r$ in the limit.[30]

Prices and price changes contain two terms. The first reflects the updates in beliefs about expected dividends. The second arises because estimation risk declines steadily over time. Consider two cases. In a framework with risk-neutral investors (γ is zero), the second term disappears. Investor learning means past mistakes tend to reverse and price revisions are negatively autocorrelated. Only when the prior is very far from the true value and investors are confident in their wrong prior may a positive autocorrelation in price revisions arise. This is not exactly an informational friction, but, under this hypothesis, investors must suffer from a substantial behavioral bias, starting from really wrong priors most of the time.

A model with risk-averse investors and where γ is positive generates a positive covariance more easily, but at the expense of price dynamics. In fact, in such a model, because estimation risk declines with time, prices tend to drift up. This is again inconsistent with our observations: we observe positive and negative shocks with almost the same frequency (e.g., for stocks), and, if anything, we observe larger shocks when shocks are negative. So a model featuring the price drift that Eq. (17) implies is also difficult to square with our findings.

The seventh framework we evaluate is an information rigidity model based on agents' inattention; it is similar to that of Mankiw and Reis (2002), Carroll (2003), Reis (2006), or Coibion and Gorodnichenko (2012, 2015). Such models contain inattentive agents who update their beliefs each period with probability $G \in [0, 1]$, and, when they update, they acquire full information and have rational expectations. These models are able to generate price drift and aggregate underreactions to news. However, such agents are implausible in our setting.

Given our focus on short time windows, which for most traders define key events in the economic calendars, an explanation based on investors' inattention is really difficult to believe. It would require that investors do not pay attention to the FOMC statement release and wait directly for the chairman to explain the statement during the press conference. Investors surely pay attention to the release of FOMC statements (Fleming and Piazzesi, 2005). This is illustrated by the large volume of trading happening in the few minutes around the statement release (see Fig. 5).

Moreover, a model of inattention is inconsistent with our results in Section 3.2, where we documented that the positive autocorrelation was realized only during the Q&A session. We separate the press conference into two parts, the introductory statement by the chairman and the Q&A session. The introductory statement comes first, and it is a closer repetition of the post-FOMC statement, while in the Q&A session it is difficult to follow a script. A model of inattention predicts that our results should be concentrated in the opening statement implying a larger autocorrelation during that time. This is the opposite of what we find and report in Fig. D.1.

Finally, as a lot of money can be made from these events, as we show in Section 3.3, an explanation based on inattention becomes even more difficult to believe. Similar to the argument made by Lucca and Moench (2015), we argument that the economic magnitude of our results is difficult to square with an inattention-based story. In sum, investors surely pay attention to the FOMC events, both around the statement release and during the press conference.

6. Concluding remarks

Our paper posits a novel methodology by which to study investors' expectations formation in events available for public observation. We apply recent advances in machine learning to scrape the videos of post-FOMC-meeting press conferences, extract the words, and time-stamp these words at the millisecond. We then align the transcripts with high-frequency data for a wide range of financial assets. To the best of our knowledge, this is the first paper to add the time dimension to textual analysis and to study agents' expectations formation at such a granular level. Our approach not only improves on the identification of the effect of words on financial investors' beliefs but also extends the set of questions that can be asked. The recipe we have developed can find applications in numerous settings in which someone wants to bridge linguistics with economics using market prices.

We show that at the moment the chairman discusses the changes between the current and the previous policy statements, price volatility and trading volume spike dramatically and prices move on average in the same direction as they did around the statement release before the press conference. This movement generates a strong positive correlation between price changes around the statement release and the subsequent press conference. These minutes also account for the large drops in interest rate uncertainty that we document for the press conference.

We have discussed a number of potential forces driving our results. We have examined explanations ranging from model parameter uncertainty to the *Fed put*; microstructure effects or liquidity; learning about the chairman's type or political independence; investors' inattention, etc. We have argued the difficulty in squaring these explanations with all of the empirical evidence. On the other hand, the models most directly consistent with our results are those

[30] The function $f(t)$ takes the form of $f(t) = \sum_{k=1}^{\infty} \frac{1}{(1+r)^k}\left(1+\frac{1}{r(t+k)}\right)^2 \frac{t+k}{t+k-1}$.

that explicitly feature traders' differential interpretation of public signals.

Declaration of Competing Interest

Roberto Gomez Cram: We have received financial support from a London Business School Research Center (The AQR Institute). The total amount of financial support (for data purchases) was 10,000. I have nothing else to disclose.

Marco Grotteria: We have received financial support from a London Business School Research Center (The AQR Institute). The total amount of financial support (for data purchases) was 10,000. I have nothing else to disclose.

Appendix A. Example statement news

We report in red the words that were present in the previous statement and removed in the new statement. We report in green the words added relative to previous statement. We highlight the words to which the question reported below the statement refers.

A1. January 2019

A1.1. Statement

Information received since the Federal Open Market Committee met in December November indicates that the labor market has continued to strengthen and that economic activity has been rising at a solid strong rate. Job gains have been strong, on average, in recent months, and the unemployment rate has remained low. Household spending has continued to grow strongly, while growth of business fixed investment has moderated from its rapid pace earlier last in the year. On a 12-month basis, both overall inflation and inflation for items other than food and energy remain near 2 percent. Although market-based measures of inflation compensation have moved lower in recent months, survey-based measures Indicators of longer-term inflation expectations are little changed, on balance. Consistent with its statutory mandate, the Committee seeks to foster maximum employment and price stability. In support of these goals, The Committee decided to maintain judges that some further gradual increases in the target range for the federal funds rate at 2-1/4 to 2-1/2 percent. The Committee continues to view will be consistent with sustained expansion of economic activity, strong labor market conditions, and inflation near the Committee's symmetric 2 percent objective as the most likely outcomes over medium term. The Committee judges that risks to the economic outlook are roughly balanced, but will continue to monitor In light of global economic and financial developments and muted inflation pressures, assess their implications for the economic outlook. In view of realized and expected labor market conditions and inflation, the Committee will be patient as it determines what future adjustments decided to raise the target range for the federal funds rate may be appropriate to support these outcomes 2-1/4 to 2-1/2 percent. In determining the timing and size of future adjustments to the target range for the federal funds rate, the Committee will assess realized and expected economic conditions relative to its maximum employment objective and its symmetric 2 percent inflation objective. This assessment will take into account a wide range of information, including measures of labor market conditions, indicators of inflation pressures and inflation expectations, and readings on financial and international developments.

A1.2. Question

Second question in the press conference:

HEATHER LONG. Heather Long from the Washington Post. Last week, the IMF said risks are clearly skewed to the downside for the U.S. and global economy. Can you clarify—does the FOMC see risks as skewed to the downside, particularly after you removed the statement about risks being balanced?

CHAIRMAN POWELL. We had an extensive discussion of the baseline and also of the risks to the baseline, and the risks are, of course, the fact that financial conditions have tightened, that global growth has slowed, as well as some, let's say, government-related risks like Brexit and trade discussions, and also the effects and ultimate disposition of the shutdown. So we looked at—we look at those, and the way we think of it is that policy—we will use our policy, and we have, to offset risks to the baseline. So we view the baseline as still solid, and part of that is the way we adjusted our baseline to address those risks. So that's the way we're thinking about that now.

A2. January 2020

A2.1. Statement

Information received since the Federal Open Market Committee met in December October indicates that the labor market remains strong and that economic activity has been rising at a moderate rate. Job gains have been solid, on average, in recent months, and the unemployment rate has remained low. Although household spending has been rising at a moderate strong pace, business fixed investment and exports remain weak. On a 12-month basis, overall inflation and inflation for items other than food and energy are running below 2 percent. Market-based measures of inflation compensation remain low; survey-based measures of longer-term inflation expectations are little changed. Consistent with its statutory mandate, the Committee seeks to foster maximum employment and price stability. The Committee decided to maintain the target range for the federal funds rate at 1-1/2 to 1–3/4 percent. The Committee judges that the current stance of monetary policy is appropriate to support sustained expansion of economic activity, strong labor market conditions, and inflation returning to near the Committee's symmetric 2 percent objective. The Committee will continue to monitor the implications of incoming information for the economic outlook, including global developments and muted inflation pressures, as it assesses the appropriate path of the target range for the federal funds rate. In determining the timing and size of future adjustments to the target range for the federal funds rate, the Committee will assess realized and expected economic conditions relative to its maximum employment objective and its symmetric 2 percent inflation objective. This assessment will take into account a wide range of information, including measures of labor market conditions, indicators of inflation pressures and inflation expectations, and readings on financial and international developments.

A2.2. Question

First question in the press conference:

CHRISTOPHER CONDON. Thank you. Chris Condon, Bloomberg News. Mr. Chairman, I would like you to comment in a little bit more depth about one small change I've noted in the statement. It notes that policy will be appropriate to bring—the Committee believes—inflation back to the Committee's 2 percent symmetric inflation objective. That's a slight change from the last time, when you were expecting it to bring inflation outcomes back near the objective. And I would put this also in the context of a comment you made at the last press conference where you drew attention to the fact that a number of policymakers had projected inflation overshoots two or three years out under appropriate monetary policy. Should we take all of this together to mean simply that the Committee is more confident that a 2 percent outcome for inflation is already baked in the cake, or that this is a signal that the Committee has a stronger resolution to bring inflation at least to the 2 percent objective and put-bring into play an informal makeup strategy for inflation?

CHAIRMAN POWELL. Yes. So, in making that change, our goal was, really—that was, changing "near" to "returning to"—was to avoid possible misinterpretation. So you may remember, in the December minutes we noted that a few Committee members suggested that the language that stated that monetary policy would support inflation near 2 percent could be misinterpreted as suggesting that policymakers were comfortable with inflation running below that level. So we thought about that in the intermeeting period and concluded that it would be appropriate to adjust that language to send a clearer signal that we're not comfortable with inflation rising persistently—running persistently below our 2 percent symmetric objective. So, yes, there is something in that. It's just that we wanted to underscore our commitment to 2 percent not being a ceiling to inflation running around—symmetrically around 2 percent, and that we're not satisfied with inflation running below 2 percent, particularly at a time such as now where we're a long way into an expansion and a long way into a period of very low unemployment when, in theory, inflation should be moving up.

Appendix B. Complementary dictionary

Table B.1
Complementary Dictionary.

Press conference	Statement
mandate consistent	consistent committee's dual mandate
moderate-growth	moderate pace economic growth
statutory mandate	dual mandate
inflation goal	inflation run level consistent committee's dual mandate
economic outlook	economic growth
short-term securities	treasury security remaining maturity approximately 3 year less
maintain accommodation	maintain highly accommodative stance
highly accommodative policy stance	highly accommodative stance
the exit strategy put consistent statement today	begin remove policy accommodation
inflation readings	inflation running
fiscal issues	fiscal retrenchment
unemployment come down	improvement labor conditions
weakness economy	strength broader economy
hold funds rate	keeping target fund rate level
end bond purchases	asset purchase program end
decided make another reduction pace asset purchases	committee end current program asset purchase
inflation fomc's objectives	inflation running committee's longer-run objective
normalizing policy	committee end current program asset purchase
raise funds rate target range	increase fund rate
2 percent target	2 percent objective
despite risks abroad	global economic development pose risks
labor expected tighten	strengthening labor market
risks outlook	global economic development pose risks
global economic developments	net export
economy growing roughly trend	economic activity expand moderate pace
labor conditions continued improve	labor indicator strengthen
wage growth	labor indicator strengthen
case rate increase strengthened	case increase fund rate strengthened
bring inflation back 2 percent	inflation stabilize around 2 percent
undertake beginning plan	begin implementing balance sheet normalization program
broader measures labor utilization continued strengthen	solid labor condition remain strong
raising target range	increase target range
gradual increases rate	expects gradual increase target range
conditions likely call three rate increases	committee judge gradual increase target range
future adjustment policy	adjustment target range fund rate appropriate

(*continued on next page*)

Table B.1 (*continued*)

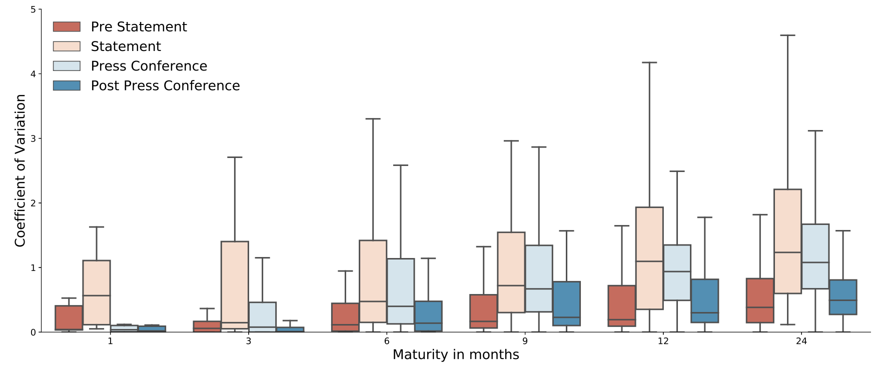
Press conference	Statement
policy stance appropriate	adjustment target range fund rate appropriate
weakness global growth trade	export weakened
particularly weak global growth trade	export weakened
understanding word “appropriate”	appropriate path target range fund rate
“appropriate” statement	appropriate path target range fund rate
believes-inflation back committee’s 2 percent symmetric inflation objective	inflation returning committee’s symmetric 2 percent objective
stance monetary policy remains accommodative	monetary policy accommodative
core inflation running 2	inflation declined running 2 percent

The table reports the dictionary we use to complement the algorithm described in Section 4.1 to identify policy statement news within the press conference.

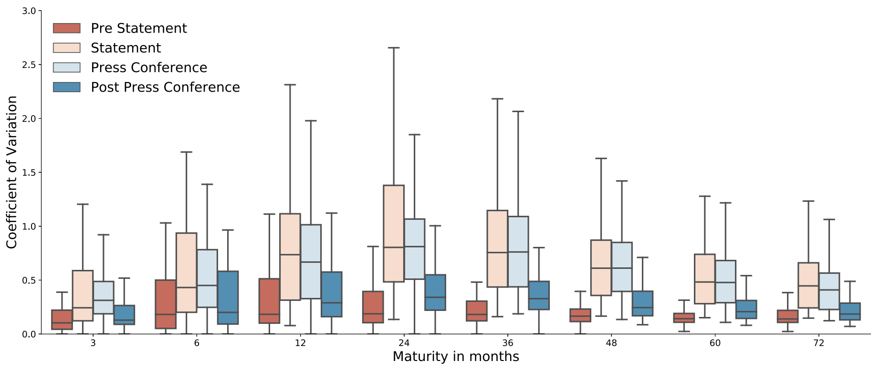
Appendix C. Variation in FOMC days

We separate time into four nonoverlapping periods. The prestatement period starts 45 min before the FOMC statement release and ends one second before the FOMC statement release. The statement period starts with the FOMC statement release and ends one second before the FOMC press conference starts. The press conference period considers the entire duration of the press conference. The post-press conference period starts one second after the FOMC press conference and ends 45 min after.

For each FOMC press conference day and each of the subperiods, we compute the ratio between the standard deviation and the average (coefficient of variation) of minute-level changes in the rates implied from federal funds and Eurodollar futures contracts. Fig. C.1 displays the distribution across all FOMC press conferences of the coefficient of variation so computed for each of the four subperiods. Panel A shows the results for federal funds rate futures, while Panel B for Eurodollar futures. They both include a large range of maturities.



Panel A –Federal funds futures



Panel B – Eurodollar futures

Fig. C.1. The figure shows the distribution of the coefficient of variation (CV), i.e., the ratio of the standard deviation to the average value, for federal funds futures and Eurodollar futures for different expiration dates. We present the CV distribution over four nonoverlapping subperiods. The sample consists of all 41 FOMC meetings containing a press conference from January 2011 to January 2020.

Appendix D. When is the autocorrelation realized?

We run four tests describing when the strong autocorrelation we have documented in Section 3 is more likely to happen. In the first two tests, we ask whether our results are stronger in periods of larger monetary policy or macroeconomic uncertainty. We use as a measure of monetary policy uncertainty the standard deviation of analysts' forecasts about the next policy rate decision, as reported by Bloomberg (short-term monetary policy uncertainty). We construct a dummy variable equal to one if the standard deviation of forecasts is above its median value in our sample, and zero otherwise. We then estimate the following equation:

$$\Delta p_{it,PC} = a_k + b_k \Delta p_{it,ST} + c_k \ \Delta p_{it,ST} \cdot I_{j,t} + \epsilon_{it}, \qquad \text{(D.1)}$$

where $\Delta p_{it,PC}$ is the change in asset i's price during the date-t press conference, $\Delta p_{it,ST}$ is the change in asset i's price around the date-t FOMC statement release, $I_{j,t}$ is the dummy variable, and asset i belongs to bucket k.

Our measure of macroeconomic uncertainty instead follows Neuhierl and Weber (2020). We compute the difference between VIX 15 days before the meeting and the trailing five-year average VIX. We construct a second dummy variable equal to one when the difference is above zero, and equal to zero otherwise. We then estimate the same equation, but we now use the new dummy variable in place of the old one. In all regressions, we double cluster standard errors at the date-asset level.

Table D.1 reports the regression results. As point estimates suggest, the strong positive relation that we document in the paper between $\Delta p_{it,PC}$ and $\Delta p_{it,ST}$ is concen-

Table D.1
Press conference shocks against statement shocks.

	Dispersion in analyst forecast about FOMC rate decision				Macro uncertainty				Changes between consecutive statements			
	Fed funds		Eurodollar		Fed funds		Eurodollar		Fed funds		Eurodollar	
	1–6	9–15	6–12	24–70	1–6	9–15	6–12	24–70	1–6	9–15	6–12	24–70
Coef.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
a	0.06	−0.17	0.04	−0.22	0.04	−0.21	0.00	−0.21	0.11	−0.13	0.04	−0.30
	[0.44]	[−0.57]	[0.13]	[−0.45]	[0.25]	[−0.66]	[0.01]	[−0.43]	[0.81]	[−0.39]	[0.14]	[−0.50]
b	−0.01	−0.04	0.03	0.26	0.05	0.07	0.10	0.27	0.07	0.14	0.18	0.42
	[−0.10]	[−0.21]	[0.42]	[2.00]	[0.43]	[0.47]	[3.14]	[2.49]	[0.49]	[0.87]	[2.65]	[2.83]
c	0.28	0.37	0.28	0.06	0.47	0.44	0.32	0.19	0.20	0.05	0.02	−0.23
	[1.52]	[1.43]	[3.59]	[0.38]	[1.81]	[2.57]	[5.26]	[0.72]	[1.14]	[0.20]	[0.21]	[−0.92]
R^2	14.81	11.73	12.93	17.06	24.70	12.40	13.64	17.31	11.19	5.63	8.45	22.30

For each asset bucket k, the table reports the regression estimates for the following equation:

$$\Delta p_{it,PC} = a_k + b_k \Delta p_{it,ST} + c_k \ \Delta p_{it,ST} \cdot I_{j,t} + \epsilon_{it},$$

where $\Delta p_{it,PC}$ is the change in asset i's price during the date-t press conference, $\Delta p_{it,ST}$ is the change in asset i's price around the date-t FOMC statement release, and asset i belongs to bucket k. $I_{j,t}$ is an indicator variable. For Columns (1) through (4), $I_{j,t}$ takes a value of one when the standard deviation of analysts' forecasts about the next policy rate decision is above its median value in our sample and zero otherwise. For Columns (5) through (8), $I_{j,t}$ takes a value of one when the VIX 15 days before the FOMC meeting was above its five-year average. For Columns (9) through (12), $I_{j,t}$ takes a value of one when the statement is very different from the previous statement and zero otherwise. Two consecutive statements are very different whenever the number of words changed between statements (scaled by the total number of words in the document) is above the median computed separately for each Chair of the Federal Reserve. The price changes, $\Delta p_{it,PC}$ and $\Delta p_{it,ST}$, are in basis points and are computed over two nonoverlapping, nonconsecutive time intervals. t-statistics are in brackets. Standard errors are double clustered at the date-asset level. R^2 statistics are expressed as a percentage.

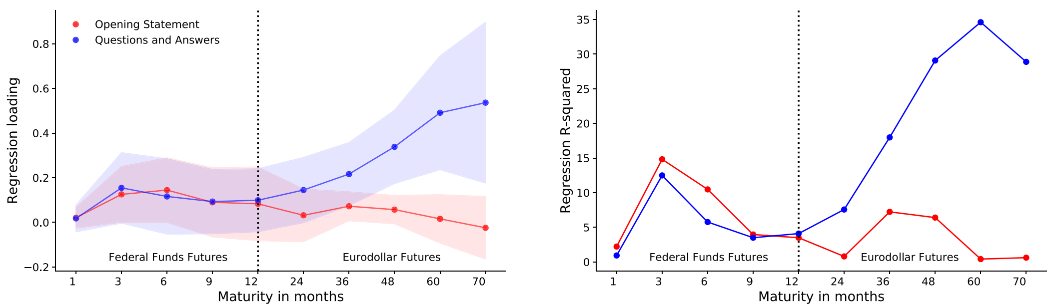


Fig. D.1. The figure shows the slope coefficient (left panel) and R-squared (right panel) from the following equation:

$$\Delta p_{it,PC} = a_k + b_k \Delta p_{it,ST} + \epsilon_{it},$$

where $\Delta p_{it,ST}$ is the change in asset i's price around the date-t FOMC statement release. We consider two different windows for price changes inside the press conference, $\Delta p_{it,PC}$. The red lines consider price changes during the start and end of the opening statement (approx. 10 min). The blue lines denote price changes during the Q&A section (approx. 45 min). The x-axis shows results for different maturities. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

trated in periods of high uncertainty: the coefficient on the variable interacted with the dummy is positive, providing evidence for a stronger relation when uncertainty is larger. For long-term Eurodollar futures, we do not find any statistical difference in the estimates: the coefficient on the dummy is positive, but not statistically different from zero. This is probably because both our measures reflect uncertainty in the short term.

In the third test, we ask whether our results are stronger when the statement is very different from the prior statement. We count the number of words changed between consecutive statements and scale it by the total number of words in the document. We now define the dummy to be one if the number of changes between two consecutive statements are above the median for a given Chair of the Federal Reserve. We then estimate Eq. (D.1) again. The last four columns in Table D.1 show the results. The main takeaway is that we do not find evidence suggesting stronger results when there are more changes in the statement. Except for longer-term Eurodollar futures, results point to a more positive relation when there is more statement news, but the difference is not statistically significant; in fact, fewer changes can also provide important news.

In the fourth test, we ask whether our results are stronger or weaker when the information in the statement and in the press conference is more similar. We compute a measure of cosine similarity between the FOMC statement and two specific parts of the press conference: the Chairman's opening statement and the Chairman's answers to the journalists' questions in the Q&A session. We find that the opening statement is a closer repetition of the initial statement with very few additions, while answers to questions are more different. So, we compute asset price changes around two narrow windows within the press conference (the opening statement and the Q&A session) and use those two variables separately as regressands in Eq. (D.1). Results are shown in the figure below. Price changes during the opening statement have a smaller correlation with price changes around the FOMC statement release, while the larger effect is visible for price changes of medium-term Eurodollar futures during the Q&A session.

Appendix E. Additional figures and tables

Tables E.4 and E.5 offer robustness of the results in Table 13 and 14 using log volatility or log volume as dependent variable.

Table E.1
Press conference shocks against statement shocks – Federal funds futures, Eurodollar futures.

Federal funds futures				Eurodollar futures			
Maturity	a	b	R^2	Maturity	a	b	R^2
1 month	−0.088	0.044	2.916	3 months	0.117	0.338	37.579
	[−0.700]	[0.775]	–		[0.493]	[3.801]	–
3 months	0.003	0.293	24.138	6 months	0.459	0.335	33.177
	[0.020]	[3.385]	–		[1.475]	[3.071]	–
6 months	0.081	0.262	13.915	12 months	−0.221	0.174	6.162
	[0.300]	[2.446]	–		[−0.428]	[1.600]	–
9 months	−0.082	0.201	6.995	24 months	−0.114	0.165	5.439
	[−0.208]	[1.691]	–		[−0.164]	[1.498]	–
12 months	−0.218	0.180	5.808	36 months	−0.221	0.277	18.319
	[−0.456]	[1.531]	–		[−0.316]	[2.957]	–
15 months	−0.199	0.160	4.700	48 months	−0.190	0.386	30.064
	[−0.346]	[1.333]	–		[−0.302]	[4.095]	–
18 months	−0.344	0.138	3.731	60 months	−0.078	0.497	33.450
	[−0.514]	[1.131]	–		[−0.133]	[4.427]	–
24 months	−0.190	0.061	0.697	70 months	−0.010	0.510	27.055
	[−0.150]	[0.325]	–		[−0.016]	[3.704]	–

For each asset bucket k, the table reports the regression estimates for the following equation:

$$\underbrace{\Delta p_{it,PC}}_{\Delta\text{p at press conference: e.g., 14:30-15:30}} = a_k + b_k \underbrace{\Delta p_{it,ST}}_{\Delta\text{p around statement: 13:50-14:20}} + \epsilon_{it},$$

where $\Delta p_{it,PC}$ is the change in asset i's price during the date-t press conference, $\Delta p_{it,ST}$ is the change in asset i's price around the date-t FOMC statement release, and asset i belongs to bucket k. The two price changes, in basis points, are computed over two nonoverlapping, nonconsecutive time intervals. The times (13:50–14:20 and 14:30–15:30) are only examples. We always use the price change from 10 min before the statement to 20 min after the statement, as well as the price change during the press conference. t-statistics are in brackets. Standard errors are double clustered at the date-asset level. R^2 statistics are expressed as a percentage.

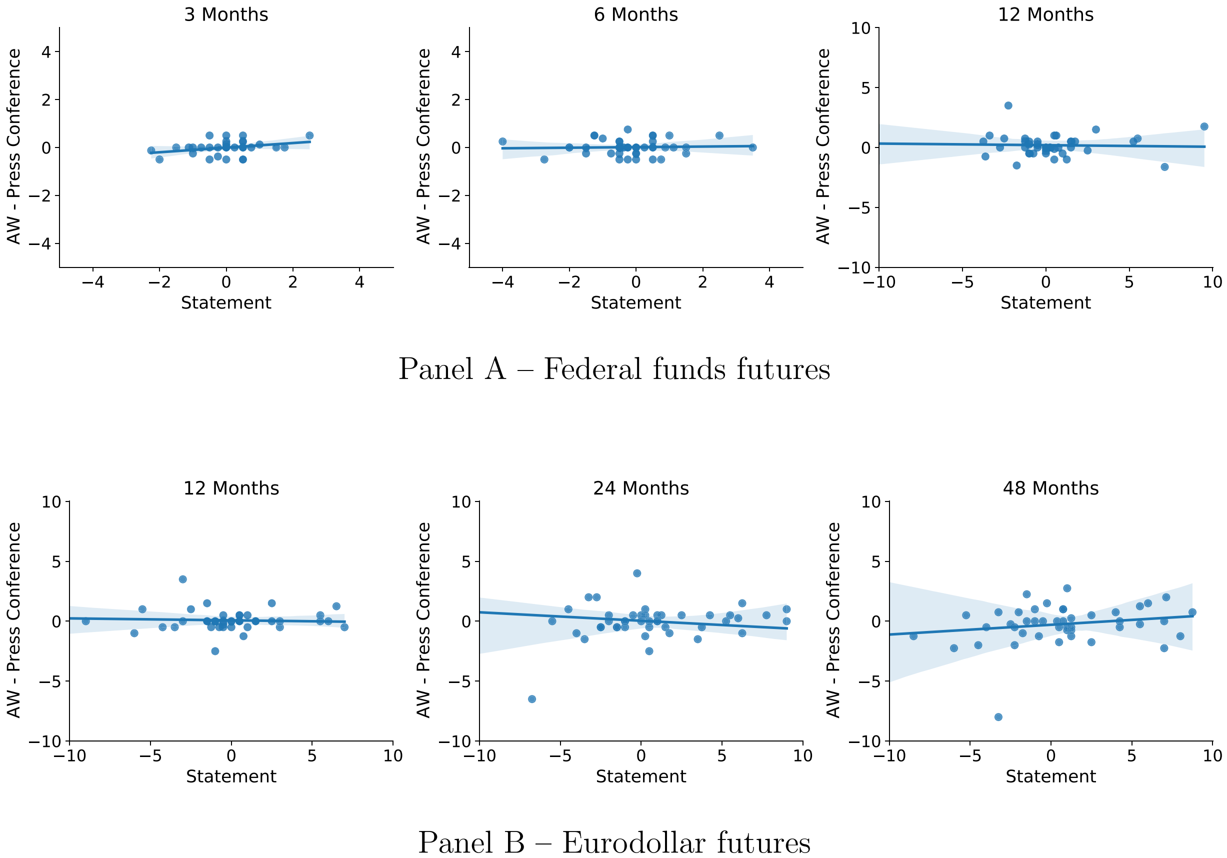


Fig. E.1. We produce an analog of Fig. 2 for a "placebo" event period: we use FOMC days without a press conference and compute price changes around the statement release and around an alternative window that mimics the average press conference time (from 14:30 to 15:24 ET). The figure shows the statement shocks on the *x*-axis, and the pseudo press-conference shocks on the *y*-axis for the 30-day federal funds futures expiring in 3 months, 6 months, and 12 months (Panel A) and Eurodollar futures expiring in 12, 24, and 48 months (Panel B). The shocks are in basis points. The straight line is the regression fit line, and the dashed area around the line is the 95% confidence interval bands.

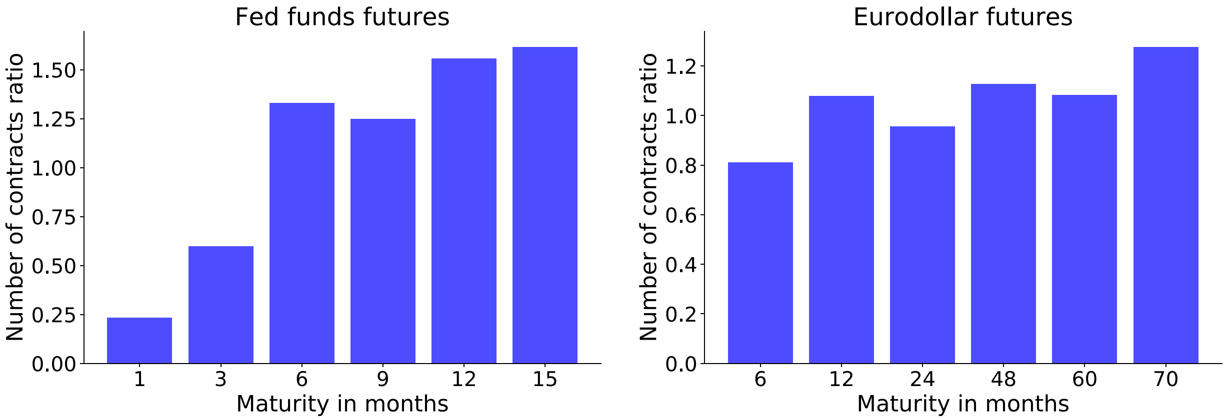


Fig. E.2. For each FOMC day with a press conference, we compute the ratio between the trading volume (number of traded contracts) during the press conference and the trading volume around the statement release. The windows to compute price changes are the same as in Section 3. The figure shows the average ratio across all FOMC days with a press conference for several contract maturities. The left panel reports results for the 30-day federal funds futures, while the right panel reports results for Eurodollar futures.

Table E.2
Press conference shocks against statement shocks – Stock portfolios, foreign exchange rates.

Stocks				Foreign Exchange			
Portfolio	a	b	R^2	- vs. usd	a	b	R^2
SPY	−7.115	0.515	19.635	aud	−8.005	0.231	9.086
	[−0.988]	[3.087]	–		[−1.390]	[1.949]	–
Mining	−6.236	0.333	8.555	eur	−6.303	0.225	9.954
	[−0.517]	[1.885]	–		[−1.415]	[2.050]	–
Utilities	−4.133	0.387	27.675	gbp	−2.269	0.252	13.157
	[−0.641]	[3.712]	–		[−0.637]	[2.399]	–
Manufacturing	−3.299	0.524	19.962	nzd	−7.771	0.235	9.851
	[−0.403]	[3.079]	–		[−1.316]	[2.038]	–
Fabricated Metal	−8.296	0.578	26.110	chf	−5.813	0.271	13.231
	[−1.054]	[3.517]	–		[−1.313]	[2.407]	–
Retail	−3.310	0.403	12.041	jpy			
	−2.099	0.323	16.099				
	[−0.471]	[2.281]	–		[−0.497]	[2.700]	–
Information	−3.402	0.445	14.275	cad	−5.193	0.361	17.491
	[−0.406]	[2.516]	–		[−1.230]	[2.838]	–
Finance and Insurance	−1.758	0.243	3.650				
	[−0.200]	[1.200]	–				

For each asset bucket k, the table reports the regression estimates for the following equation:

$$\underbrace{\Delta p_{it,PC}}_{\Delta\text{p at press conference: e.g., 14:30-15:30}} = a_k + b_k \underbrace{\Delta p_{it,ST}}_{\Delta\text{p around statement: 13:50-14:20}} + \epsilon_{it},$$

where $\Delta p_{it,PC}$ is the change in asset i's price during the date-t press conference, $\Delta p_{it,ST}$ is the change in asset i's price around the date-t FOMC statement release, and asset i belongs to bucket k. The two price changes, in basis points, are computed over two nonoverlapping, nonconsecutive time intervals. The times (13:50–14:20 and 14:30–15:30) are only examples. We always use the price change from 10 min before the statement to 20 min after the statement, as well as the price change during the press conference. t-statistics are in brackets. Standard errors are double clustered at the date-asset level. R^2 statistics are expressed as a percentage.

Table E.3
Press conference shocks against statement shocks.

	Fed funds futures		Eurodollar futures	
	1m–6m	9m–15m	6m–12m	24m–70m
a	−0.003	−0.011	−0.011	−0.029
	[−0.587]	[−0.908]	[−0.783]	[−1.144]
b	−0.029	−0.007	−0.041	−0.042
	[−0.455]	[−0.178]	[−0.969]	[−0.947]
c	0.206	0.205	0.241	0.374
	[1.624]	[1.487]	[1.813]	[3.237]
R^2	2.873	3.155	3.008	6.304

For each asset bucket k, the table reports the regression estimates for the following equation:

$$\underbrace{\Delta p_{it,PC}}_{\Delta\text{p around 14:30-15:30}} = a_k + b_k \underbrace{\Delta p_{it,ST}}_{\Delta\text{p around 13:50-14:20}} + c_k\ \Delta p_{it,ST} \underbrace{\mathbb{1}_{PC}}_{\text{FOMC day with PC}} + \epsilon_{it},$$

where $\Delta p_{it,PC}$ and $\Delta p_{it,ST}$ denote prices changes, and $\mathbb{1}_{PC}$ is an indicator variable that takes a value of one on FOMC days that contain a press conference and zero otherwise. On FOMC days, $\Delta p_{it,PC}$ and $\Delta p_{it,ST}$ denote price changes during the date-t press conference and $\Delta p_{it,ST}$ is the change in asset i's price around the date-t FOMC statement release. On non-FOMC days, we compute the price changes $\Delta p_{it,PC}$ and $\Delta p_{it,ST}$ using the times of the previous FOMC meeting. The times in the equation above (13:50–14:20 and 14:30–15:30) are only examples. We always use the price change from 10 min before the statement to 20 min after the statement, as well as the price change during the press conference. The two price changes, in basis points, are computed over two nonoverlapping, nonconsecutive time intervals. t-statistics are in brackets. Standard errors are double clustered at the date-asset level. R^2 statistics are expressed as a percentage.

Table E.4
Log volatility during FOMC days.

	Fed funds futures		Eurodollar futures		Stocks	Forex
	1m–6m	9m–15m	6m–12m	24m–70m		
a	−3.6859	−2.7182	−2.4145	−1.9234	0.9305	0.4128
	[−21.542]	[−14.589]	[−20.113]	[−20.926]	[11.517]	[4.9645]
b	0.2860	0.1110	0.3789	0.1859	0.2546	0.1650
	[1.1201]	[0.4704]	[3.0546]	[1.8124]	[2.5293]	[2.3933]

For each asset bucket k, the table reports the regression estimates for the following equation:

$$\log(\sigma_{i,t}) = a_k + b_k \cdot I_t + \epsilon_{it},$$

where $\sigma_{i,t}$ denotes the realized volatility on FOMC day t, in basis points, of asset i; asset i belongs to bucket k. I_t is an indicator variable that takes the value of one when the implied volatility from options on Eurodollar futures is above its median value computed separately for each Chair of the Federal Reserve. t-statistics are in brackets. Standard errors are double clustered at the date-asset level.

Table E.5
Log trading volume during FOMC days.

	Fed funds futures		Eurodollar futures	
	1m–6m	9m–15m	6m–12m	24m–70m
a	0.9634	0.6301	0.4542	0.5492
	[4.9841]	[4.0220]	[3.3865]	[6.5945]
b	0.0584	−0.3701	0.3225	0.2218
	[0.3045]	[−1.1479]	[1.3757]	[1.9989]

For each asset bucket k, the table reports the regression estimates for the following equation:

$$\log(V_{it}) = a_k + b_k \cdot I_t + \epsilon_{it},$$

where V_{it} denotes the trading volume during FOMC day t expressed as the percentage change relative to the trading volume from the previous business day. I_t is an indicator variable that takes the value of one when the implied volatility from options on Eurodollar futures is above its median value computed separately for each Chair of the Federal Reserve. Standard errors are double clustered at the date-asset level. t-statistics are in brackets.

Table E.6
The Effect of Words on Asset Prices: Alternative Word Dictionaries.

Panel A. Effect on Stocks

		Word categories as defined in Loughran and Mc Donald (2011)						
Coef.	Dovish or Hawkish (1)	Positive (2)	Negative (3)	Uncertainty (4)	Litigious (5)	StrongModal (6)	WeakModal (7)	Constraining (8)
a	4.17	4.38	4.34	4.34	4.34	4.35	4.38	4.32
	[7.74]	[7.86]	[7.84]	[7.90]	[8.00]	[8.07]	[7.89]	[8.07]
b_S	0.36	−0.59	−0.17	−0.15	−0.18	−0.20	−0.47	0.06
	[1.88]	[−1.71]	[−0.52]	[−0.42]	[−0.71]	[−0.87]	[−1.35	[0.18]
b_D	1.63	0.57	0.55	0.60	0.50	0.57	0.50	0.57
	[3.09]	[2.16]	[1.91]	[2.17]	[1.85]	[1.98]	[1.77]	[1.89]
b_{S-D}	−1.98	−0.80	−0.62	−0.91	−0.15	−1.14	−0.07	−0.82
	[−1.43]	[−1.42]	[−1.01]	[−1.27]	[−0.14]	[−1.95]	[−0.09]	[−1.16]

(continued on next page)

Table E.6 (*continued*)

Panel B. Effect on Forex

Coef.	Dovish or Hawkish (1)	Positive (2)	Negative (3)	Uncertainty (4)	Litigious (5)	StrongModal (6)	WeakModal (7)	Constraining (8)
		Word categories as defined in Loughran and Mc Donald (2011)						
a	2.54	2.67	2.67	2.65	2.65	2.65	2.66	2.65
	[10.44]	[10.71]	[10.59]	[10.42]	[10.44]	[10.50]	[10.24]	[10.64]
b_S	0.25	−0.24	−0.23	−0.03	−0.05	−0.04	−0.13	0.02
	[1.78]	[−1.12]	[−1.56]	[−0.18]	[−0.28]	[−0.21]	[−0.70]	[0.13]
b_D	0.67	0.39	0.36	0.39	0.35	0.36	0.37	0.32
	[2.63]	[2.13]	[1.95]	[2.02]	[1.99]	[1.90]	[1.91]	[1.79]
b_{S-D}	−0.59	−0.42	−0.11	−0.34	0.18	−0.07	−0.20	0.48
	[−1.63]	[−0.77]	[−0.22]	[−0.80]	[0.27]	[−0.10]	[−0.45]	[0.57]

Panel C. Fed Fund Futures

Coef.	Dovish or Hawkish (1)	Positive (2)	Negative (3)	Uncertainty (4)	Litigious (5)	StrongModal (6)	WeakModal (7)	Constraining (8)
		Word categories as defined in Loughran and Mc Donald (2011)						
a	0.14	0.14	0.15	0.14	0.14	0.14	0.15	0.15
	[6.22]	[6.61]	[6.47]	[6.54]	[6.66]	[6.58]	[6.50]	[6.83]
b_S	0.02	−0.01	−0.03	0.01	−0.01	0.01	−0.03	−0.02
	[2.62]	[−0.45]	[−2.13]	[0.39]	[−0.63]	[1.26]	[−1.87]	[−2.13]
b_D	0.03	−0.00	−0.01	−0.01	−0.00	−0.01	−0.01	−0.01
	[1.84]	[−0.27]	[−0.53]	[−0.41]	[−0.25]	[−0.57]	[−0.49]	[−0.36]
b_{S-D}	−0.06	−0.06	−0.02	−0.03	−0.10	0.00	−0.04	−0.05
	[−1.57]	[−1.72]	[−0.58]	[−0.74]	[−1.68]	[0.09]	[−1.24]	[−1.77]

Panel D. Eurodollar Futures

Coef.	Dovish or Hawkish (1)	Positive (2)	Negative (3)	Uncertainty (4)	Litigious (5)	StrongModal (6)	WeakModal (7)	Constraining (8)
		Word categories as defined in Loughran and Mc Donald (2011)						
a	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25
	[6.79]	[6.61]	[6.26]	[6.88]	[6.15]	[6.36]	[16.76]	[16.93]
b_S	0.01	−0.01	−0.04	0.00	0.00	−0.01	−0.03	−0.01
	[1.86]	[−1.26]	[−1.65]	[0.85]	[0.45]	[−1.21]	[−2.24]	[−1.98]
b_D	0.06	0.02	0.02	0.03	0.02	0.01	0.01	0.02
	[4.35]	[4.42]	[2.81]	[3.90]	[3.23]	[2.17]	[2.41]	[3.38]
b_{S-D}	−0.08	−0.05	−0.05	−0.11	−0.09	0.13	0.08	−0.03
	[−1.52]	[−1.39]	[−2.19]	[−1.42]	[−1.34]	[2.57]	[2.42]	[−1.48]

We estimate the following equation:

$$|r_{it}| = a_k + b_{S,k} \cdot I_{S,t-1} + b_{D,k} \cdot D_{t-1} + b_{S-D,k} \cdot I_{S,t-1} \cdot D_{t-1} + \epsilon_{it},$$

where r_{it} denotes the minute-level returns, in basis points, of asset i belonging to bucket k. D is the dummy variable constructed as in Section 4.1. In Column (1), $I_{S,t-1}$ is an indicator variable that takes the value of one if minute $t-1$ in the press conference contains a *dovish* or *hawkish* phrase as defined by Neuhierl and Weber (2019). In Columns (2) through (8), $I_{S,t-1}$ is an indicator variable that takes the value of one whenever sentiment measure S is above its 90 percentile.. We consider seven different measures of linguistic information, as defined by Loughran and Mc Donald (2011): Positive, Negative, Uncertainty, Litigious, StrongModal, WeakModal, and Constraining. To compute these linguistic measures, for each minute in press conference i, we count the fraction of words that fall in each of these seven word categories. t-statistics are in brackets. Standard errors are double clustered at the date-asset level.

Appendix F. Linguistic analysis of the statement message

In the main text, we have shown how financial investors perceive statement-related messages. In this section, we analyze the linguistics of the messages directly. The goal is to identify the different language patterns and styles that characterize the minutes in which the Chairman talks about the statement. We use a rather standard word-count strategy. The search words are categorized into language categories following the Linguistic Inquiry and Word Count (LIWC) by Pennebaker et al. (2015).

For each minute, we count the words in a given category and divide by the total number of words in that minute. We then regress the frequency variable onto the dummy variable constructed as in Section 4.1. Let D_t be such a dummy, and Freq_{it} the frequency value for the semantic category i in minute t. We estimate the following equation:

$$\text{Freq}_{it} = a + bD_t + \epsilon_{it}. \tag{F.1}$$

The intercept represents the average frequency in all non-statement-related minutes. The slope coefficient represents by how much the frequency value changes on average in statement-related minutes. Table F.1 reproduces the estimates.

First, statement-related minutes exhibit fewer negations (16.5% less). From a linguistic perspective this is important. Psychology literature suggests that there is a fundamental asymmetry between negative and affirmative propositions in natural language: negative sentences are less valuable

Table F.1
Linguistic Analysis: Part of the speech.

	Negations	Comparisons	Numbers	Insight	Relativity	Motion	Time	Past	Present	Future
a	0.97	2.48	1.66	2.30	11.84	1.92	3.50	2.43	16.9	1.69
	[46.68]	[71.65]	[30.68]	[67.73]	[141.97]	[63.59]	[70.57]	[59.88]	[146.14]	[53.92]
b	−0.16	0.24	0.31	0.42	1.65	0.38	1.15	−0.15	−1.93	0.37
	[−2.26]	[2.02]	[1.62]	[3.52]	[5.7]	[3.65]	[6.65]	[−1.05]	[−4.8]	[3.42]

The table reports the regression estimates for the following equation:

$$\text{Freq}_{it} = a + bD_t + \epsilon_{it},$$

where Freq_{it} is the frequency value for words in category i in minute t, and D_t is the dummy variable constructed as in Section 4.1. t-statistics are in brackets. The search words are categorized into language categories following the Linguistic Inquiry and Word Count (LIWC) by Pennebaker et al. (2015). Each column corresponds to one category.

than affirmative ones, less specific, and less informative. The fewer negations may suggest a larger informational value of statement-related minutes.

Second, we find more comparison words such as “than” or “as” (about 10% more) and numbers (almost 20% more number usage). Beyond providing more tangible information, comparisons and numbers serve to give the sense of the ideas expressed. Besides, numbers are often considered a neutral and transparent sign of the reality.[31]

Third, both relativity words, such as “during” or “when,” and insight words, such as “consider,” “know,” or “think,” increase (18% and 14% respectively). For an intuition as to why this adds nuances to the statement, imagine the following sentence: “I think you are wrong in this instance.” Removing signals of insight, we have: “you are wrong in this instance,” and then removing relativity we have: “you are wrong.” Relativity and insight words tend to moderate the sentence meaning. They tend to reflect opinions rather than accepted truths and qualify that opinion to a specific environment, case, and time relative to which the statement holds.

Fourth and finally, in terms of the usage of words, it is interesting to notice that words describing motion (e.g., where the economy is *going*) or time (past, present, and future) go up by 20% and 33%, respectively.

Given that time is a more important dimension of statement-related minutes, we analyze the tense and the time focus of those minutes. The last three columns of Table F.1 show that in the minutes in which the statement is discussed, messages feature fewer words related to the past or present. On the other hand, the attention to the future (captured again by the word frequency variable) goes up by 22%.

In sum, during statement-related minutes, messages talk more about the future and less about the present or past; have a larger informational value captured by fewer negations, more comparisons, and more numbers; and also add qualifying phrases that may reflect the fact that the chairman tends to mention his own view or that may add nuances about a specific situation to which that statement applies.

[31] The use of numbers also has been found to have a positive impact on the audience perceptions because it suggests competence and skills.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jfineco.2021.12.004.

References

Altavilla, C., Brugnolini, L., Gürkaynak, R.S., Motto, R., Ragusa, G., 2019. Measuring euro area monetary policy. J. Monet. Econ. 108, 162–179.
Altavilla, C., Brugnolini, L., Gürkaynak, R.S., Motto, R., Ragusa, G., 2020. How do financial markets react to monetary policy signals? In: Research Bulletin, p. 73.
Amodei, D., Ananthanarayanan, S., Anubhai, R., Bai, J., Battenberg, E., Case, C., Casper, J., Catanzaro, B., Cheng, Q., Chen, G., et al., 2016. Deep speech 2: end-to-end speech recognition in English and Mandarin. In: International Conference on Machine Learning, pp. 173–182.
Andersen, T.G., Bollerslev, T., Diebold, F.X., Vega, C., 2003. Micro effects of macro announcements: real-time price discovery in foreign exchange. Am. Econ. Rev. 93, 38–62.
Arteaga-Garavito, M.J., Croce, M., Farroni, P., Wolfskeil, I., 2021. When the Markets Get CO.V.I.D: Contagion, Viruses, and Information Diffusion. Working paper. Bocconi University.
Banerjee, S., Kaniel, R., Kremer, I., 2009. Price drift as an outcome of differences in higher-order beliefs. Rev. Financ. Stud. 22, 3707–3734.
Banerjee, S., Kremer, I., 2010. Disagreement and learning: dynamic patterns of trade. J. Finance 65, 1269–1302.
Barone-Adesi, G., Whaley, R.E., 1987. Efficient analytic approximation of American option values. J. Finance 42, 301–320.
Barro, R.J., Gordon, D.B., 1983. A positive theory of monetary policy in a natural rate model. J. Polit. Economy 91, 589–610.
Barro, R.J., Gordon, D.B., 1983. Rules, discretion and reputation in a model of monetary policy. J. Monet. Econ. 12, 101–121.
Bauer, M.D., Swanson, E.T., 2020. The Fed's Response to Economic News Explains the Fed Information Effect. Working Paper 27013. National Bureau of Economic Research.
Berkelmans, L., 2011. Imperfect information, multiple shocks, and policy's signaling role. J. Monet. Econ. 58, 373–386.
Bernanke, B.S., Kuttner, K.N., 2005. What explains the stock market's reaction to federal reserve policy? J. Finance 60, 1221–1257.
Bianchi, F., Kind, T., Kung, H., 2019. Threats to Central Bank Independence: High-Frequency Identification with Twitter. Tech. Rep. National Bureau of Economic Research.
Bikbov, R., Chernov, M., 2009. Unspanned stochastic volatility in affine models: evidence from eurodollar futures and options. Manage Sci 55, 1292–1305.
van Binsbergen, J.H., Diamond, W.F., Grotteria, M., 2021. Risk-free interest rates. J. Financ. Econ.. (forthcoming)
Black, F., 1976. The pricing of commodity contracts. J. Financ. Econ. 3, 167–179.
Born, B., Ehrmann, M., Fratzscher, M., 2014. Central bank communication on financial stability. Econ. J. 124, 701–734.
Brooks, J., Katz, M., Lustig, H., 2018. Post-FOMC Announcement Drift in U.S. Bond Markets. Working Paper 25127. National Bureau of Economic Research.
Calvo, G.A., 1978. On the time consistency of optimal policy in a monetary economy. Econometrica 46, 1411–1428.
Carroll, C.D., 2003. Macroeconomic expectations of households and professional forecasters. Q. J. Econ. 118, 269–298.

Choi, H., Mueller, P., Vedolin, A., 2017. Bond variance risk premiums. Rev. Financ. 21, 987–1022.
Cieslak, A., 2018. Short-rate expectations and unexpected returns in treasury bonds. Rev. Financ. Stud. 31, 3265–3306.
Cieslak, A., Morse, A., Vissing-Jorgensen, A., 2019. Stock returns over the FOMC cycle. J. Finance 74, 2201–2248.
Cieslak, A., Schrimpf, A., 2019. Non-monetary news in central bank communication. J Int Econ 118, 293–315.
Cieslak, A., Vissing-Jorgensen, A., 2020. The economics of the Fed put. Rev. Financ. Stud.. (forthcoming)
Cochrane, J.H., Piazzesi, M., 2002. The fed and interest rates - a high-frequency identification. Am. Econ. Rev. 92, 90–95.
Coibion, O., Gorodnichenko, Y., 2012. What can survey forecasts tell us about information rigidities? J. Polit. Economy 120, 116–159.
Coibion, O., Gorodnichenko, Y., 2015. Information rigidity and the expectations formation process: a simple framework and new facts. Am. Econ. Rev. 105, 2644–2678.
Coibion, O., Gorodnichenko, Y., Kamdar, R., 2018. The formation of expectations, inflation, and the Phillips curve. J. Econ. Lit. 56, 1447–1491.
Cook, T., Hahn, T., 1989. The effect of changes in the federal funds rate target on market interest rates in the 1970s. J. Monet. Econ. 24, 331–351.
Cukierman, A., Meltzer, A.H., 1986. A theory of ambiguity, credibility, and inflation under discretion and asymmetric information. Econometrica 54, 1099–1128.
Ederington, L.H., Lee, J.H., 1996. The creation and resolution of market uncertainty: the impact of information releases on implied volatility. J. Financ. Quant. Anal. 31, 513–539.
Ellingsen, T., Soderstrom, U., 2001. Monetary policy and market interest rates. Am. Econ. Rev. 91, 1594–1607.
Fleming, M.J., Piazzesi, M., 2005. Monetary policy Tick-by-Tick. Working paper. Stanford University.
Gardner, B., Scotti, C., Vega, C., 2021. Words speak as loudly as actions: central bank communication and the response of equity prices to macroeconomic announcements. J. Econ.. (forthcoming)
Gentzkow, M., Kelly, B., Taddy, M., 2019. Text as data. J. Econ. Lit. 57, 535–574.
Gentzkow, M., Shapiro, J.M., 2010. What drives media slant? Evidence from U.S. daily newspapers. Econometrica 78, 35–71.
Gentzkow, M., Shapiro, J.M., Taddy, M., 2019. Measuring group differences in high-dimensional choices: method and application to congressional speech. Econometrica 87, 1307–1340.
Graves, A., Fernández, S., Gomez, F., Schmidhuber, J., 2006. Connectionist temporal classification: labelling unsegmented sequence data with recurrent neural networks. In: Proceedings of the 23rd International Conference on Machine Learning, pp. 369–376.
Gürkaynak, R.S., Sack, B., Swanson, E., 2005. Do actions speak louder than words? The response of asset prices to monetary policy actions and statements. Int. J. Cent. Bank. 1, 55–93.
Handlan, A., 2020. Text Shocks and Monetary Surprises: Text Analysis of FOMC Statements with Machine Learning. Working paper. Brown University.
Hannun, A.Y., Case, C., Casper, J., Catanzaro, B., Diamos, G., Elsen, E., Prenger, R., Satheesh, S., Sengupta, S., Coates, A., Ng, A.Y., 2014. Deep speech: Scaling up end-to-end speech recognition. CoRR. abs/1412.5567.
Hansen, S., Mc Mahon, M., 2016. Shocking language: understanding the macroeconomic effects of central bank communication. J. Int. Econ. 99, S114–S133.
Hansen, S., Mc Mahon, M., Prat, A., 2017. Transparency and deliberation within the FOMC: acomputational linguistics approach. Q. J. Econ. 133, 801–870.
Hassan, T.A., Hollander, S., van Lent, L., Tahoun, A., 2019. Firm-level political risk: measurement and effects. Q. J. Econ. 134, 2135–2202.
Jarociński, M., Karadi, P., 2020. Deconstructing monetary policy surprises-the role of information shocks. Am. Econ. J. 12, 1–43.
Kuttner, K.N., 2001. Monetary policy surprises and interest rates: evidence from the fed funds futures market. J. Monet. Econ. 47, 523–544.
Kydland, F.E., Prescott, E.C., 1977. Rules rather than discretion: the inconsistency of optimal plans. J. Polit. Economy 85, 473–491.
Lakdawala, A., Bauer, M., Mueller, P., 2019. Market-based Monetary Policy Uncertainty. Working Papers 2019-2. Michigan State University, Department of Economics.
Leombroni, M., Vedolin, A., Venter, G., Whelan, P., 2020. Central bank communication and the yield curve. J. Financ. Econ.. (forthcoming)
Lewellen, J., Shanken, J., 2002. Learning, asset-pricing tests, and market efficiency. J. Finance 57, 1113–1145.
Loughran, T., Mc Donald, B., 2011. When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. J. Finance 66, 35–65.
Lucas, R.E., 1972. Expectations and the neutrality of money. J. Econ. Theory 4, 103–124.
Lucas, R.E., 1973. Some international evidence on output-inflation tradeoffs. Am. Econ. Rev. 63, 326–334.
Lucas, R.E., 1976. Econometric policy evaluation: a critique. Carnegie-Rochester Conf. Ser. Public Policy 1, 19–46.
Lucca, D.O., Moench, E., 2015. The pre-FOMC announcement drift. J. Finance 70, 329–371.
Lucca, D.O., Trebbi, F., 2009. Measuring Central Bank Communication: An Automated Approach with Application to FOMC Statements. NBER Working Papers 15367. National Bureau of Economic Research, Inc..
Mankiw, N.G., Reis, R., 2002. Sticky information versus sticky prices: a proposal to replace the new Keynesian Phillips curve. Q. J. Econ. 117, 1295–1328.
Melosi, L., 2016. Signalling effects of monetary policy. Rev. Econ. Stud. 84, 853–884.
Mueller, P., Tahbaz-Salehi, A., Vedolin, A., 2017. Exchange rates and monetary policy uncertainty. J. Finance 72, 1213–1252.
Nakamura, E., Steinsson, J., 2018. High-frequency identification of monetary non-neutrality: the information effect. Q. J. Econ. 133, 1283–1330.
Neuhierl, A., Weber, M., 2019. Monetary policy communication, policy slope, and the stock market. J. Monet. Econ. 108, 140–155.
Neuhierl, A., Weber, M., 2020. Time Series Momentum around FOMC Meetings. Working paper. University of Chicago, Becker Friedman Institute, Fama-Miller Working Paper.
Pennebaker, J., Boyd, R., Jordan, K., Blackburn, K., 2015. The Development and Psychometric Properties of LIWC2015. University of Texas at Austin.
Porter, M.F., 1980. An algorithm for suffix stripping. Program 14, 130–137.
Reis, R., 2006. Inattentive consumers. J. Monet. Econ. 53, 1761–1800.
Stein, J.C., 1989. Cheap talk and the fed: a theory of imprecise policy announcements. Am. Econ. Rev. 79, 32–42.
Swanson, E., 2020. Measuring the Effects of Federal Reserve Forward Guidance and Asset Purchases on Financial Markets. Working paper. University of California, Irvine.
Swanson, E.T., 2017. Measuring the Effects of Federal Reserve Forward Guidance and Asset Purchases on Financial Markets. Working Paper 23311. National Bureau of Economic Research.
Tetlock, P.C., 2007. Giving content to investor sentiment: the role of media in the stock market. J. Finance 62, 1139–1168.