Informativeness of the Federal Reserve Chair Communication's Sentiment

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ABSTRACT

We estimate the personal communication risk profile of the U.S. Federal Reserve (Fed) Chair by measuring a new dataset of the sentiment revealed by their public statements during their tenure. We analyze the impact of such Fed communications' sentiment risk on the market price discovery process of interest rates, and the uncertainty of the monetary policy, in the aftermath of the Federal Open Market Committee (FOMC) meetings. After controlling for the evolving state of the economy surrounding the meetings, we find that there is a significant statistical and economic difference in the communications' sentiment that is heterogeneous across Chairs, depending on their personal traits, and that affects the reaction of the market to monetary policy announcements. The sentiment in the Chairs' communications plays a role in moderating the potential surprises in the Fed announcements, and it can be effectively used as a tool for controlling and measuring monetary policy shocks.

This version: May, 2022.

JEL classification: G12, G14, G18, G21, G28, G41.

Keywords: Federal Reserve, Monetary Policy, Communications, Monetary Policy Uncertainty, Fed Funds Rate, Machine Learning

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I. Introduction

During the last two decades, empirical research on the interaction between monetary policymakers and other economic agents through the application of a continuous stream of communications, and research on the theory behind such dynamics, has been increasing (Bernanke et al., 1999; Bernanke and Gertler, 2000; Clarida et al., 2000; Bernanke and Gertler, 2001; Bernanke and Reinhart, 2004; Myatt and Wallace, 2014; Cieslak et al., 2019a). In that period, the literature has advanced in identifying the surroundings conditions and the spillover effects that the FOMC meeting triggers in certain assets: interest rates (Lucca and Trebbi, 2009), stocks (Lucca and Moench, 2015; Cieslak et al., 2019b; Bodilsen et al., 2021; Indriawan et al., 2021), and foreign exchange markets (Ahn and Melvin, 2007). In particular, there has been a growing attention on the control and the effects that the participants of the FOMC meeting (the Fed board members and the other participants such as the regional governors) have over the communication process of the monetary policy (Smales and Apergis, 2016; Bordo and Istrefi, 2018; Gertler and Horvath, 2018; Harmon, 2018; Istrefi, 2019; Romelli and Bennani, 2021). In parallel, the measurement of sentiment in the media and in communications and its effect on financial markets has received growing attention since Tetlock (2007), Tetlock et al. (2008), and Loughran and McDonald (2011) introduced this type of analysis into the financial literature.[1]

Under such developments in monetary policy communications and sentiment analysis, two questions draw our attention: (i) **are the sentiments of the statements by the Chairs of the Federal Reserve different in tone, such that the institutional text processing mechanism does not erase the personal flavor?** and, (ii) if there exists such a difference

[1]There is a growing body of research on central banks' communications textual analysis: Hansen et al.'s (2018) leading study reveals that, by analyzing the FOMC transcripts, the discipline channel has a stronger effect than the conformity channel when balancing the amount of transparency occurring during the deliberation process; Apel et al. (2019) analyzed – for the specific case of FOMC meetings' minutes – the *Hawkish/Dovish* monetary policy stance of the FOMC members, and their disagreement. Apel et al.'s (2019) analysis is based on a dictionary constructed in Apel and Grimaldi (2012), where bigrams of words are used to characterize qualitative *Hawkish/Dovish* information from the Swedish Central Bank minutes; Smales and Apergis (2017a) and Smales and Apergis (2017b) provide a measure of language complexity, and estimate the effects of FOMC language complexity on trading, finding that more complex language increases trading activity; Shapiro and Wilson (2019) used textual analysis techniques on FOMC transcripts, to estimate Federal Reserve inflation objectives.

in the personal tone of the communication, **can a single personal communication have a significant influence on the monetary policy process?** In the present study, we try to respond to these questions by measuring the sentiment of Federal Reserve Chair communications, using a machine learning technique – Naïve Bayes classifier.

Our results show that there exists a significant difference in the sentiment of the Fed Chair statements, sufficient to create a *textual sentiment profile* of every Chair: Ben Bernanke's statements being more neutral (less sentimental), and Paul Volcker's statements being more emotional (more sentimental). We also find that the sentiment in statements and speeches of the Chair of the Federal Reserve has a predictive power over the outcome of the monetary policy to be implemented during the FOMC meetings, in regard to the variable that measures the *surprise effect* of the policies over the interest rate.

Our contributions are twofold: (i) first, our contribution to the central bank communications' management literature is that, by providing a *textual sentiment profile* of the Chair – that in the case of the Federal Reserve plays a leading role in the implementation of monetary policy – the institution can have an improved measure of efficiency in the implementation of an intended shock: a more neutral (less sentimental) statement will produce the biggest surprise in the market when a decision over monetary policy is made and finally transmitted. Our dataset of sentiment is unique and the longest spanning, as it starts from January, 1971 when Arthur Burns was Chair of the Fed (all other datasets start from the mid-1990s); (ii) second, our contribution to the uncertainty and asset pricing literature, we provide a new measure of monetary policy uncertainty based on arbitrage relationships between the interest rate futures and the Federal Reserve Target Rate (FFTR). Then, we calibrate this uncertainty measure with the interest rates and assess the effects that the Fed Chair communications sentiment has over it. We find that for the more 'sentimental' Chairs (Volcker and Greenspan) there is a significant impact of their communications sentiment in reducing the uncertainty.

In our identification method, we establish a relationship between the interest rate discovery process and the sentiment of the communication, by exploring the effects of the Fed Chair last statement sentiment, and its correlation with interest rates after the FOMC meeting decision on the FFTR. To assess the effects of communications after the FOMC meeting decision, we construct a surprise variable that is measured after the FOMC announcements, following Kuttner (2001). Bordo and Istrefi (2018) analyzed the personal characteristics of the FOMC board members effects on FFTR estimation via a Taylor rule parametric model enhanced with the textual sentiment of the FOMC board members developed by Istrefi (2019).[2] Our contribution to this previous literature stands between behavioral economics and market equilibrium, as we found that personal characteristics influence the process of the Fed Chair communication, and then has an impact on the monetary policy transmission of information to the markets. In this regard, we find three main results: (i) the communications' sentiment across Chairs of the Federal Reserve differs significantly, controlling for the economic conditions: the business cycle, inflation, industrial production, unemployment rate, stock and credit markets indices, (ii) Chair sentiment is rooted in personal characteristics: age, academic background, gender, and (iii) the existence of sentiment has an inverse effect on the interest rate surprise variable: the surprise of the interest rate after the FFTR change announcement, and during the market discovery process of its real value, is reduced by the existence of a positive/negative sentiment in the communications analyzed (and increased when the sentiment of the communication is neutral).

Our work differs from that of Bordo and Istrefi (2018) as: (i) we focus only on the individual Fed Chair contribution to the FFTR change decision (Bordo and Istrefi, 2018 considered a specification where the Fed Chair yields an 80% weight inside the board decision on the FFTR change), (ii) our main identification method is non-parametric/non-dependent on the specification, (iii) we incorporate and analyze the second mandate of the Federal Reserve on maximum employment in the FFTR change function decision, and (iv) we yield an equilibrium result – in an asset pricing style: the Fed Chair statement neutral sentiment tone explains about 7%–8%

[2] Istrefi (2019) provides a initial risk profile of the Fed Chair by tagging their *Hawkish/Dovish* monetary policy stance

of the FFTR surprise, controlling for macroeconomic variables and financial market variables of the state of the economy. Every additional 10% of neutral sentiment in the Fed Chair statement contributes towards a 9% jump surprise.[3] Nevertheless, this linear impact in the surprise has been reduced from a window of observation of 2 weeks in the 1970s, to a couple of days in the 1990s–2000s (considering the results of the of the effects of the sentiment of the communications with a daily uncertainty index in Section V), and to just a few hours in the 2010s (see for example Nakamura and Steinsson, 2018; Gómez-Cram and Grotteria, 2022; Gorodnichenko et al., 2021): this is due to the advances of the market in processing the information faster. Still, the non-linear effects of the Fed Chair statement tone on the FFTR discovery process remain valid across the full sample. Our work differs from Harmon (2018), as we focus on the equilibrium/interest rates/asset pricing results and monetary policy implications, instead of the institutional implications of the management side. Our descriptive results and informational channel results on Fed Chair communications can be used jointly with Cieslak et al.'s (2019b) results on the asset prices around the FOMC meeting, to further understand the role of the Fed Chair in the monetary policy communication process to the economy.

To identify the relationships between the Fed Chair statements' sentiment and the monetary policy decisions of the FFTR we analyze the relationship of the last Fed Chair statement (before the FOMC meeting) tone and a surprise variable (J) that accounts for the unexpected change (surprise) by the market, defined in Section III (see Figure 1).

[Place Figure 1 about here]

The surprise variable constructed to disentangle the reaction of interest rates to the communications' sentiment uses the "surprise" of the interest rate market after the FOMC meeting decision release.[4] We analyze the impact of the Fed announcements (FOMC, Chair statements/press

[3] In the Online Appendix we provide these additional interest rate pricing results with a OLS with fixed-effects regression.

[4] Lucca and Moench (2015), Nakamura and Steinsson (2018), and Caldara and Herbst (2019) use a higher-frequency identification event study around the 30-minutes post-FOMC statement announcement to avoid spurious factors in the analysis. In our case, we consider a lag of 1 week – interest rates on the FOMC announcement

releases) by measuring the difference between the FFTR and the short-term/medium-term interest rate: every time the FFTR is adjusted during the FOMC meeting days or during other announcement days, there is an immediate adjustment of the short-term interest rate to eliminate the arbitrage possibility (Ahn and Melvin, 2007; Jiang et al., 2012); this immediate adjustment is observed in other maturities of the spot interest rate term structure and in the short-term interest rate futures contracts (Piazzesi and Swanson, 2008). Our surprise variable measures the ratio of the difference between the closing price of the short-term interest rate of the week previous to the FFTR announcement, and the FFTR announced, and the absolute change in the FFTR; this ratio proxies the volatility generated by the structural changes to monetary policy. Our particular interest in studying the volatility of the structural shock over the interest rates is rooted in the importance of volatility risk for the markets.

In addition, we provide a second identification method were we assess the effects of the Fed Chair communications sentiment over a new measure of monetary policy uncertainty. We construct a uncertainty measure based on an arbitrage-free model, to estimate the effects of the sentiment of the Fed Chair official speeches/statements in the reduction/increase of monetary policy uncertainty. Monetary policy uncertainty has been explored by Mueller et al. (2017), Husted et al. (2020), and Bauer et al. (2021), among others, following the leading papers on economic uncertainty approaches by Jurado et al. (2015) (macroeconomic variables based), Baker et al. (2016) (news/media based), and Ederington and Lee (1996) (options volatility based). In particular, the Husted et al. (2020) and Bauer et al. (2021) monetary policy uncertainty measures are related to ours. Husted et al. (2020) uncertainty measure is provided on a monthly, quarterly, and per FOMC meeting base. We need to measure the monetary policy uncertainty on a daily basis before and after the FOMC, to track changes during Fed Chair speeches/statements, that does not allows us to compare with Husted et al. (2020) uncertainty

and previous week average 1-month Eurodollar, as we are interested in identifying the "arbitrage surprise" on the general decision of the FOMC over the FFTR, and not high-frequency events that occur during the day of the announcement.

measure. In addition, news coverage before the 1990s is limited (and our Fed Chair statement sentiment dataset starts from 1971). Similarly, Bauer et al. (2021) provide a market measure of monetary policy uncertainty using the variance measure over a dataset of interest rate futures and options; in our case, we use an entropy measure from information theory that is more robust to multimodal distributions (that is relevant in the case of bi-modal monetary policy decisions – *Hawkish* vs. *Dovish*). In addition, the interest rate option prices dataset before the 1990s is limited, while interest rates future prices were available.

Our results are aligned with the Federal Reserve system of communications' hypotheses, where the communications that are produced by the Chair play a compelling role, and this role is not unusual in other governance structures.

The paper is organized as follows: Section II describes the datasets and the textual sentiment analysis methodologies used. Section III constructs the variable that will proxy the causal relationship between the Fed Chair announcements and FOMC meeting decisions. Section IV presents the results and Section VI concludes.

II. Data and Textual Analysis

A. Data Description

Two types of Federal Reserve documents are used to estimate the sentiment contained in communications issued by the Fed: (i) FOMC meeting statements and (ii) Federal Reserve Chair statements and press releases. The FOMC statements are included to have an institutional, objective reference point on which to leverage to infer the *personality*-driven contents of other Fed Chair's communications: while FOMC statements are the result of the Committee's deliberations and discussions, where every statement is carefully reviewed, discussed, and approved by all members of the FOMC board, the Fed Chairs' statements (may) display a more personal tone and therefore we use them to reveal the sentiment and personality of each

Chairperson against the background of the formal FOMC statements. The data covering the personal Fed Chairs' statements span the period January 1, 1971 through December 31, 2015. The Fed Chairs' communication sentiment database is therefore constructed with reference to all speeches (released to the press) delivered by the Chairs Arthur Burns, William Miller, Paul Volcker, Allan Greenspan, Ben Bernanke, and Janet Yellen. The data on the formal FOMC statements in instead span the period from February 1, 1994, when they were first made available to the public, through December 31, 2015, even though the FFTR decisions are available since January 1971, of course.

Table I presents some descriptive statistics for the FOMC and Federal Reserve Chair statements. Panel A shows the statistics concerning the FOMC statements, that are classified in two groups: meetings (in the physical presence, that comprise about 93% of the sample), and telephone conferences (the remaining 7% of the sample). Phone conferences have been held during emergency situations, such as when crisis events erupted, and were typically shorter in terms of word count. Panel B shows descriptive statistics for the Federal Reserve Chair statements. The Fed Chairs' statements are much more diverse. We apply two types of classification: (i) per *type of document*, and (ii) per Chair. Sorting by the *type of document* allows us to explore the sentiment tones in different circumstances: it is different to offer a statement before the Congress –the House of Representatives, the Senate, or a Joint Committee, where the Chair is under oath– vs. speaking before the general public when delivering some prepared remarks at an event. The classification on a per-Chair basis matches our investigation goals, as we have discussed in the Introduction. Table I shows the existence of considerable heterogeneity in the average length and frequency of the communications by each Chairperson. For instance, in terms of average number of words, the range is between 2,442 average per document for Janet Yellen to 3,590 average per document for Paul Volcker; in the case of the average number of days in between communications, the spread goes between 10 days for William Miller and 21 days for Janet Yellen, which already emphasizes the existence of distinctly personal communication styles.

[Place Table I about here]

In our analysis we use the 1-month Eurodollar interest rates, as proposed by Cochrane and Piazzesi (2002), to study the effects of the communications by the Fed's Chairpersons on interest rates and their volatility. In detail, we collect data for the sample January 01, 1971 – December 15, 2015. The FFTR is extracted from Bloomberg with reference to the period January 01, 1971 – December 15, 2008. From December 16, 2008 through December 31, 2015 the FFTR has changed from being announced as a pointwise rate to be communicated in the form of an interval defined by two rates, an upper and a lower target rate; for concreteness, after February 2008, we average the interval bounds and use the resulting mean as a proxy for the point FFTR. This assumption is unlikely to materially affect our results, as changes in the FFTR under the band system are conducted as parallel shifts: historically, the basis points increases of the upper and lower bands have always been equal.

In Figure 2 we show a time series of the interest rate (1-month Eurodollar) and the FFTR. We can observe an inconsistency in the monetary policy implementation by the Federal Reserve officials during the turbulent times before the 1990s: between November 21, 1980 and January 16, 1981, the FFTR was eased and tightened in the space of only two months by at least as much as 400 basis points.

[Place Figure 2 about here]

Given this volatility of the decisions, by mid 1980s–early 1990s the Federal Reserve started to introduce reforms in the monetary policy implementation process that generates the two regimes observable in Figure 2 (Before and after 1994). In line with the 1980s–1990s reforms, Taylor (1993) proposed a reduced form equation for the estimation of the response of interest rates to changes in the macroeconomic variables:

$$i_t = \pi_t + r_t^* + a_\pi \left(\pi_t - \pi_t^*\right) + a_y \left(y_t - \bar{y}_t\right), \tag{1}$$

where i_t is the short-term target nominal interest rate, π_t is the rate of inflation (PCE), π_t^* is the desired rate of inflation, y_t is the log real output (GDP), and $\bar{y}_t$ is the expected output. Since then, monetary policy has been more stable and predictable. Due to this new set of measures implemented by the late 1980s and early 1990s, we consider robustness checks on the datasets by splitting the results before and after the introduction of the FOMC statement release (1994).

Table II presents some descriptive statistics on the interest rates' environment for our sample period. For allowing our analysis to reflect the remarkable changes implemented in the FOMC meeting mentioned earlier, we divide the sample into two sub-periods, 1971–1993 and 1994–2015. Table II shows that, when compared to the first sub-sample, the 1994–2015 period was characterized by lower average rates, lower volatility, and consequently by a smaller number of FFTR changes (2.9 FFTR changes per year in comparison to 7.9 FFTR changes per year between 1971 and 1993).

[Place Table II about here]

We use three sets of control variables in an attempt to obtain unbiased estimates of the sentiment expressed through the Fed Chairs' statements via their impact on interest rates and on proxies of rate volatility: (i) macroeconomic state variables, (ii) financial market state variables, and (iii) the personal characteristics of the Chairpersons.

As for the macroeconomic state variables, according to the Taylor rule in Equation (1), we include the inflation rate represented by the return of the Personal Consumption Expenditure (PCE) inflation and the output growth rate represented by the return of the Industrial Production Index. (in tables and plots we denote the return by the symbol Δ to simplify the notation). We also include a few additional macroeconomic variables: the rate of growth in the money supply (the return of M1) and the unemployment rate; these two variables of course reflect the Fed's dual mandate of price stability and of maximum employment. All macroeconomic variables are collected from ALFRED at the Federal Reserve Bank of St. Louis, considering *vintage* data to match the date of the announcement with their historical release. The use of vintage data is critical to our strategy, since it allows us to capture the effects of any statements on the day they are delivered and to provide unbiased estimates of the *impact of communication-related events*.

The financial market state variables are bound to reflect market expectations on the future state of the economy. We include stock market (the Standard & Poor's 500 lagged quarter returns since FOMC meetings are held every month and a half, and the financial variables reacts to expectations faster than macroeconomic indicators), and credit market (the spread between the yields on Baa-rated corporate bonds and that on 10-year Treasury notes) variables. The data are collected from FRED at the St. Louis Fed for our 1971– 2015 sample.

We consider an additional set of macroeconomic control variables, available at a higher-frequency but for a shorter period given that this dataset time-span is limited, April 27, 2000 – December 31, 2015: these are market surprises from macroeconomic news announcements, as in Faust et al. (2007). In practice, surprises are computed as the difference between the Thomson Reuters EIKON's macroeconomic survey average expected announcement and the final macroeconomic release (available in ALFRED). This set of macroeconomic news surprises concerns personal consumer expenditures (PCE) inflation, gross domestic output (GDP), consumer sentiment (CS), the unemployment rate (UR), initial job claims (IJC), non-farm payroll employment (NFP), retail sales (RS), the international trade balance deficit (TD), and housing starts (HS).

The final set of controls is related to the individual, personal traits of the Chairpersons under examination: their age (at the moment in which a public statement was issued), gender, and academic background (number of years in formal academic education).[5]

B. Methodology for Inferring Sentiment

In behavioral economics, the first concern with any sentiment-driven research design is with finding a proper definition of a *sentiment*. In a social science perspective, "sentiment" may receive numerous definitions and the process of finding the correct one exposes a researcher to considerable lack of robustness of the ensuing empirical results. Because we focus on inter-personal comparisons of Fed Chairpersons' inferred sentiment, in this paper we draw our definition of sentiment from previous studies that have empirically estimated sentiment from managers' statements/communications.

Our method for estimating sentiment follows a machine learning approach, a mixed approach between the "Bag of Words" (BoW) approach typical of earlier literature, and the *proxy function method*. Following Li (2010), we use a Naïve Bayes classifier applied to a BoW feature set, trained with two widely used datasets for sentiment measurement: a sentiment database (including positive/negative tone), and a subjectivity database (neutral/not-neutral tone).[6] As a robustness check, to make sure that our design based on an innovative machine learning research design is not the main driver of our empirical findings, we also include the Harvard IV General Inquirer dictionary (Tetlock et al., 2008) sentiment and Loughran and McDonald (2011)'s dictionary. Of course, to support the robustness of our empirical results, we expect that all these sentiment measures will lead towards homogeneous empirical findings.

III. Fed Chairs' Sentiment as a Proxy of FOMC Decisions

In this section, we construct a surprise variable to analyze the effects on the term structure of interest rates of the sentiment revealed by the Fed Chairpersons' communications in the

[5]Source: https://www.federalreservehistory.org.

[6]See the Online appendix for a detailed description of the Naïve Bayes machine learning approach for sentiment measurement.

aftermath of FOMC decisions. We have two main research questions: (i) are the sentiments of the statements by the Chairs of the Federal Reserve different in tone, such that the institutional text processing mechanism does not erase the personal flavor? (ii) if there exists such a difference in the personal tone of the communication, can a single personal communication have a significant influence on the monetary policy process?

We measure the effects of the personal characteristics on the sentiment of the communication to answer the first question. To do it, we also control by the state of the economy and the financial market. From a technical point of view, we estimate an logit model adding fixed effects (following Huang et al., 2013; Loughran and McDonald, 2011, 2013). We answer the second question by constructing a variable that recovers the "jump surprise effect". This effect corresponds to the amount of "market overreaction" when the FOMC statement is released. In this way, we correlate the sentiment with the "jump surprise" of the market. From a technical point of view, we estimate logit with fixed/random-effects panel regressions to identify the effects of the communications' sentiment over the 1-month Eurodollar future.

A. Market Surprise to FOMC Meeting Decisions

Our market surprise variable is a modified version of the Kuttner (2001) monetary policy surprise variable. In our setting, we consider a "ratio" of the surprise by the size of the FFTR change that helps to account for changes during different interest rates periods (small changes during lower interest rates might have the same impact as larger changes during higher interest rates periods).

First, to start the variable construction, we consider the second differences, volatility, or surprise measures of the interest rates. Directional changes of the interest rates are important for traders, but it is harder to get statistically significant conclusions on the interest rate direction's relationship with Fed Chair statement information, considering that markets are efficient. Moreover, a surprise/volatility analysis can provide statistically significant results, even in an efficient markets framework (examples are the stylized facts on volatility clustering, tail dependent correlations, and VIX analyses).

Second, we control the impact implied by the Taylor's (1993) rule over the decisions, represented by the implementation and the communication of monetary policy. From Equation (1), we can observe that prices (inflation) and output (GDP) are two of the most relevant macroeconomic variables analyzed by FOMC members when taking a decision on the FFTR.

Third, we control the endogeneity of the process. The decisions of the Federal Reserve on monetary policy are tracked by the market, the macroeconomic environment and financial market state are observed by the Fed officials. Usually both observations happen before a decision is made by them.[7] In our analysis, we consider a lag of 1 period to reduce the endogeneity. We also test a SVAR (Rigobon and Sack, 2003) as a robustness check for endogeneity and the results are provided in Section IV.D.

Considering all these previous elements and using weekly data to avoid asynchronous data problems, in the logit panel event study we define as the dependent variable the 1-week jump lagged difference between the FFTR on the day of the announcement (post-announcement) and the 1-month Eurodollar future observed one-week before the announcement, $f_{t-1}^{(1)}$:

$$J_t = \left| \frac{FFTR_t - f_{t-1}^{(1)}}{FFTR_t - FFTR_{t-1}} \right|. \tag{2}$$

We aim to explore a *adjustment surprise* measure. For this reason, we consider an absolute value of the surprise, J_t, as the dependent variable.[8] We rely on the 1-Month Eurodollar instead of the 30-day Federal Funds Futures since we want to incorporate the risk-premium associated with the spread of the 1-Month Eurodollar and the 30-day Federal Funds Futures. For example,

[7] Sometimes the market has an advantage by being responsive in a 24x7x365 environment, such as in FX markets, but sometimes the Fed might react in the same 24x7x365 environment, as some call conferences by the FOMC meetings and their statements are released on Sundays before the opening of the market on Monday.

[8] Robustness checks were conducted considering regressions with J_t^2 in the Online Appendix. Results using this modified dependent variable were similar. Equivalently, the adjustment surprise might be inverted to analyze how efficient the transmission of monetary policy is to the markets. This measure, $(1/J_t)$, is defined as the adjustment efficiency and the results shown in the Online Appendix are equal to the ones obtained with J_t.

using the 1-Month Eurodollar we can understand better the increased spread signals problems or distortions in the economy – such as the deteriorated financial liquidity environment of September/October 2008. We can capture that effect using 30-day Federal Funds Futures. Moreover, this additional spread value is an intrinsic reaction from the market to the intensity of the monetary policy shock.

Figure 3 shows the evolution of the J_t *adjustment surprise* variable. The variable J_t accounts for two effects: (i) one effect is the difference between the FOMC meeting announced rate, $FFTR_t$, and the market expected change, retrieved by measuring the 1-month Eurodollar Future closing prices of the previous week, $f_{t-1}^{(1)}$, and (ii) a second effect, that is how this *adjustment surprise* is representative for the decision in terms of the change. This effect works as a standardization of the first effect. For instance, suppose the first effect (numerator) is 50bp and the second effect is 50bp, then the variable reports $J_t = 1 = 100\%$ that means the *adjustment surprise* is of the same scale as the FFTR change. Meanwhile, if the numerator is 0bp, then there is no *adjustment surprise*, as we can observe in Figure 3 for some decisions between 1998 and 2004. The maximum value observed is about 10 (or 1000%), that means the *adjustment surprise* was 10 times the FFTR change announced: that might happen under two circumstances, a low-interest rate environment (for example, the 2007/2008 implementation of quantitative easing) and a high-inflationary period (for example, the Middle East oil wars during the 1970s). Still, during these periods, the market is able to predict the FFTR changes with some accuracy ($J_t < 1$).

[Place Figure 3 about here]

B. Federal Reserve Chair Opinion and FOMC Decisions

But, which causality are we trying to explore? How do we relate Fed Chair statements' sentiment to the J_t variable? And what does this variable mean for the markets and the Federal

Reserve interaction? An answer to these questions comes by doing a historical review of the FOMC FFTR decision process. On one hand, from Thornton and Wheelock (2014) we know that from the last 755 FOMC meetings from April 19, 1939 to December 31, 2015, 100% of the time (755 meetings), the Chair decision was aligned with the decision taken by the FOMC to tighten or to ease the monetary policy. One the other hand, it is hard to think that Fed Chairs can preserve their leadership by changing their view during the meeting. Then, in line with Ehrmann and Fratzscher (2007), considering that the communication process of the Federal Reserve decisions is done by the members, but the Chair is the leading voice in this process, then all the Chair's public opinions before the FOMC meeting are immediate proxies to the FOMC decisions.[9]

Given the importance of the Fed Chair opinions in the final FFTR decision during the FOMC meeting, we explore four dimensions of the communication process: we analyze the relationship of (i) *adjustment surprise* J_t with the neutral sentiment of the Chair statements, $NeutSentFRC_t$, (ii) the number of days between the last Chair statement release and the FOMC meeting decision on the FFTR change, (iii) the FOMC statement neutral sentiment, $NeutSentFOMC_t$, and (iv) the agreement between the Chair statement *Hawkish/Dovish* stance, FRC_Stance_t, and the previous *Hawkish/Dovish* stance on the FFTR decision, $FFTR\_Stance_{t-1}$ (See Figure 4 with corresponding sub-figures). The latter, the agreement dimension, is defined as:

$$FRC\_MPAgreement_t = \left| FRC\_Stance_t - FFTR\_Stance_{t-1} \right|, \tag{3}$$

where FRC_Stance_t is the *Hawkish/Dovish* tone of the Fed Chair statement, measured by counting the number of words in each category using the dictionary defined in Table C1 in the Online Appendix, and standardizing by by the total number of words of the two categories; and

[9] It is common to observe press conferences where one of the members of the FOMC discusses proposals by the Chair, and then the Chair responds to the FOMC member through a press release or an interview to the media.

$FFTR\_Stance_{t-1}$ is the *Hawkish/Dovish* stance of the last FFTR decision.

Figure 4 and Sub-figures 4a, 4b, and 4c show results of descriptive analysis relationships between Fed Chair statement neutral sentiment and the jump surprise J_t. By observing Sub-figures 4a, 4b, and 4c, we can infer some initial conjectures on our second question, on the effects of the Fed Chair statement neutral sentiment on the interest rate behavior during the FOMC meeting announcements; first, we explore conjectures on the direction of the surprise and the sentiment of the communication, and we find that a greater amount of *neutrality* in the communication's sentiment seems to be associated with a greater jump surprise. 'Neutral likelihood' refers to the probability that a communication will be tagged as neutral. Communications with a likelihood over 0.5 will be tagged as *neutral* and communications below that level will be tagged as *emotional* (not-neutral). Second, we explore the relationship of the number of days between the Fed Chair statement release and the FFTR decision; if the number of days were high (> 30 days), and those cases had a high jump surprise J_t from the market, there will be a need to condition the surprise analysis on the cases with only few days between the Chair statement release and the FFTR decision; however, we find that the more the number of the days between the Chair statement release and the FFTR decision, the lower the J_t variable is, signaling there is no need to condition,[10] and signaling as well that there might be an important information content for the market with the Chair statement.

Finally, the agreement between the *Hawkish/Dovish* tone of the Chair statement and the last monetary policy decision signals that changes in the tone by the Fed Chair signal a higher surprise variable J_t, indicating that changes in the *Hawkish/Dovish* tone might signal a shock.

[Place Figure 4 about here]

[10]Still, we provide robustness checks in the Online Appendix to filter the sample to Fed Chair statements issued with 60 and 30 days or less before the FFTR change announcement. The mean number of days between the Fed Chair statement release and the FFTR decision is 15.93 days and the 90-*th* percentile is 37.5 days which means most of the sample is in a 40-day window before the FFTR change announcement.

C. Baseline Models – Controls

We divide our analysis in two: (i) first, we find the relationship between the state of the economy variables and the personal characteristics of the Fed Chair statement neutral sentiment; then, we construct a response variable that represents the surprise of the market to the FFTR changes, and we find the relationship between the control variables and the sentiment with the surprise. Figure 5 shows a causality diagram.

[Place Figure 5 about here]

For the first stage, the sentiment of the statement is regressed by the following fixed-effects model:

$$\begin{aligned} NeutSentFRC_t &= \beta_0 + MacroVariables_{t-1} + FinancialVariables_{t-1} + \\ &\quad PersonalCharacteristics_{t-1}, \end{aligned} \tag{4}$$

where

$$\begin{aligned} MacroVariables_{t-1} &= BC_{t-1} + \beta_1 \Delta PCE_{t-1} + \beta_2 \Delta IP_{t-1} + \beta_3 \Delta M1_{t-1} + \beta_4 \Delta UR_{t-1}, \\ FinancialVariables_{t-1} &= \beta_5 \Delta SP500_{t-1} + \beta_6 Baa10YT_{t-1}, \\ PersonalCharacteristics_{t-1} &= CHAIR_{t-1} + \beta_7 AGE_{t-1} + \beta_8 EDUC_{t-1} + \beta_9 GEND_{t-1}, \end{aligned}$$

with BC the business cycle dummy (1 for expansion, 0 for recession), ΔPCE the change between the last two PCE announcements, ΔIP the change between the last two Industrial Production announcements, $\Delta M1$ the change between the last two $M1$ announcements, UR the unemployment rate, $\Delta SP500$ the return of the S&P500 during the last quarter, $Baa10YT$ the credit spread between the corporate "Baa" rated bonds and the 10-year Treasury notes, $CHAIR$ an index of the Fed Chairs sorted by the neutral sentiment (by Naïve Bayes classifier, Volcker=1, Greenspan =2, Yellen=3, Miller =4, Burns=5, Bernanke=6), AGE the age of the Fed Chair at the moment of the statement release, $EDUC$ the Fed Chair academic background, and $GEND$ the Fed Chair gender. In this analysis, we consider the weekly data defined in Section II.A. Given that the Fed Chair issues statements in a bi-weekly/monthly frequency (approximately), we maintain the Fed Chair statement neutral sentiment variable while the Fed Chair does not issue a new statement.

Next, in the second stage of our analysis, we study the *surprise jump* J_t of the market after the FFTR change decision. Initially, we want to test if the most simple classification of sentiment might have effects of the *surprise jump* J_t. Following Loughran and McDonald (2011), Huang et al. (2013), and Loughran and McDonald (2014), we create a jump surprise event with two categories, and regress the jump surprise as the dependent variable with a logistic regression over the neutral sentiment, in the following way: (i) expected: the *surprise jump* J_t is lower than 100%, which means that the difference between the last Friday 1-month Eurodollar rate before the FOMC meeting, and the FFTR decided during the FOMC meeting is less than the size of the change in the FFTR taken during the FOMC meeting, and (ii) surprised: J_t is greater than 100%. We produce robustness checks over this specification, changing the *surprise jump* J_t threshold to $\pm 20\%$, and the results are maintained.

To control the results for the macroeconomic environment we introduce fixed-effects with three sets of controls as explained in Section II.A, (i) macroeconomic state variables, (ii) financial market state variables, and (iii) the Fed Chair personal characteristics. Then, we test the following models:

$$
\begin{aligned}
J_t \quad = \quad & \beta_0 + MacroVariables_{t-1} + FinancialVariables_{t-1} + PersonalCharacteristics_{t-1} + \\
& SentimentVariables_{t-1}, \qquad (5)
\end{aligned}
$$

for testing the effects that the Fed Chair statement neutral sentiment might have on the jump surprise J_t and the monetary policy price discovery by the market, where

$$SentimentVariables_{t-1} = \gamma_1 NeutSentFRC_t + \gamma_2 StanceFRC_t,$$

with $NeutSentFOMC_t$ the last Fed Chair statement neutral sentiment measured by any of the sentiment measures (emotional measures of sentiment in Equation (B1), (B2), and (B3) of the Online Appendix), $StanceFRC_t$ the Fed Chair statement agreement with the current monetary policy stance (Hawkish/Dovish), and,

$$J_t = \beta_0 + MacroVariables_{t-1} + FinancialVariables_{t-1} + \gamma_1 NeutSentFOMC_t, \quad (6)$$

with $NeutSentFOMC_t$ the current FOMC statement neutral sentiment, for testing the effects of the FOMC statement on the jump surprise J_t, as a baseline to measure the institutional sentiment level. Data for the logit panel event analysis of the model in Equation (5) are from January 01, 1971 to December 31, 2015, and of the model in Equation (6) are from February 01, 1994 to December 31, 2015 (first FOMC meeting statement release was from February 01, 1994).

IV. Results

This section presents results on the textual sentiment profile per Federal Reserve Chair, and the results on the effects and the economic significance of the Fed Chair statements' sentiment on the interest rate price discovery by the market.

A. *Sentiment of FOMC and Fed Chair Statements*

Table III presents the results of the FOMC and Fed Chair statements' sentiment, using three different textual sentiment methodologies: Panel A.1 and B.1 results use the Naïve Bayes classifier, and Panel A.2 and B.2 results use the proportion of positive/negative words of the

Harvard General Inquirer IV (Tetlock et al., 2008) and the Loughran and McDonald (2011) dictionaries. Panel A.1 shows the proportion of documents that have as a final tag a neutral tag, or emotional (not-neutral) tag; the latter is tagged as positive or as negative. Panel A.2 shows the proportion of word count that every statement has. Panel B.1 shows the likelihood of every document being tagged as neutral or as emotional; and the latter as a positive or as negative; Panel B.2 shows the word proportion adjusted by the term weighting (tf.idf) standardization applied to the total number of words (over all documents). The results show, by the three different sentiment measures, that the Fed Chair statements have a greater amount of sentiment than the FOMC statements. In the case of FOMC statements, meetings tend to have more sentiment than telephone conferences, and this is expected as there is more space for discussion. Regarding the Fed Chair statements, when the Chair presents a statement in the Congress, it seems to have a bias for being more emotional and positive, than when presenting in other circumstances.

[Place Table III about here]

The next important analysis is over the first main question of this research: can Fed Chairs be tagged by their statements' sentiment? As in a textual risk-profile style? If that is the case, we should observe that their statements' sentiment cluster, and we will need every cluster to be statistically significant different from each other. Table IV presents the results. Panel A.1 and B.1 results use the Naïve Bayes classifier, and Panel A.2 and B.2 results use dictionary methods. Panel A.1 counts the proportion of documents that have a neutral tag, or emotional (not-neutral) tag; the latter being a positive or negative tag. Panel A.2 shows the proportion of word count that every statement has. Panel B.1 presents the neutral or emotional, and for the latter the positive- and negative-likelihood of being tagged in such a category. Panel B.2 presents the word count adjusted by the tf.idf standardization method.

[Place Table IV about here]

We provide the Kolmogorov–Smirnov test of sample differences in Table V. The results show that there is a statistically significant difference (*** equals a p-value of less than 0.01) between the textual sentiment profile of every Chair: we can say that the *Fed Chairs have a personal tone profile in their statements, and that this textual sentiment profile differs significantly between Chairs, with Ben Bernanke the more neutral, and Paul Volcker the more sentimental.* Fed Chair statements' negative content is reduced: on average only 1% of the statements, as a whole, are tagged as negative, and the average negative words' content is only 7% in comparison to the 14% of positive content and 77–78% of neutral content by the Harvard IV dictionary. The Loughran and McDonald's (2011) dictionary reports a higher content of negative words than the Harvard IV (twice that of the positive), but this is due to the Loughran and McDonald's (2011) base dictionary size of negative and positive words: their negative base includes 2,337 words vs. 353 words in their positive base.

We still need to check if the textual sentiment profile differences are due to the macroeconomic environment, or to other personal characteristics, and that is addressed in Section IV.B, but by looking into the interest rate levels (see Figure 2), and the macroeconomic situation during the two different regimes observed, the one between Burns, Miller and Volcker, and the other during Greenspan, Bernanke, and Yellen, we can infer that this result of the differences in textual sentiment profile will be maintained. For example, Arthur Burns and Paul Volcker experienced similar problems by the end of the 1970s and by the beginning of the 1980s, regarding the issue of high inflation and high unemployment rate. Nevertheless, the sentiment in their documents, on average, is quite opposite: while Burns has a very neutral position, Volcker was quite emotional and positive. This is the first important contribution of our study. The FOMC and Fed Chair statements that were tagged as negative documents, are almost not present, with less than 3% of the total sample.

[Place Table V about here]

Given that we use three different sentiment methodologies, as a robustness measure, we explore the intersection of the two dictionary methodologies, by counting the words' proportion of the FOMC and Fed Chair statements, by each of the dictionaries.[11] Table B1 in the Online Appendix shows the results and we can observe that the different sentiment methodologies can extract the similar features, and this intersection is consistent in the different analysis we explore in this study.

B. Federal Reserve Chair Statements' Sentiment and Personal Characteristics

Table VI shows the results that confirm our conjecture on our first question: the sentiment of the Fed Chair public statements reflects a personal tone, that is recognizable given the personal characteristics, controlling for the state of the economy and the financial markets; the institutional mechanism is less important in these statements. The state of the economy and financial market explains 1% – 8% of the Fed Chair statement neutral sentiment, but personal characteristics explain an additional 3% – 14% (Adjusted R^2).

[Place Table VI about here]

The sub-panels in columns (1), (3), and (5) show the fixed-effects regressions of model in Equation (4) without the personal characteristics, and columns (2), (4), and (6) show model in Equation (4) controlling for personal characteristics. Columns pairs (1,2), (3,4), and (5,6) correspond to the measurement of the Fed Chair statement neutral sentiment by the Naïve Bayes classifier, Harvard IV (Tetlock, 2007), and Loughran and McDonald (2011) dictionaries' methods. The base model in the Naïve Bayes classifier case (column (1)) shows that money supply and labor market are the drivers of the sentiment, but the other two measures show that all macroeconomic and financial market state variables influence the sentiment of the Chair. Nevertheless, the most interesting result is that personal characteristics are also significant and important in finding the source of the sentiment in the Fed Chair statements.

[11]In line with Loughran and McDonald (2011) Table III, and Hansen et al. (2018) Figures III, IV, and V.

C. Interest Rate Jump Surprise and Federal Reserve Chair and FOMC Statements Sentiment

In this section, the results to elucidate the effects of the Fed Chair statement neutral sentiment over the interest rate price discovery process by the market after the FOMC meeting, are presented. Table VII shows the main results on our second question: a single personal communication has a statistically significant influence on the monetary policy process. The economic explanation for our results is that the Fed Chair plays a leading role in constructing consensus withing the FOMC Board, but at the same time a leading role in signaling the decisions to be made during the FOMC meeting: the market reads carefully the public statements of the Fed Chair, and elaborates an expectation on the severity of the decisions based on this estimate; an increase in the neutrality of the statement sentiment creates more uncertainty on the market about the opinion of the Fed Chair about the economy, and in consequence on the expected consensus on decisions.

The results for the baseline models for the first set of controls, the macroeconomic state variables, the Models (5) and (6), are presented in Tables VII and VIII, for the Fed Chair and the FOMC statements, respectively. The Table VII results on the Fed Chair statement effect are divided into nested sub-panels organized in columns: column (1) presents the results for the logit regressions of the jump surprise J_t for the base model in Equation (5) only with macroeconomic and financial state variables; columns (2), (4), and (6) are the results of model in Equation (5) adding the Fed Chair last statement neutral sentiment ($NeutSentFRC_{t-1}$) observation to the previous specification; columns (3), (5), and (7) are the results for the full model in Equation (5) when controlling for personal characteristics. Pair columns (2,3), (4,5), and (6,7) correspond to the measurement of the Fed Chair last statement neutral sentiment by the Naïve Bayes classifier, Harvard IV (Tetlock, 2007), and Loughran and McDonald (2011) dictionaries' methods.

The Table VII results show that higher unemployment reports are associated with a higher interest rate market surprise: the market tends to underestimate FFTR decisions based on the job market. This result is consistent with the Federal Reserve mandate on maximum employment and with results found by Piazzesi and Swanson (2008) on the significant relationship between employment growth and the Federal Funds interest rates' excess returns. Expectations of the market (last-quarter return) seem to have a minor effect. However, when we include the sentiment in the model (columns (2), (4), and (6)) there is an increase of an additional $5\% - 7\%$ in the deviance fit, and the Fed Chair last statement neutral sentiment is significant across the different sentiment measures (the principal and the proxies). Still, when we control results by adding the personal characteristics of the Fed Chair, we observe there is an additional increase in the fit of about $8\% - 10\%$, but with the neutral sentiment still being significant. Our interpretation is that the Fed Chair last statement neutral sentiment does have an effect in the surprise jump J_t, and this effect, although it is personal to every Chair and situation, has a particular effect beyond the personal characteristics: Chairs use a personal tone in communications that is related to their personal characteristics, but in addition the tone has a personal flavor that they use as a personal signature. Figure 6 shows that all the previous results on the importance of the Fed Chair last statement neutral sentiment are confirmed by analyzing the Granger causality of the variables on the jump surprise J over various lags.

[Place Table VII about here]

[Place Figure 6 about here]

We check on FOMC statements sentiment and changes on the FFTR. Table VIII shows the results when analyzing the FOMC statement neutral sentiment effect. Column (1) has the logit regressions with the base model in Equation (6) without the FOMC last statement neutral sentiment, and columns (2), (3), and (4) show the results when including the FOMC neutral sentiment measured by the Naïve Bayes classifier, the Harvard IV (Tetlock, 2007), and the Loughran and McDonald (2011) dictionaries' methods. We observe that the sentiment of the

FOMC statements seems not to have any significant relationship with the surprise jump variable J_t when controlling for the macroeconomic and financial market state variables, that altogether can explain with a deviance of 37.99, most of the surprise, with the exception when the neutral sentiment is measured by the Loughran and McDonald (2011) dictionary as in Equation B3 of the Online Appendix; the neutral sentiment still not being significant in that specification. Although we find some sentiment in the FOMC statements (Table III of main document), it is not relevant in the FFTR discovery process by the market. We provide two interpretations of these results: (i) the institutional mechanism of communication "enhancement" of the Federal Reserve during the FOMC meeting eliminates any signs of sentiment (emotion) that could signal more information that the Federal Reserve wants to signal, and (ii) the market might have absorbed previously any information by the FOMC board members' previous week statements' release. This result complements Lucca and Trebbi (2009) by exploring the market surprise at the FOMC neutral sentiment content: in Lucca and Trebbi (2009) the FOMC statements' analytical sentiment (inflation/monetary policy stance) is relevant for the market; we find that emotional sentiment is not.

[Place Table VIII about here]

D. Endogeneity – SVAR: Sentiment, Macro Variables, and Jump Surprise J_t: SVAR

The sentiment of the communications is a variable that will be dependent on the current economic conditions. In Section IV.A we found that there exists a sentiment associated to every Chair, driven by their personal characteristics, but that sentiment is in particular driven by changes in the economic conditions (such as the changes in levels of liquidity – M1). To disentangle any endogeneity effects, we test a conditional SVAR (Rigobon and Sack, 2003), establishing the FOMC event as the shock event, and using the Jump-surprise J_t variable as a measure of our shock. Figures 7 and 8 show the results. Every lag period represent one

FFTR change event. We observe in the impulse response function of the sentiment, that is 1-lag increasing and statistically significant, even in this SVAR with 7 variables, that includes 4 macroeconomic variables (monthly returns in PCE, M1, and industrial production, and the monthly unemployment rate) and 2 financial variables (returns on S&P500 and credit spreads). The other variables that seem to be significant are the industrial production (increasing after 9-lags), the unemployment rate (increasing in 1-lag), and the credit spread (decreasing after 5-lags). Figure 8 shows the historical decomposition that the sentiment drives most of the variation relatively in comparison with the other variables. It seems that sentiment "exacerbates" the response in certain instances but its mean after 2 lags in most of the cases.

[Place Figure 7 about here]

[Place Figure 8 about here]

V. Structural Model: Arbitrage and Market Beliefs' – Effects on Sentiment the Target Rate Discovery Process

Cochrane and Piazzesi (2002) in their concluding remarks posed a "puzzle" in which the market anticipation to the Federal Reserve decisions for the short-term interest rate might be due to an anticipation of a higher output in the future, making it somehow quite difficult to identify which of the two agents reacted first, if the Federal Reserve by implementing a shock that followed a long-term monetary policy decision, or the market by anticipating the next short-term interest rate decision of the FOMC. In this Section we shed some light on solving the identification puzzle, by using the 1- and 3-month Eurodollar future instrument. Our approach follows a *grid of probability scenarios* to price the futures in the physical measure, similar to what Stutzer (1996) and Stutzer and Chowdhury (1999) did in the risk-neutral measure.

Consider the 1-month Eurodollar future of the short-term interest rate $f_t^{(1)}$, the Federal Funds Effective Rate $FFER_t$, the Federal Funds Target Rate $FFTR_t$, for $t = 1, \ldots, T$, the time in days. Assume that T represents the period during which the FOMC maintains the $FFTR_t$ without any change. The market expects that:

$$\text{average}_{t=1,\ldots,T}(FFER_t) = E\left(\sum_{t=1}^{T} \frac{FFER_t}{T}\right) = FFTR_1.$$

Given that the 1-month Eurodollar future reflects the expectations of the short-term interest rate for the next month, we have that, by arbitrage conditions, if there is no expected change of the FFTR for the next month, $T \geq 30$, and

$$\left(1 + \frac{f_1^{(1)}}{12}\right)^{1/12} = \left(1 + \frac{E\left(\sum_{t=1}^{T} \frac{FFER_t}{T}\right)}{12}\right)^{1/12} = \left(1 + \frac{FFTR_1}{12}\right)^{1/12},$$

that implies

$$f_1^{(1)} = \sum_{t=1}^{T} \frac{E\left(FFER_t\right)}{T} = FFTR_1, \tag{7}$$

and it will explain why on so many occasions the 1-month Eurodollar future has the same rate of the FFTR just after the FFTR announcement, considering that most of the FFTR decisions are taken at regular FOMC meetings held every month a half ($T \geq 30$). Nevertheless, decisions on the FFTR can appear before the regular scheduled FOMC meetings due to the economy or market conditions, and in that case $T \leq 30$.[12] Using an expectations' model the 1-month Eurodollar future should reflect the implied probability of the FOMC stepping forward and taking a decision before the 30-days' maturity of the future, or the implied probability of the

[12]Notice that T refers to the date when the FOMC takes a decision to change the FFTR, not the date of the FOMC meeting; a FOMC meeting can be expected in less than 30 days but that does not imply the FFTR will be changed.

month average $FFER_t$ not being equal to $FFTR_1$:

$$f_t^{(1)} = \mathbb{P}_t(T < 30)\left(\frac{T}{30}FFTR_t + \frac{30-T}{30}FFTR_{T+1}\right) + (1 - \mathbb{P}_t(T < 30))\,(FFTR_t)\,, \tag{8}$$

for $t < T$, where $\mathbb{P}_t(T < 30)$ is the probability at t that the FFTR change will occur in less than 30 days and $FFTR_{T+1}$ is the new FFTR, different to $FFTR_1$. If $\mathbb{P}_t(T < 30)$ is close to zero we have the equality between $f_1^{(1)}$ and $FFTR_1$, as in Equation (7). But if not, then the market is signaling a distrust that the FFTR will be maintained for one month. That difference might be due to two factors:

(i) There is policy shock and the market needs a time to absorb the shock, or

(ii) The market is not surprised by the shock but anticipates that the Federal Reserve will not be able to maintain the current monetary policy during the next month.

In a permanent observation and reaction process, the market adjusts the 1-month Eurodollar future every day, and that is reflected days after the FOMC policy decision, when the 1-month Eurodollar continues to decrease in the case the market has detected a *Dovish* policy by the Fed, or when the 1-month Eurodollar rate continues to increase in the case the market has detected a *Hawkish* policy (see Figure 10).

[Place Figure 10 about here]

In Equation (8), we know at time $t = 1$, $f_1^{(1)}$ and $FFTR_1$. $\mathbb{P}_t(T < 30)$, T and $FFTR_{T+1}$ are unknown, but they can be estimated by considering the monetary policy in place. In line with Stutzer (1996), we set a *grid of probabilities* in the physical measure for all the N future possible scenarios by setting an increasing/decreasing scale of policy shocks, $FFTR_{t+1} = FFTR_t \pm \delta = FFTR_t \pm 12.5bp, 25bp, 37.5bp, 50bp, \ldots, \max(change)bp, \delta \in (\delta_1, \ldots, \delta_N)$. A positive vector of probabilities is assigned for the future scenarios: $(\pi_{\delta_1}, \ldots, \pi_{\delta_N})$. Then, $FFTR_t + \delta_1$ has a probability of occurring of $\mathbb{P}_{t,\delta_1}$. We can estimate the probability of every $FFTR_{T+1}$ scenario change in comparison to the probability that the FFTR will remain the same for at least 30 days. Using this setup, define $\mathbb{P}_{t,\delta}(T < 30)$ as the probability at t of the change δ bp occurring in $T < 30$, then we will have N Equations similar to Equation (8), where every scenario has a probability of occurrence $\pi_{\delta_i}, i \in \{1, \ldots, N\}$, where N is the number of different FFTR changes:

$$
\begin{aligned}
f_{1,t}^{(1)} &= \mathbb{P}_{t,\delta_1}(T < 30)\left(\frac{T}{30} FFTR_t + \frac{30-T}{30}\left(FFTR_t + \delta_1\right)\right) + \left(1 - \mathbb{P}_{t,\delta_1}(T < 30)\right)\left(FFTR_t\right), \\
&\vdots \\
f_{N,t}^{(1)} &= \mathbb{P}_{t,\delta_N}(T < 30)\left(\frac{T}{30} FFTR_t + \frac{30-T}{30}\left(FFTR_t + \delta_N\right)\right) + \left(1 - \mathbb{P}_{t,\delta_N}(T < 30)\right)\left(FFTR_t\right),
\end{aligned} \tag{9}
$$

where $\delta_i = \{-\max(change)bp, \ldots, -12.5bp, +12.5bp, \ldots, +\max(change)bp\}$. Assume, without loss of generality, that the N scenarios have the same probability in the initial setup: this is similar to assuming a prior distribution in a Bayesian framework. Setting all the δ changes on average yields the expected change implicit in the 1-month Eurodollar future; then, Equation (8) can be transformed into

$$
\begin{aligned}
f_{N+1,t}^{(1)} = (1/N) \sum_{\delta_i} \Bigg(& \mathbb{P}_{t,\delta_i}(T < 30)\left(\frac{T}{30} FFTR_t + \frac{30-T}{30}(FFTR_t + \delta_i)\right) + \\
& \left(1 - \mathbb{P}_{\delta_i}(T < 30)\right)\left(FFTR_t\right)\Bigg).
\end{aligned} \tag{10}
$$

But by arbitrage conditions, we have that:

$$
f_{1,t}^{(1)} = f_{2,t}^{(1)} = \cdots = f_{N+1,t}^{(1)}. \tag{11}
$$

Equations (10) and (11), jointly with the N Equations as (9) for each δ_i will produce $N+2$ equations, with $N+1$ unknowns $(\mathbb{P}_{t,\delta_1}(T < 30), \mathbb{P}_{t,\delta_2}(T < 30), \ldots, \mathbb{P}_{t,\delta_N}(T < 30), T)$, and we can identify the N probabilities and T. In addition, expectations longer than the 1-month maturity of the 1-month Eurodollar future can be affected by the possibility of a FFTR change. The 3-month Eurodollar futures are included to balance those expectations:

$$f_{i,t}^{(3)} = \mathbb{P}_{t,\delta_i}(T<90)\left(\frac{T}{90}FFTR_t + \frac{90-T}{90}\left(FFTR_t+\delta_i\right)\right) + \left(1-\mathbb{P}_{t,\delta_i}(T<90)\right)\left(FFTR_t\right), \quad (12)$$

for $i=\{1,\ldots,N\}$, and

$$f_{N+1,t}^{(3)} = (1/N)\sum_{\delta_i}\left(\mathbb{P}_{t,\delta_i}(T<90)\left(\frac{T}{30}FFTR_t + \frac{90-T}{90}(FFTR_t+\delta_i)\right) + \left(1-\mathbb{P}_{t,\delta_i}(T<90)\right)\left(FFTR_t\right)\right). \quad (13)$$

Our set of Equations (9), (10), (11), (12), and (13) will produce an over-identified system of $2(N+1)+1$ equations with $2(N+1)$ unknowns. To close the system, we add an additional restriction on the minimum number of days for a change in the FFTR change to occur:

$$T \geq MinDaysNextChange/(\mathit{DiffDaysLastChange}_t + 2), \quad (14)$$

where $\mathit{MinDaysNextChange}_t$, is a variable that represents the number of days they FOMC board can take for deciding on changes to the FFTR, and $\mathit{DiffDaysLastChange}_t$ is the number of days at time t since the last interest rate change occurred. We select Equation (14) between several other candidates, given that (i) the optimization problem to solve Equations (9), (10), (11), (12), and (13) will implicitly reduce T, then we need a constraint based on an inverse function on T, and (ii) the inverse function on T must be on the number of days since the last FFTR change: while there are more days, the Equation (14) restriction on T is reduced, and the probability on FFTR is allowed to increase.[13] We use the daily close prices of the 1- and 3-month Eurodollar futures interest rate to solve the system of $2(N+1)+1$ equations, extracted from the Federal

[13]The number selected is close to the average days between FFTR changes: in Table I in Section II we observe some descriptive statistics of the FFTR changes from which we estimate this number.

Reserve Economic Data (FRED) repository, from January, 1971 to December, 2015.

Figure 11 shows the resulting implicit probabilities' surface. We observe that, most of the time, the probability surface with the implicit relationship between the 1- and the 3-month Eurodollar futures with the FFTR, shows a bias towards an expected increase in the FFTR, principally during the quantitative easing period (November 2008–January 2014), but there are some particular periods where there is a bias towards a decrease in the interest rate: the U.S. inflationary period of 1974–1976 due to the Middle East oil wars, and the peak of the Dot-Com bubble business cycle in 2001.

[Place Figure 11 about here]

A. Entropy and Uncertainty in the Market Beliefs

The solution to the arbitrage model of the difference between the: 1- and 3-month Eurodollar future prices, and the FFTR in the previous section, provides a framework for understanding the interaction between the Federal Reserve decisions and the market expectations. But how can that analysis help in finding a Fed Chair textual sentiment profile (our first main question), or in elucidating the impact of the Fed Chair statements' sentiment on the interest rates (our second main question)? We use information theory (Shannon, 1948), to explore a link between (i) the market expectations, (ii) the Federal Reserve decisions (Market Price Discovery feature), and (iii) the Fed Chair statements' sentiment signaling mechanism; this link will be useful in responding to our two main questions: the textual sentiment profile of the Fed Chair, and the Fed Chair statements' sentiment implications for the monetary policy.

Let $\mathbb{P}_{t,\text{Hawkish}} = \mathbb{P}_{t,\delta_1}(T < 30) + \dots \mathbb{P}_{t,\delta_i}(T < 30)$ with $\delta_1, \dots, \delta_i < 0$, be the probability at date t of a *Hawkish* decision in the next FOMC meeting occurring in less than 30 days, and $\mathbb{P}_{t,\text{Dovish}} = \mathbb{P}_{t,\delta_{i+1}}(T < 30) + \dots \mathbb{P}_{t,\delta_N}(T < 30)$ with $\delta_{i+1}, \dots, \delta_N > 0$ be the probability at date t of a *Dovish* decision in the next FOMC meeting occurring in less than 30 days. We define, following Chernov and Zin (2014), the sample entropy absolute growth in the market expectations between *Hawkish* and *Dovish* decisions, and between dates $t_1, t_2, t_1 \leq t_2$ as:

$$E_{t_1,t_2} = \left|\mathbb{P}_{t_2,\text{Hawkish}} - \mathbb{P}_{t_2,\text{Dovish}}\right| - \left|\mathbb{P}_{t_1\text{Hawkish}} - \mathbb{P}_{t_1,\text{Dovish}}\right|. \tag{15}$$

The sample entropy absolute growth number E_{t_1,t_2} increase is associated with an increase in the uncertainty, and a decrease with a reduction in the uncertainty of the markets about FFTR decisions in the next 30 days.

The next step is to measure the sentiment of the Federal Reserve communications, and associate that sentiment to the sample entropy growth E_t.

We use the results on the daily uncertainty to extend our identification method. Figure 9 shows the identification window in gray, where we explore the immediate effects of the Fed Chair statement's neutral sentiment on the interest rates. We choose to assess the uncertainty instead of the interest rates reaction, as our exploration of the effects of the Fed Chair statement's neutral sentiment over the interest rates is not in respect to the direction of the interest rates, but in respect to the "informativeness" that the sentiment provides to reduce the future decisions (that can be upward or downward measures over the FFTR).

[Place Figure 9 about here]

B. *Empirical Results*

Figure 12 shows the resulting average sample entropy growth E_{t_1,t_2} of the market beliefs, as in Equation (15), conditional on the sentiment of the Fed Chair statement released, *neutral* in the gray line, and *emotional* in the blue line, with 95% confidence intervals in the shaded gray and the shaded blue, respectively. We use as a measure of sentiment the principal measure: the Naïve Bayes classifier. The sample entropy growth is calculated between the day before the Fed Chair statement release ($t_1 = -1$), and the next four days: the day of the statement release

($t_2 = 1$), and the next three days after the statement release ($t_2 \in \{1, 2, 3\}$). For the day of the statement release, sample entropy growth E_{t_1,t_2} has a value different to zero (it is not the starting point of observation), given that we consider closing day prices, and during that day the interest rate closing prices had already been affected. Sub-figures 12b, 12c, 12d, 12e, 12f, and 12g present the sample entropy growth results for Chairs Burns, Miller, Volcker, Greenspan, Bernanke, and Yellen, respectively. The full period results in Sub-figure 12a shows that there is a clear and significant increase (interval confidence of 95% results not crossing is equivalent to a positive hypothesis test of the different means) in the *uncertainty* shock when the Fed Chair statement has a neutral sentiment, for at least three days ($t_2 = 0, 1, 2$) after the statement release, and a significant reduction of the *uncertainty* for almost three days ($t_2 = 0, 1, 2$) after the statement release. No other macroeconomic variable, nor the Hawkish/Dovish stance of the Fed Chair statement, is clear significant for changes in the uncertainty (see Online Appendix uncertainty figures). When analyzing the Fed Chair statements' sentiment effects on *uncertainty* per Chair, we observe a clear difference in terms of the textual sentiment profile: the statements of the two most emotional Chairs; as in Table IV, Volcker and Greenspan have a statistically significant increase/decrease in the market *uncertainty* about FFTR decisions in the next 30 days, while the statements of the less emotional, Burns, Miller, Bernanke, and Yellen, do not impact market uncertainty. Textual emotional Chair statements results dominate, as they represent almost 60% (673/1134 statements) of the full sample.

[Place Figure 12 about here]

VI. Conclusions

The Federal Reserve communications' process is a delicate mechanism that the economic policy institution uses to control monetary policy. We find that there is sentiment present in the Federal Open Market Committee (FOMC) and the Federal Reserve Chair statements, that there exists a textual sentiment profile of the Fed Chairs that is produced by personal choice over the macroeconomic circumstances and personal characteristics, and that we have indications that the sentiment actually relates to the monetary policy uncertainty and that affects the market surprise in the interest rates price discovery process, at least during the day the Federal Fund Target Rate (FFTR) is changed. The Fed Chair statements' sentiment is significant and provides the markets with a signal of the future monetary policy decisions.

The Fed Chair statements' sentiment impact on monetary policy shocks has decreased over time, as the Federal Reserve has improved in the implementation of monetary policy, including the communications' mechanisms. The reduction of effects of the Fed Chair statements' sentiment is associated with a greater effectiveness in the implementation of the monetary shock, by reducing the sentiment and increasing the *"market uncertainty"*. Our results provide a framework for policymakers to ensure that future decisions are known to the market in advance only when there is no need to implement a shock. In the case a monetary policy shock is needed, the sentiment of the communications should be reduced.

Future analysis might explore the additional effects that other members of the FOMC board provide to the interest rate and asset price formation, or the relationship of the Fed Chair statements' sentiment under an unconventional monetary policy scheme, in light of the adoption of this system in recent years by the most important central banks, including the Federal Reserve. Additional sentiment analysis with other sources of non-digital information, such as audio and video recordings of the Fed Chair press releases could an interesting area for exploration.

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Table I
Federal Reserve Communications

The table shows a description of the two communications' documents analyzed, the FOMC and Fed Chair statements. Panel A shows the FOMC statements. The period for the Panel A sample is from February 01, 1994 to December 31, 2015 (first FOMC statement was made available to the public since January 01, 1994). Meetings are scheduled events, while telephone conferences are unscheduled. FOMC statements are released immediately after finishing the meeting/telephone conference, with the exception of 4 statements issued outside normal trading hourse due to the 2007/2008 financial crisis: August 17, 2007, January 22, 2008, March 11, 2008, and October 8, 2008. Panel B shows the Fed Chair statements statistics. Two sub-panels are presented, one with document statistics per type of document, and other sub-panel with per Chair statistics. The period for the Panel B sample is from January 01, 1971 to December 31, 2015. The Average days before the FFTR change is calculated with a sub-sample: only the last Fed Chair statement issued before an FFTR is included ($N = 244$ statements). The standard error of the average is between parentheses.

Panel A: FOMC Statements

	Number	(%)	Average Number of Words	Average Days Between Statements
FOMC Statements	164	100.00%	374.35	51.22
			(18.59)	(4.18)
Meeting	153	93.29%	384.64	54.93
			(19.49)	(4.38)
Telephone Conference	11	6.71%	231.18	586.50
			(38.33)	(235.38)

Panel B: Fed Chair Statements

	Number	(%)	Average Number of Words	Average Days Between Statements	Average Days Before FFTR Change ($N = 244$)
Fed Chair Statements	1134	100.00%	2870.50	14.77	16.64
			(58.40)	(0.49)	(1.04)
Per Type of Document					
Testimony before the House of Representatives	231	20.37%	2979.97	72.63	71.05
			(178.22)	(5.26)	(4.69)
Testimony before the Senate	196	17.28%	3005.53	84.17	83.48
			(176.04)	(6.43)	(5.21)
Testimony before a Joint Committee	76	6.70%	2705.08	222.99	152.05
			(358.41)	(18.75)	(9.89)
Remarks before an Institution	579	51.06%	2017.47	28.85	42.50
			(61.82)	(1.54)	(2.85)
Other (Press Briefing, Dedication, Interview)	52	4.59%	2292.08	317.55	295.64
			(289.03)	(45.05)	(14.91)
Per Chair					
Arthur Burns	146	12.87%	2951.19	20.12	18.06
			(118.95)	(1.60)	(1.88)
George W. Miller	50	4.41%	3018.54	10.14	12.95
			(157.26)	(1.64)	(3.28)
Paul Volcker	168	14.81%	3589.70	17.22	20.08
			(254.32)	(1.48)	(2.68)
Alan Greenspan	505	44.53%	2748.61	13.24	15.22
			(78.67)	(0.66)	(1.57)
Ben Bernanke	233	20.55%	2616.06	12.45	9.54
			(87.65)	(0.87)	(1.38)
Janet Yellen	32	2.82%	2442.41	21.29	13.00
			(303.74)	(4.04)	(0.00)

Table II
Interest Rates and FOMC Decisions

The table shows statistics from the interest rates – Federal Funds, Eurodollar and Treasuries – during the period of the Fed Chair communications' sample, from January 01, 1971 to December 31, 2015. Since December 16, 2008, the FFTR is reported in a upper and lower limit, we consider the upper limit for our sample. Panel A shows the mean and the volatility of the interest rates, divided in two sub-panels: from January 01, 1971 to December 31, 1993 (before FOMC statements' availability), and between January 01, 1994 and December 31, 2015. Panel B shows the number of changes applied to the FFTR before and after February 01, 1994 when the FOMC statements were made immediately available after the FOMC Board FFTR decision, the average absolute change applied, and the unexpected 1-Month Eurodollar shock the day of the announcement. The standard error of the average is between parentheses.

Panel A: Interest Rates

	1971-1993		1994-2015	
	Mean Value	Volatility	Mean	Volatility
Federal Reserve				
FFTR	7.96	3.28	2.76	2.28
FFER	8.00	3.48	2.72	2.35
Short-Term				
1-Month Eurodollar Deposit	8.53	3.49	2.99	2.29
3-Month Eurodollar Deposit	8.70	3.39	3.12	2.26
6-Month Eurodollar Deposit	7.89	2.93	2.83	2.30
Long-term				
1-Year Treasury Constant Maturity	8.82	2.28	4.32	1.62
3-Year Treasury Constant Maturity	8.59	2.44	3.73	1.96
5-Year Treasury Constant Maturity	7.31	2.54	2.64	2.44
10-Year Treasury Constant Maturity	8.36	2.60	3.33	2.17

Panel B: FOMC Decisions

	# FFTR Changes	Average Abs FFTR Change (%)	1-Month Eurodollar Average Jump
Before February 1994			
Arthur Burns	63	0.54	1.18
		(0.08)	(0.12)
George W. Miller	20	0.19	0.65
		(0.03)	(0.11)
Paul Volcker	60	1.27	0.93
		(0.19)	(0.16)
Alan Greenspan (I)	40	0.28	0.37
		(0.02)	(0.06)
After February 1994			
Alan Greenspan (II)	47	0.33	0.19
		(0.02)	(0.02)
Ben Bernanke	13	0.44	1.10
		(0.06)	(0.39)
Janet Yellen	1	0.25	0.20
		(0.00)	(0.00)
Total	244		

Table III
Federal Reserve Communications' Sentiment – Type of Communication

The table shows the sentiment of the FOMC and Fed Chair statements. The FOMC statements' sample is from February 01, 1994 to December 31, 2015 (first FOMC statement was made available to the public since January 01, 1994), and the Fed Chair statements' sample is from January 01, 1971 to December 31, 2015. Panel A.1 shows the proportion from the complete set of documents that are tagged as Neutral, Positive or Negative by the NLTK Naïve Bayes classification method. For example, for FOMC statements – Meeting, there are 76 documents tagged as Neutral (49.67%). Panel A.2 shows the average word count proportion per document using the Harvard IV (Tetlock et al., 2008) and Loughran and McDonald (2011) dictionaries. Panel B.1 shows the average sentiment Likelihood per document with the Naïve Bayes classification method. Panel B.2 shows the average tf.idf function per document normalized to the total tf.idf per tag. The standard error of the average is between parentheses.

	Panel A: Communications' Sentiment Tone								
	Panel A.1: Proportion			Panel A.2: Average Word Count					
	Naïve Bayes (NLTK) (%)			Harvard IV (Tetlock) (%)			Loughran & McDonald (%)		
	Neut	Pos	Neg	Neut	Pos	Neg	Neut	Pos	Neg
FOMC Statements	50.61	46.34	3.05	85.47 (0.27)	10.97 (0.25)	3.56 (0.16)	94.27 (0.19)	2.76 (0.11)	2.97 (0.15)
Meeting	49.67	47.71	2.61	85.16 (0.27)	11.19 (0.25)	3.65 (0.17)	94.15 (0.19)	2.89 (0.11)	2.96 (0.15)
Telephone Conference	63.64	27.27	9.09	89.72 (1.10)	7.98 (0.78)	2.29 (0.65)	95.94 (0.88)	0.97 (0.32)	3.09 (0.76)
Fed Chair Statements	51.50	46.65	1.85	77.82 (0.09)	14.91 (0.07)	7.27 (0.06)	90.37 (0.05)	3.68 (0.03)	5.95 (0.05)
Testimony before the House of Representatives	41.99	56.28	1.73	78.08 (0.18)	14.55 (0.13)	7.37 (0.11)	90.23 (0.11)	3.43 (0.06)	6.34 (0.10)
Testimony before the Senate	50.00	48.98	1.02	78.09 (0.19)	14.58 (0.15)	7.33 (0.12)	90.10 (0.12)	3.59 (0.06)	6.31 (0.11)
Testimony before a Joint Committee	55.26	42.11	2.63	79.21 (0.34)	13.47 (0.24)	7.32 (0.20)	89.80 (0.20)	3.61 (0.10)	6.59 (0.18)
Remarks before an Institution	55.09	43.52	1.38	77.35 (0.12)	15.38 (0.11)	7.28 (0.09)	90.50 (0.08)	3.83 (0.05)	5.67 (0.08)
Other (Press Briefing, Dedication, Interview)	53.85	36.54	9.62	78.84 (0.48)	14.63 (0.46)	6.53 (0.35)	91.50 (0.29)	3.51 (0.16)	5.00 (0.28)

	Panel B: Communications' Sentiment Average Intensity Per Document								
	Panel B.1: Likelihood			Panel B.2: tf.idf					
	Naïve Bayes (NLTK)			Harvard IV (Tetlock)			Loughran & McDonald		
	Neut	Pos	Neg	Neut	Pos	Neg	Neut	Pos	Neg
FOMC Statements	51.51 (2.19)	66.36 (0.95)	33.03 (0.88)	86.46 (0.26)	72.67 (1.14)	27.33 (1.14)	89.13 (0.43)	43.27 (2.18)	56.73 (2.18)
Meeting	50.95 (2.25)	66.71 (0.89)	33.29 (0.89)	86.16 (0.25)	72.55 (1.14)	27.45 (1.14)	88.99 (0.44)	44.67 (2.23)	55.33 (2.23)
Telephone Conference	59.32 (9.54)	61.46 (6.85)	29.45 (4.23)	90.54 (1.17)	74.44 (6.47)	25.56 (6.47)	91.04 (1.99)	19.89 (6.95)	80.11 (6.95)
Fed Chair Statements	51.51 (0.87)	72.76 (0.41)	26.98 (0.39)	76.55 (0.10)	63.94 (0.25)	36.06 (0.25)	86.86 (0.10)	30.40 (0.37)	69.60 (0.37)
Testimony before the House of Representatives	45.87 (1.93)	70.03 (0.93)	29.11 (0.84)	76.91 (0.20)	62.94 (0.45)	37.06 (0.45)	86.09 (0.16)	26.75 (0.54)	73.25 (0.54)
Testimony before the Senate	50.04 (2.08)	71.65 (0.88)	28.35 (0.88)	77.04 (0.22)	63.13 (0.51)	36.87 (0.51)	85.82 (0.18)	27.94 (0.66)	72.06 (0.66)
Testimony before a Joint Committee	53.82 (3.36)	70.00 (1.57)	30.00 (1.57)	78.06 (0.37)	61.97 (0.81)	38.03 (0.81)	85.60 (0.31)	27.66 (0.95)	72.34 (0.95)
Remarks before an Institution	53.79 (1.21)	75.32 (0.53)	24.68 (0.53)	75.92 (0.14)	64.72 (0.38)	35.28 (0.38)	87.54 (0.17)	32.71 (0.58)	67.29 (0.58)
Other (Press Briefing, Dedication, Interview)	53.45 (4.15)	64.60 (2.54)	33.48 (2.30)	77.83 (0.59)	65.63 (1.94)	34.37 (1.94)	88.32 (0.41)	34.19 (2.51)	65.81 (2.51)

Table IV
Federal Reserve Chair Statements' Sentiment

The table shows the sentiment of the Fed Chair statements. The Fed Chair statements' sample is from January 01, 1971 to December 31, 2015. Panel A.1 shows the proportion from the complete set of documents that are tagged as Neutral, Positive or Negative by the Naïve Bayes classification method. For example, for Arthur Burns, there are 97 documents tagged as Neutral (66.44%). Panel A.2 shows the average word count proportion per document using the Harvard IV (Tetlock et al., 2008) and Loughran and McDonald (2011) dictionaries. Panel B.1 shows the average sentiment Likelihood per document with the Naïve Bayes classification method. Panel B.2 shows the average tf.idf function per document normalized to the total tf.idf per tag. The standard error of the average is between parentheses.

	Panel A: Communications' Sentiment Tone								
	Panel A.1: Proportion			Panel A.2: Average Word Count Per Document					
	Naïve Bayes (NLTK) (%)			Harvard IV (Tetlock) (%)			Loughran & McDonald (%)		
	Neut	Pos	Neg	Neut	Pos	Neg	Neut	Pos	Neg
Before February 1994									
Arthur Burns	66.44	31.51	2.05	77.83	14.36	7.80	90.11	3.52	6.36
				(0.25)	(0.21)	(0.15)	(0.16)	(0.09)	(0.13)
George W. Miller	60.00	38.00	2.00	77.19	15.04	7.78	89.95	3.98	6.07
				(0.30)	(0.28)	(0.23)	(0.23)	(0.13)	(0.20)
Paul Volcker	28.57	68.45	2.98	76.68	15.29	8.03	89.62	3.69	6.70
				(0.21)	(0.16)	(0.12)	(0.15)	(0.07)	(0.12)
Alan Greenspan (I)	46.32	52.59	1.09	77.98	14.73	7.29	90.64	3.73	5.63
				(0.15)	(0.12)	(0.11)	(0.09)	(0.05)	(0.09)
After February 1994									
Alan Greenspan (II)	36.96	59.42	3.62	78.38	14.20	7.42	90.41	3.35	6.24
				(0.24)	(0.18)	(0.14)	(0.15)	(0.08)	(0.13)
Ben Bernanke	72.96	25.75	1.29	78.06	15.61	6.33	90.71	3.75	5.54
				(0.20)	(0.19)	(0.13)	(0.13)	(0.08)	(0.14)
Janet Yellen	56.25	43.75	0.00	78.64	15.22	6.14	90.56	4.15	5.30
				(0.63)	(0.62)	(0.36)	(0.24)	(0.23)	(0.29)

	Panel B: Communications' Sentiment Average Intensity Per Document								
	Panel B.1: Likelihood			Panel B.2: tf.idf					
	Naïve Bayes (NLTK) (%)			Harvard IV (Tetlock)			Loughran & McDonald		
	Neut	Pos	Neg	Neut	Pos	Neg	Neut	Pos	Neg
Before February 1994									
Arthur Burns	62.71	69.41	30.59	76.33	61.40	38.60	86.22	27.50	72.50
	(2.33)	(1.20)	(1.20)	(0.29)	(0.71)	(0.71)	(0.24)	(0.77)	(0.77)
George W. Miller	59.44	71.35	28.65	75.60	62.80	37.20	86.30	31.05	68.95
	(4.31)	(1.70)	(1.70)	(0.36)	(1.00)	(1.00)	(0.36)	(1.41)	(1.41)
Paul Volcker	35.65	72.88	26.53	75.40	61.32	38.68	85.86	26.17	73.83
	(1.93)	(1.09)	(1.01)	(0.24)	(0.48)	(0.48)	(0.21)	(0.59)	(0.59)
Alan Greenspan (I)	47.59	72.52	27.21	76.58	64.09	35.91	87.62	31.65	68.35
	(1.46)	(0.69)	(0.66)	(0.18)	(0.43)	(0.43)	(0.14)	(0.63)	(0.63)
After February 1994									
Alan Greenspan (II)	40.74	71.81	27.47	77.28	61.94	38.06	86.28	26.88	73.12
	(2.25)	(1.20)	(1.10)	(0.26)	(0.62)	(0.62)	(0.50)	(0.88)	(0.88)
Ben Bernanke	66.47	75.80	24.20	77.07	68.15	31.85	87.17	34.51	65.49
	(1.74)	(0.87)	(0.87)	(0.22)	(0.62)	(0.62)	(0.24)	(1.08)	(1.08)
Janet Yellen	53.97	74.24	25.76	77.70	67.23	32.77	87.33	35.83	64.17
	(4.58)	(2.28)	(2.28)	(0.72)	(1.74)	(1.74)	(0.36)	(2.75)	(2.75)

Table V
Federal Reserve Chair Statements' Sentiment – Kolmogorov–Smirnov Test

The table shows the Kolmogorov–Smirnov (KS) pair of samples test of the sentiment of the Fed Chair statements. The Fed Chair statements' sample is from January 01, 1971 to December 31, 2015. Panel A applies the KS test to the full sample of the Fed Chair statements, while Panel B applies the KS test to the sub-sample of the last Fed Chair statement before a FFTR change decision was made (Panel B is conditional on that FFTR is changed). Panel A.1 and B.1 shows the KS test results using Naïve Bayes classification method (Equation B1 of the Online Appendix) to measure the neutral sentiment, with the rows and columns with the corresponding Fed Chair tested: the test of a Fed Chair in row i with a Fed Chair in column j tests the hypothesis: $H0 : NeutSent(FRC_i) = NeutSent(FRC_j), H1 : NeutSent(FRC_i) < NeutSent(FRC_j)$, as the rows and columns are sorted by the mean of the sample of each Fed Chair. The $*$, $**$, and $***$ represents the case when the null hypothesis is rejected with a p-values of less than $0.1, 0.05$ and 0.01, respectively. Panel A.2, B.2 and A.3, C.3 shows the KS test results using the proportion of neutral words by the Harvard IV (Tetlock et al., 2008) and Loughran and McDonald (2011) dictionaries correspondingly (Equations B2 and B3 of the Online Appendix).

Panel A: All Statements

Panel A.1: Naïve Bayes (NLTK)

	Volcker	Greenspan	Yellen	Miller	Burns	Bernanke
Volcker	–	(<) ***	(<) ***	(<) ***	(<) ***	(<) ***
Greenspan		–	(<) **	(<) ***	(<) ***	(<) ***
Yellen			–	(<) *	(<) **	(<) ***
Miller				–	(≮)	(≮)
Burns					–	(≮)

Panel A.2: Harvard IV (Tetlock) (% Neutral)

	Volcker	Miller	Burns	Bernanke	Greenspan	Yellen
Volcker	–	(<) ***	(<) ***	(<) ***	(<) ***	(<) ***
Miller		–	(<) *	(<) **	(<) ***	(<) ***
Burns			–	(≮)	(<) *	(<) *
Bernanke				–	(≮)	(≮)
Greenspan					–	(≮)

Panel A.3: Loughran & McDonald (% Neutral)

	Volcker	Greenspan	Yellen	Miller	Burns	Bernanke
Volcker	–	(<) ***	(≮)	(<) ***	(<) ***	(<) ***
Greenspan		–	(≮)	(≮)	(<) ***	(<) ***
Yellen			–	(≮)	(≮)	(≮)
Miller				–	(≮)	(<) **
Burns					–	(<) *

Panel B: Only Last Statement Before FFTR Change

Panel B.1: Naïve Bayes (NLTK) –

	Volcker	Greenspan	Miller	Burns	Bernanke
Volcker	–	(<) ***	(<) ***	(<) ***	(<) ***
Greenspan		–	(≮)	(<) ***	(<) ***
Miller			–	(≮)	(<) **
Burns				–	(<) *

Panel B.2: Harvard IV (Tetlock) (% Neutral)

	Volcker	Miller	Burns	Greenspan	Bernanke
Volcker	–	(≮)	(≮)	(<) ***	(<) ***
Miller		–	(≮)	(<) ***	(<) ***
Burns			–	(<) ***	(<) ***
Greenspan				–	(≮)

Panel B.3: Loughran & McDonald (% Neutral)

	Volcker	Burns	Miller	Greenspan	Bernanke
Volcker	–	(<) ***	(<) **	(<) ***	(<) *
Burns		–	(≮)	(<) ***	(<) *
Miller			–	(≮)	(≮)
Greenspan				–	(≮)

Table VI
Federal Reserve Chair Statements' Sentiment and Personal Characteristics

The table shows the fixed-effects regressions of the Fed Chair statement neutral sentiment as in baseline model Equation (4). The Fed Chair statements' sample is from January 01, 1971 to December 31, 2015. Panel A shows the nested model in Equation (4): columns (1), (3), and (5) only with macroeconomic and financial market variables, and columns (2), (4), and (6) with personal characteristics. The neutral sentiment dependent variable $NeutSentFRC_t$ in model in Equation (4) is measured in each of the pairs of columns (1,2), (3,4), and (5,6) by the Naïve Bayes classifier, Harvard IV (Tetlock, 2007), and Loughran and McDonald (2011) dictionaries. Macroeconomic variables with Δ are calculated with the return of the variable with respect to the previous announcement. The $*$, $**$, and $***$ represents statistical significance at a p-value of $0.1, 0.05$ and 0.01, respectively. The standard error is in parentheses.

Panel A: $NeutSentFRC_t$ Regressed by Macroeconomic and Personal Characteristics

	Naïve Bayes		Harvard IV (Tetlock)		Loughran & McDonald	
Model	(1)	(2)	(3)	(4)	(5)	(6)
Constant	60.3***	49.4**	81.2***	68.7***	92.5***	90.2***
	(3.3)	(20.4)	(0.3)	(1.9)	(0.2)	(1.1)
Macroeconomic						
Business Cycle	-1.1	0.5	-1.3***	-1.7***	-0.3**	-0.4***
	(2.2)	(2.2)	(0.2)	(0.2)	(0.1)	(0.1)
Δ PCE	-142.1	-1645.5	-135.0***	-34.4	-73.7***	-64.3*
	(230.8)	(1235.9)	(23.5)	(47.6)	(14.2)	(34.5)
Δ Industrial Production	-19.7	42.5	-4.0***	9.8	-3.1***	-1.9
	(15.0)	(66.4)	(1.5)	(16.1)	(0.9)	(1.2)
Δ M1	404.8***	326.7***	-38.5***	-27.9***	-24.9***	-16.7***
	(87.8)	(85.5)	(9.0)	(9.0)	(5.4)	(5.5)
Unemployment rate	-1.5***	-2.8	-0.2***	-0.1	-0.2***	-0.2***
	(0.4)	(1.0)	(0.0)	(0.1)	(0.0)	(0.0)
Financial						
Δ SP500	-7.7	3.9	5.0***	9.2**	1.4**	1.5
	(8.8)	(11.0)	(0.9)	(3.7)	(0.5)	(1.1)
Baa10YT	-7.0	1.4	-1.1	-2.0	-1.3***	-2.2*
	(6.8)	(9.3)	(0.7)	(1.5)	(0.4)	(1.2)
Personal Characteristics						
Chair		5.49***		0.06		0.11***
		(0.64)		(0.06)		(0.04)
Age		0.18		-0.03*		-0.02**
		(0.13)		(0.01)		(0.01)
Gender		10.90		-0.11		0.25
		(6.67)		(0.43)		(0.32)
Academic Background		-0.95		0.60***		0.15**
		(0.98)		(0.09)		(0.06)
N(weeks)	2381	2381	2381	2381	2381	2381
Adjusted R^2	0.01	0.15	0.06	0.14	0.08	0.11

Table VII
The FFTR Change and the Fed Chair Statements' Sentiment

The table shows the logit regressions of the jump surprise of the 1-Month Eurodollar interest rate (J) during the FFTR change announcement from model in Equation (5). The Fed Chair statements' sample is from January 01, 1971 to December 31, 2015. Panel A shows the nested model in Equation (5). The neutral sentiment variable (NS_t) is the Fed Chair last statement neutral sentiment before the FFTR change. Column (1) is model in Equation (5) only with macroeconomic and financial variables, columns (2), (4), and (6) is model in Equation (5) including the neutral sentiment variable, measured by the Naïve Bayes classifier, Harvard IV (Tetlock), and Loughran and McDonald (2011) dictionaries, and columns (3), (5), and (7) is the full model in Equation (5), when controlling for personal characteristics. Macroeconomic variables with Δ are calculated with the return of the variable with respect to the previous announcement. The $*$, $**$, and $***$ represents statistical significance at a p-value of $0.1, 0.05$ and 0.01, respectively. The standard error is in parentheses.

Panel A: Jump Surprise J_t Regressed by Macroeconomic, Fed Chair Neutral Sentiment and Personal Characteristics

		Naïve Bayes		Harvard IV (Tetlock)		Loughran & McDonald	
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	-2.8***	-4.2***	-12.5***	-13.3**	-20.7***	-17.5**	-27.9***
	(0.9)	(1.2)	(3.2)	(5.2)	(6.3)	(8.7)	(10.0)
Macroeconomic							
Business Cycle	-0.3	-0.4	-0.0	-0.3	0.1	-0.4	-0.0
	(0.5)	(0.5)	(0.5)	(0.5)	(0.6)	(0.5)	(0.5)
Δ PCE	-31.6	-29.0	6.4	-3.2	25.4	-12.0	28.7
	(54.1)	(56.4)	(67.5)	(56.7)	(67.8)	(56.6)	(69.0)
Δ Industrial Production	-4.2	-2.1	-1.7	-1.7	-1.7	-2.3	-1.8
	(4.0)	(4.2)	(4.7)	(4.2)	(4.7)	(4.1)	(4.7)
Δ M1	-16.4	-20.7	-11.2	-7.8	0.1	-7.1	2.8
	(20.5)	(21.2)	(24.2)	(21.1)	(25.9)	(21.2)	(26.0)
Unemployment rate	0.5***	0.5***	0.7***	0.5***	0.8***	0.5***	0.8***
	(0.1)	(0.1)	(0.2)	(0.1)	(0.2)	(0.1)	(0.2)
Financial							
Δ SP500	-4.8**	-3.3	-2.3	-4.4*	-2.8	-3.8*	-2.4
	(2.2)	(2.4)	(2.6)	(2.3)	(2.6)	(2.3)	(2.6)
Baa10YT	-2.1	-1.4	-0.8	-1.6	-0.8	-1.3	-0.5
	(1.5)	(1.6)	(1.7)	(1.5)	(1.7)	(1.5)	(1.7)
Communications' Sentiment							
Fed Chair Statement Neutral Sentiment		1.7***	1.2**	12.6**	11.1*	15.7*	17.0*
		(0.5)	(0.6)	(6.2)	(6.7)	(9.2)	(9.9)
Fed Chair Statement Stance(H/D)		-0.0	-0.2	-0.1	-0.3	-0.0	-0.2
		(0.4)	(0.5)	(0.4)	(0.5)	(0.4)	(0.5)
Personal Characteristics							
Chair			0.3**		0.3**		0.3***
			(0.1)		(0.1)		(0.1)
Age			-0.1*		-0.0		-0.0
			(0.0)		(0.0)		(0.0)
Academic Background			0.5***		0.4***		0.5***
			(0.2)		(0.2)		(0.2)
N(weeks)	230	230	230	230	230	230	230
Deviance	275.76	255.08	233.61	260.65	235.06	261.98	234.85
Fit improvement	-	0.07	0.15	0.05	0.15	0.05	0.15

Table VIII
FFTR Change and FOMC Statements' Sentiment

The table shows the logit regressions of the jump surprise of the 1-Month Eurodollar interest rate (J) during the FFTR change announcement from model in Equation (6). The FOMC statements' sample is from February 01, 1994 to December 31, 2015 (first FOMC statement was made available to the public since January 01, 1994). Panel A shows the full model in Equation (6). Column (1) is model in Equation (6) without the neutral sentiment variable, and columns (2), (3) and (4) is model in Equation (6) with neutral sentiment included, measured by the Naïve Bayes classifier, the Harvard IV (Tetlock, 2007), and the Loughran and McDonald (2011) dictionaries. Macroeconomic variables with Δ are calculated with the return of the variable with respect to the previous announcement (monthly). The $*$, $**$, and $***$ represents statistical significance at a p-value of $0.1, 0.05$ and 0.01, respectively. The standard error is in parentheses.

Panel A: Jump Surprise J_t Regressed by Macroeconomic, and FOMC Neutral Sentiment

		Naïve Bayes	Harvard IV (Tetlock)	Loughran & McDonald
	(1)	(2)	(3)	(4)
Constant	-2.7	-2.8	-3.8	41.4
	(4.0)	(5.0)	(13.9)	(27.5)
Macroeconomic				
Business Cycle	0.0	0.1	0.1	0.2
	(0.4)	(0.7)	(0.4)	(0.5)
Δ PCE	26.4	25.6	31.2	-9.0
	(216.3)	(218.2)	(223.6)	(261.3)
Δ Industrial Production	-1.7	-1.5	-1.6	20.6
	(15.8)	(17.2)	(15.9)	(21.7)
Δ M1	-4.4	-4.7	-4.1	11.7
	(40.4)	(41.8)	(40.4)	(43.3)
Unemployment rate	0.0	0.0	0.0	0.2
	(0.8)	(0.8)	(0.9)	(0.9)
Financial				
Δ SP500	-3.3	-3.2	-3.1	-7.0
	(6.9)	(7.0)	(7.2)	(7.7)
Baa10YT	15.1**	15.1**	15.2**	14.4**
	(6.2)	(6.3)	(6.2)	(6.3)
Communication's Sentiment				
FOMC Statement Neutral Sentiment		0.1	1.1	-48.5
		(2.7)	(13.5)	(29.9)
N(weeks)	59	59	59	59
Deviance	37.99	37.98	37.98	35.09
Fit improvement	-	0.00	0.00	0.08

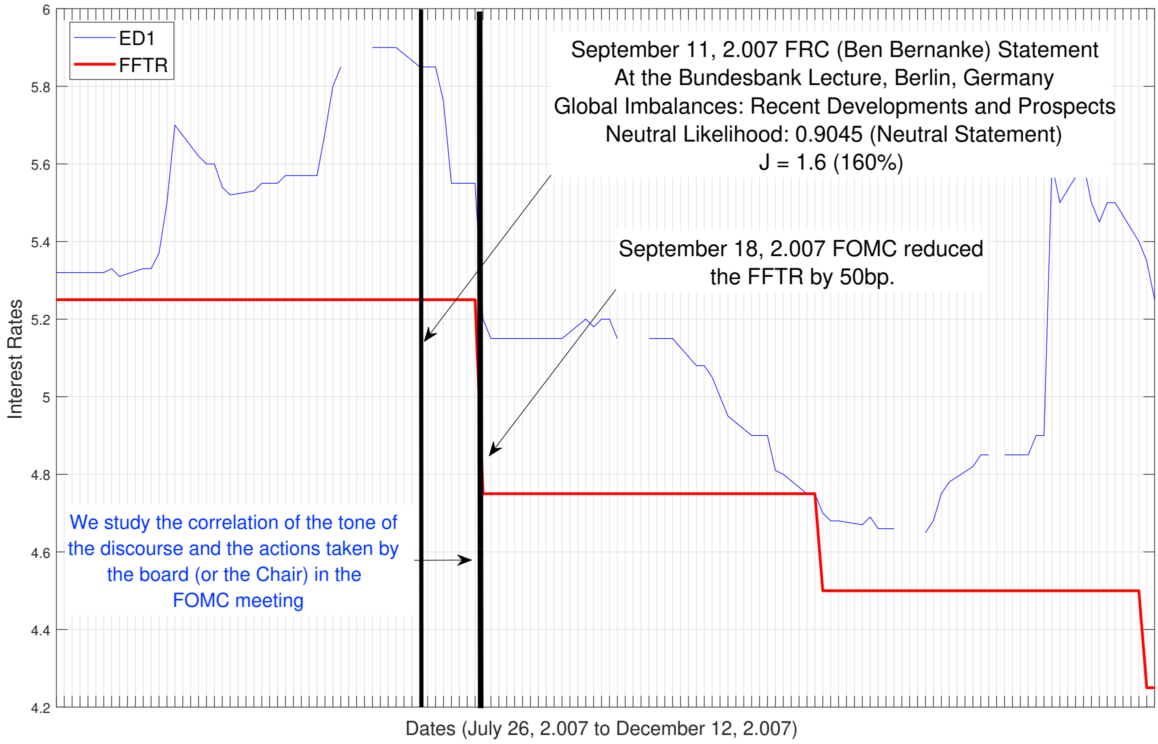


Figure 1. Identification method – Sensitivity of J (Jump surprise) to Sentiment. The 1-month Eurodollar interest rate is in blue and FFTR is in red. The interest rates' sample is from July 26, 2007 to December 12, 2007.

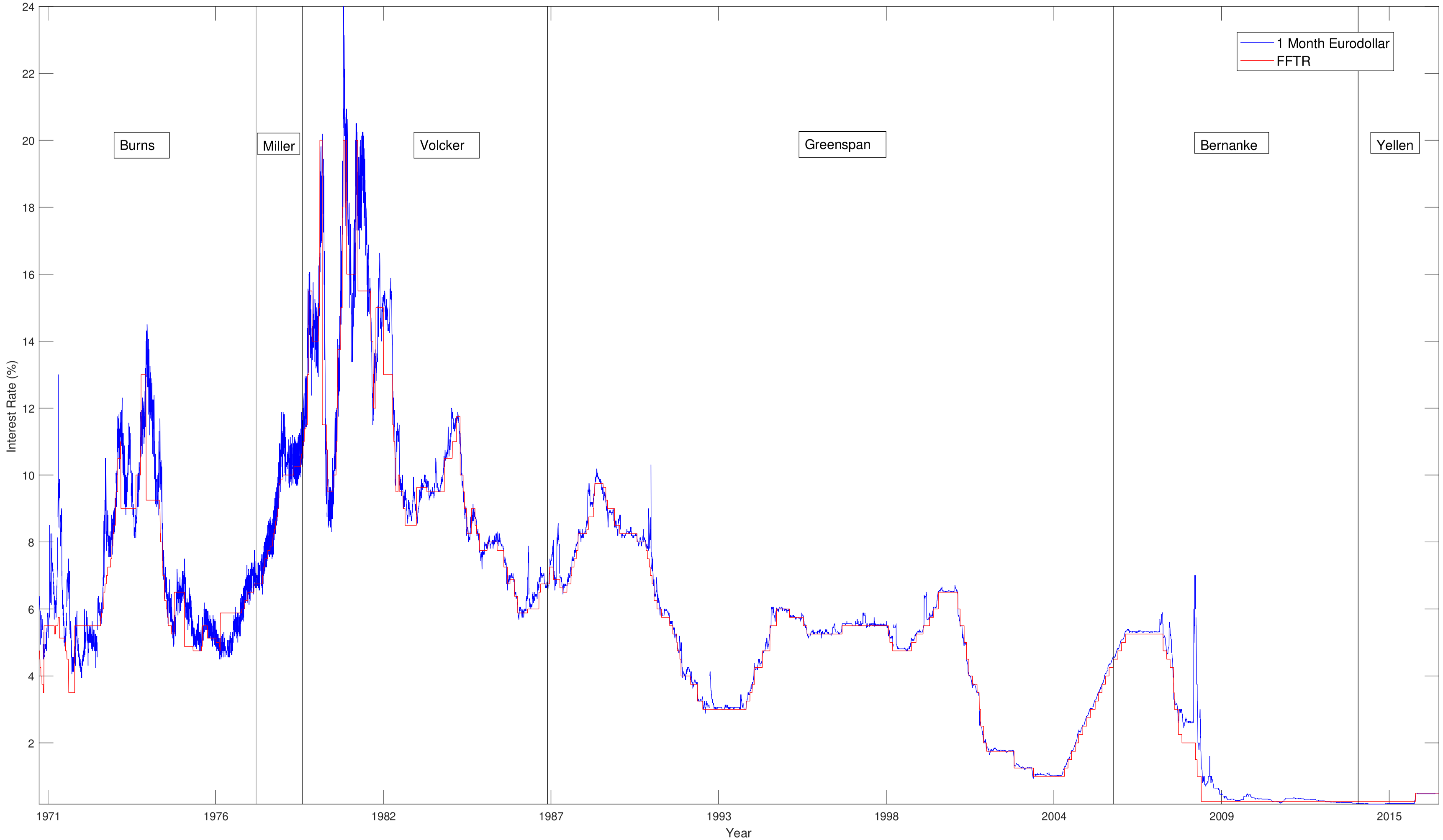
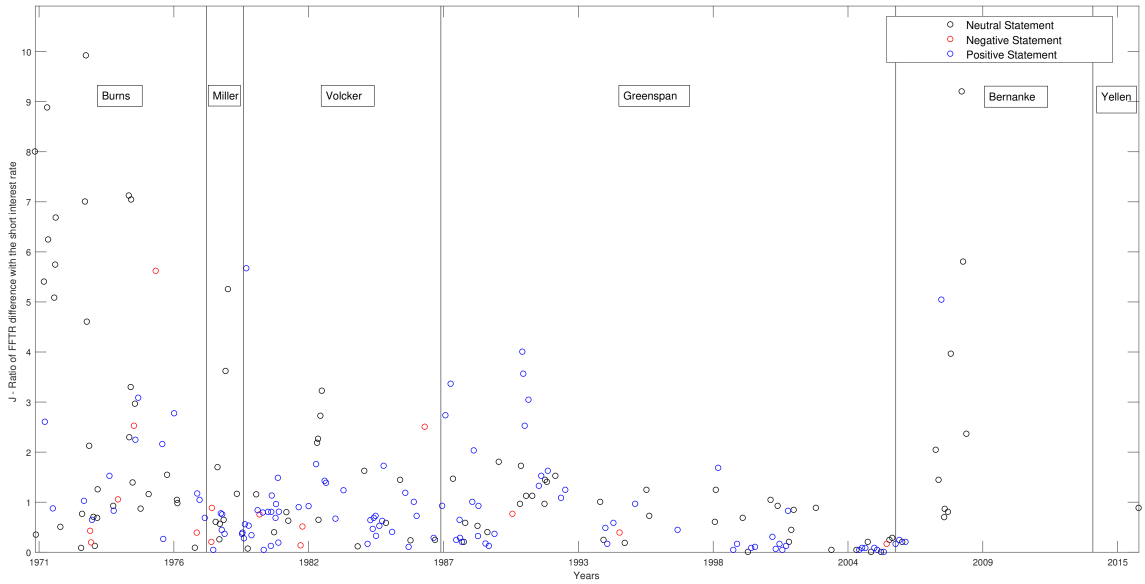
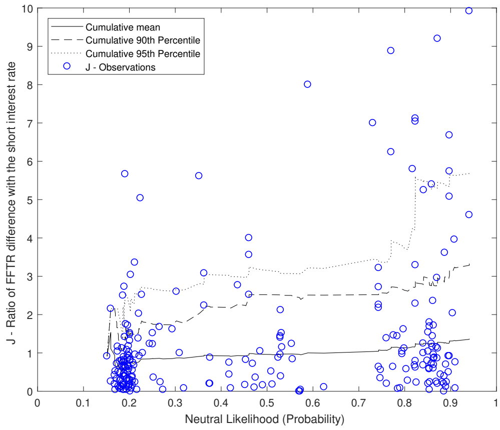


Figure 2. Interest rates (1-month Eurodollar – blue) and FFTR (red). The interest rates' sample is from January 01, 1971 to December 31, 2015. The graph is split by regions with the tenures of the different Fed Chairs.

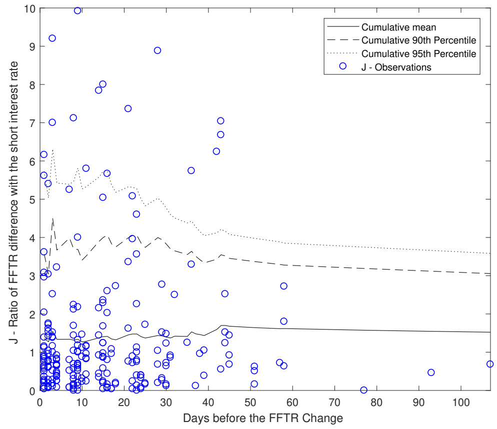


(a) Sentiment (Neutral, Positive, Negative) and FFTR-1-Month Eurodollar ratio (J)

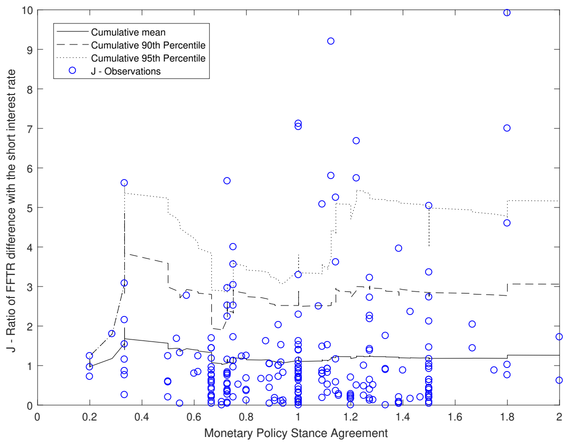
Figure 3. Jump surprise (J) ratio of difference between FFTR and the U.S. short-term interest rate (1-month Eurodollar) (in %) during the FFTR change announcement. Jump surprise (J) is calculated as in Equation (2). Sentiment is measured by the Naïve Bayes (NLTK) classifier. Jump surprises where the last Fed Chair statement was tagged as "Neutral" are in black, and when the last Fed Chair statement was tagged as "Non-neutral", it was tagged red for "Positive" ones, and blue for "Negative" ones. The data sample is from January 01, 1971 to December 31, 2015, and include $N = 244$ data points (FFTR changes occurred during the period).



(a) Sentiment (Neutral Likelihood)



(b) Days before FFTR change



(c) Agreement between the Fed Chair Statement Stance (H/D) and Previous Monetary Policy Decision

Figure 4. Jump surprise (J) of the U.S. short-term interest rate (1-month Eurodollar) (in %) during the FFTR change announcement. Jump surprise (J) is calculated as in Equation (2). Sentiment is measured by the Naïve Bayes (NLTK) classifier. The data sample is from January 01, 1971 to December 31, 2015, and include $N = 244$ data points (FFTR changes occurred during the period).

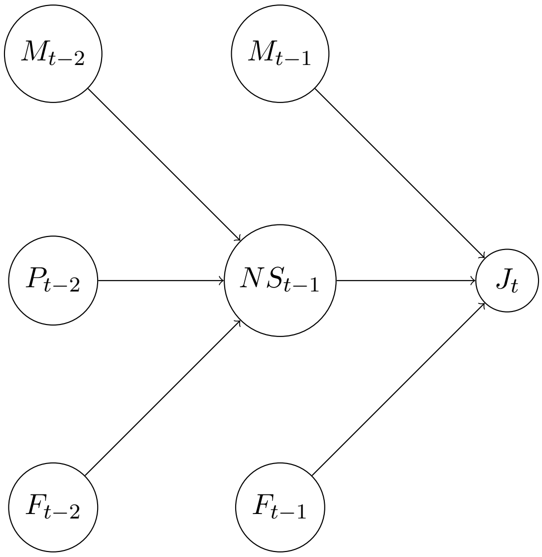


Figure 5. Identification diagram. M_i, F_i, P_i, NS_i, and J_i represent macroeconomic variables, financial variables, personal characteristics, Fed Chair neutral sentiment variable, and jump surprise at time i. Jump surprise (J) is calculated as in Equation (2). Sentiment likelihood is measured by the Naïve Bayes (NLTK) classifier, the Harvard IV (Tetlock, 2007) and Loughran and McDonald (2011) dictionaries as in Equations B1, B2, and B3 of the Online Appendix. The data sample is from January 01, 1971 to December 31, 2015.

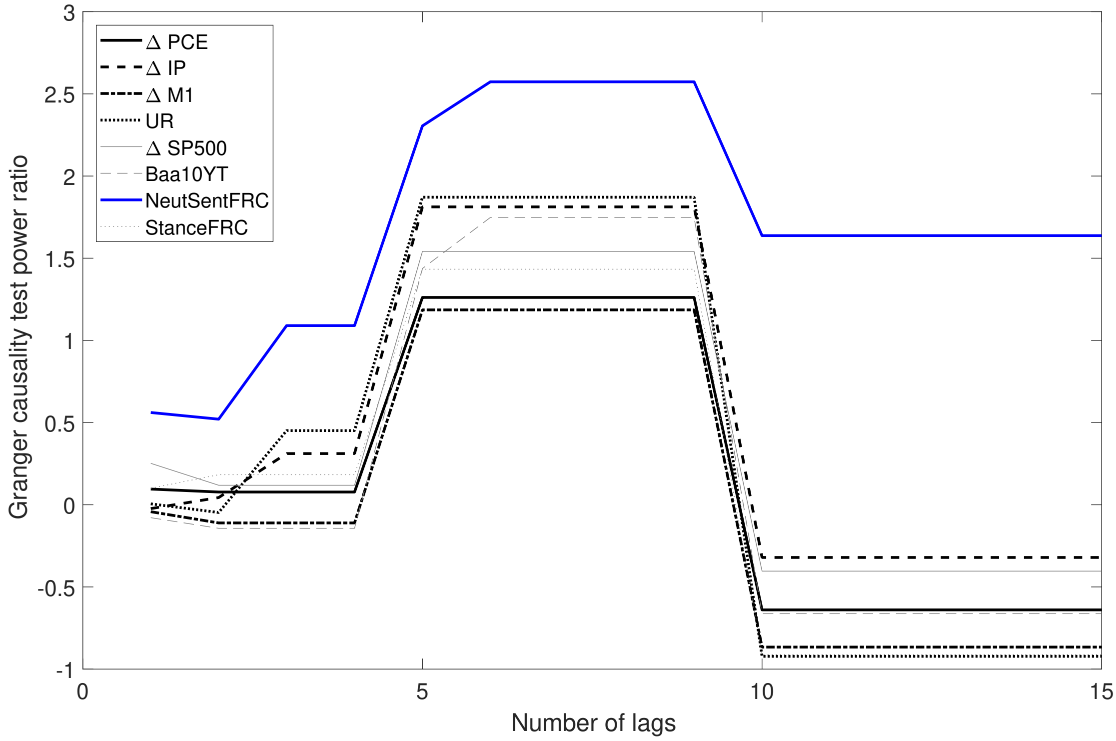


Figure 6. Granger causality test. The Granger causality tests power ratio are equal to $r_{GC} = (F - \text{critical\_value})/\text{critical\_value}$, where F is the resulting F-statistic, and critical_value is the F-distribution critical value at a p-value=0.01 over which the null hypothesis $H0$ of "no-causality" is rejected (The null hypothesis ($H0$) is that the variable to be tested – macroeconomic, financial, sentiment – does not Granger cause the jump surprise J_t. A rejection of the null hypothesis signals the existence of Granger causality. Real causality cannot be tested, but was built on the structural framework under which the Fed Chair disseminates his statements). The data sample is from January 01, 1971 to December 31, 2015, and include $N = 244$ data points (FFTR changes occurred during the period).

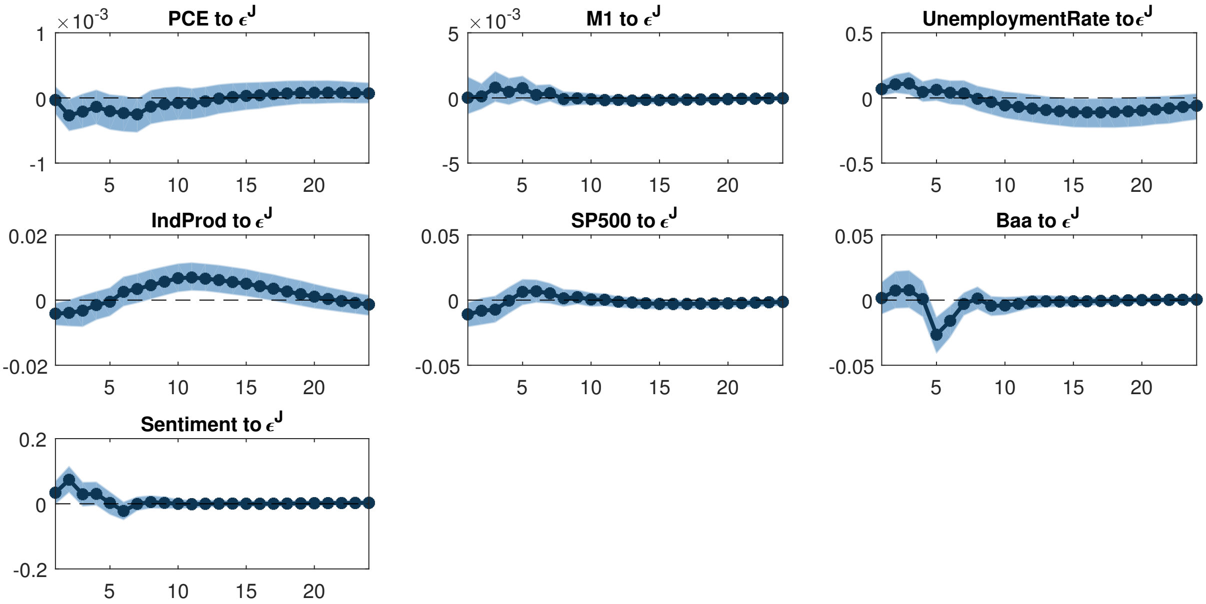


Figure 7. Conditional SVAR impulse response function. The structural-VAR (SVAR) considers the Jump surprise as the shock (instead of the FFTR), and analyze the effects of the macroeconomic variables (inflation - PCE, liquidity – M1, growth/industrial production – IndProd, and unemployment rate – UnemploymentRate), and the financial variables (stock market – SP500 and credit market – Baa). The periods (x-axis) are conditional on a FFTR change; then $t = 1, 2, \dots, 20$ represents the next FFTR change decision. The data sample is from January 01, 1971 to December 31, 2015, and include $N = 230$ data points (FFTR weekly changes occurred during the period).

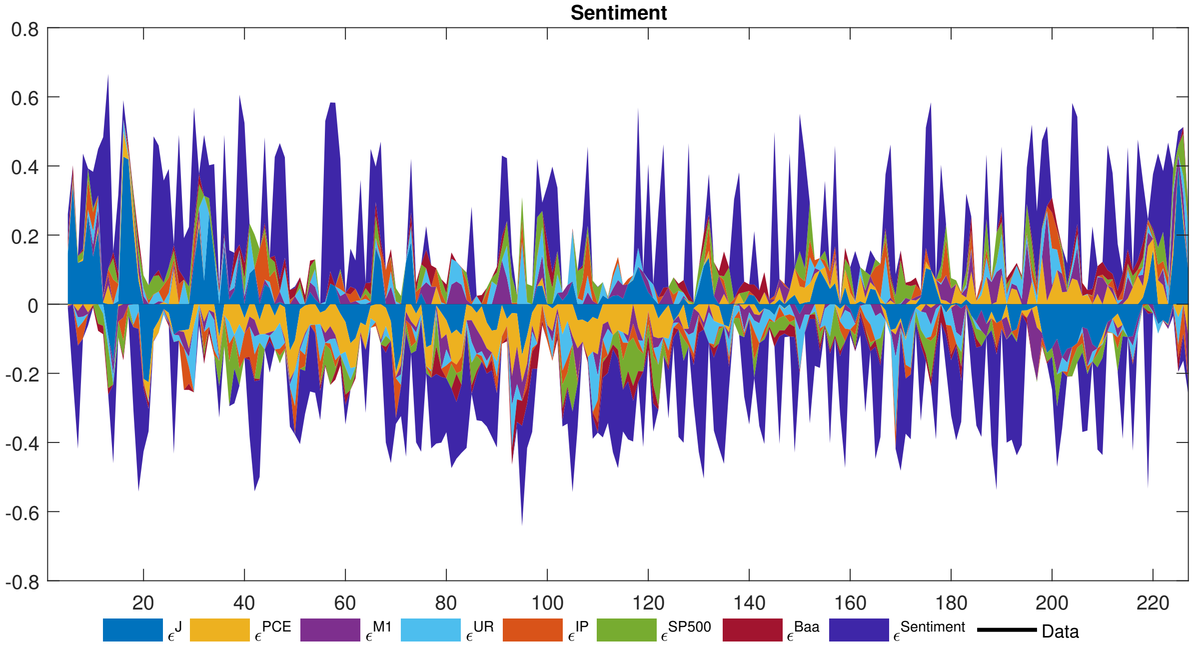


Figure 8. Conditional SVAR historical decomposition The structural-VAR (SVAR) considers the Jump surprise as the shock (instead of the FFTR), and analyze the effects of the macroeconomic variables (inflation - PCE, liquidity – M1, growth/industrial production – IndProd, and unemployment rate – UnemploymentRate), and the financial variables (stock market – SP500 and credit market – Baa). The periods (x-axis) are conditional on a FFTR change; then $t = 1, 2, \ldots, 20$ represents the next FFTR change decision. The data sample is from January 01, 1971 to December 31, 2015, and include $N = 230$ data points (FFTR weekly changes occurred during the period).

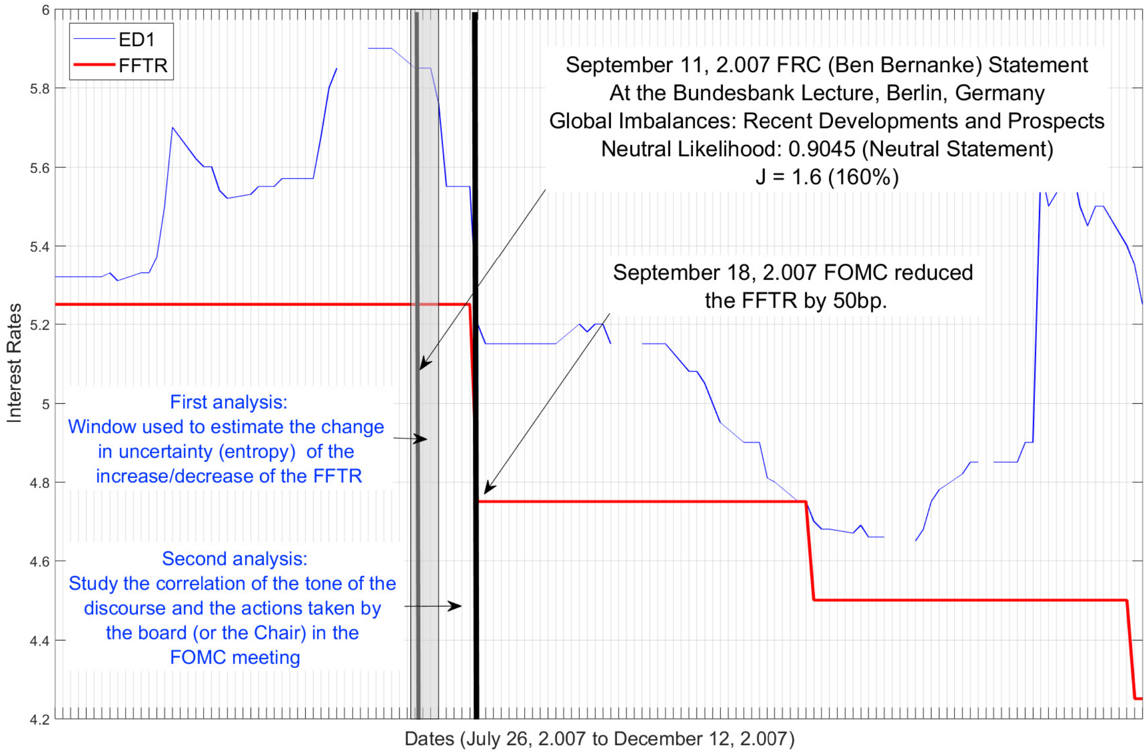


Figure 9. Second identification method – Uncertainty. The 1-month Eurodollar interest rate is in blue and FFTR is in red. The interest rates' sample is from July 26, 2007 to December 12, 2007.

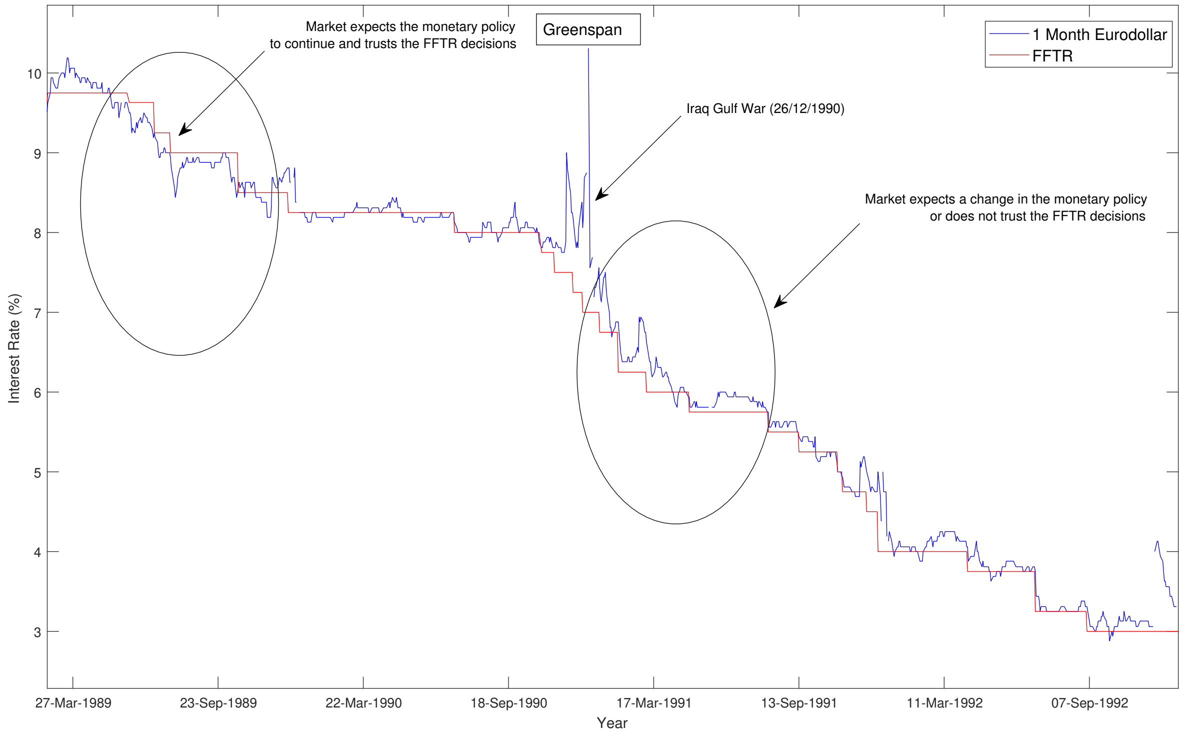


Figure 10. Market expectations over decisions of the FFTR by the FOMC. The 1-month Eurodollar interest rate is in blue and FFTR is in red. The interest rates' sample is from February 26, 2007 to December 12, 2007. The interest rates' sample is from January 23, 1989 to December 26, 1992.

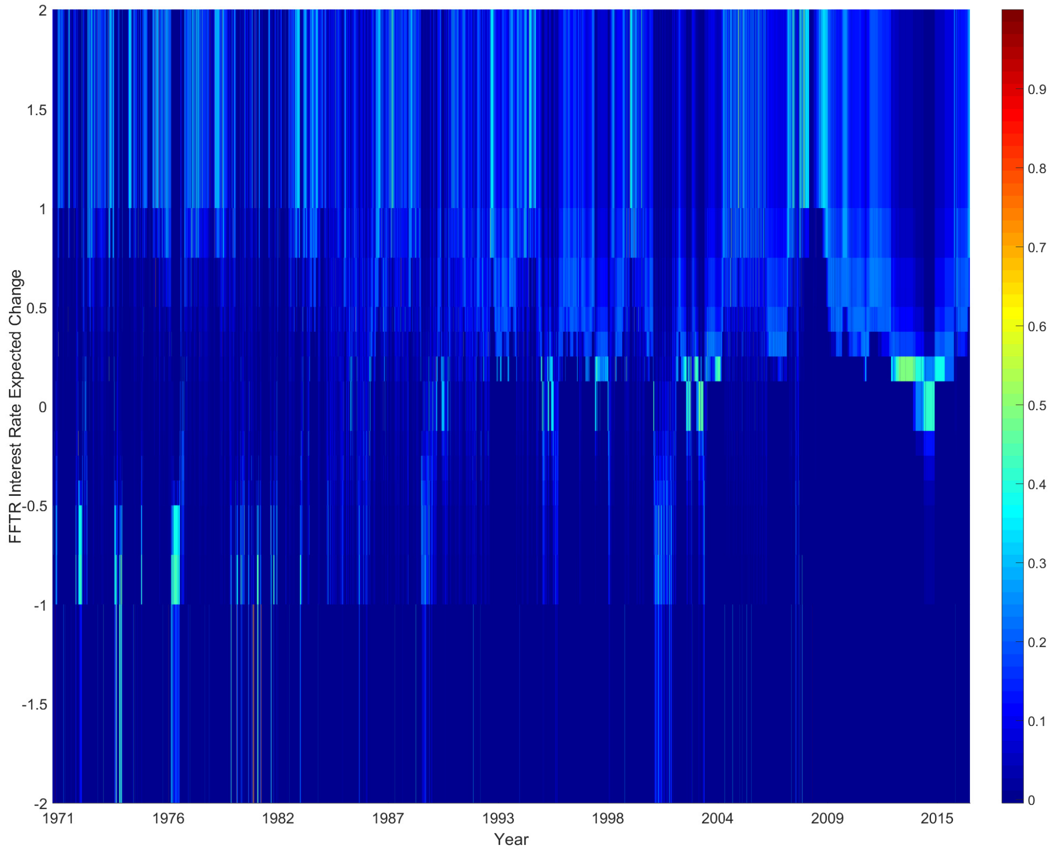
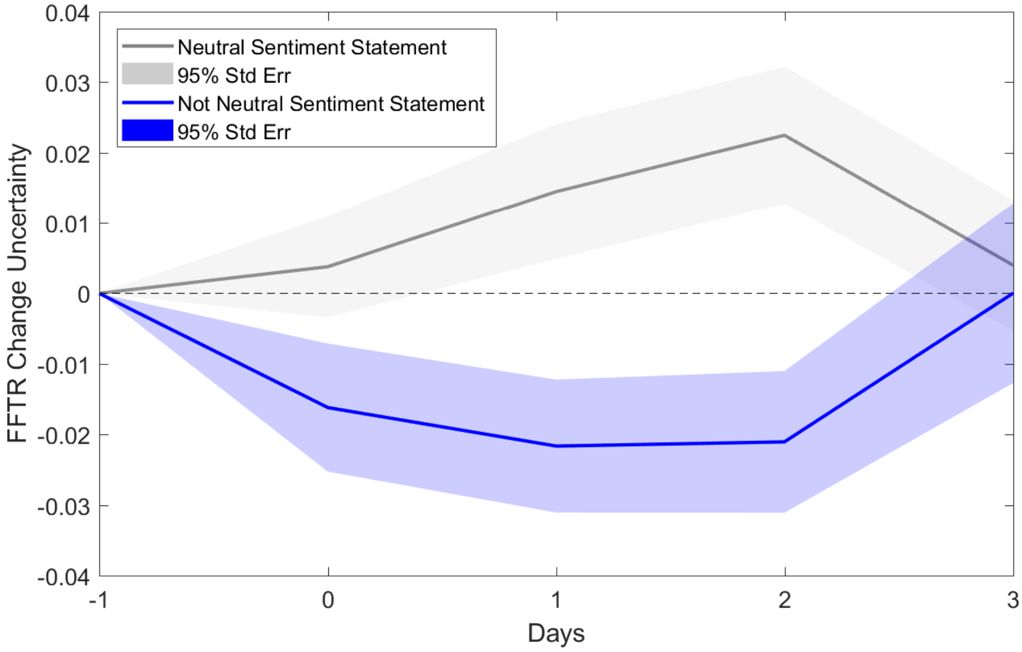
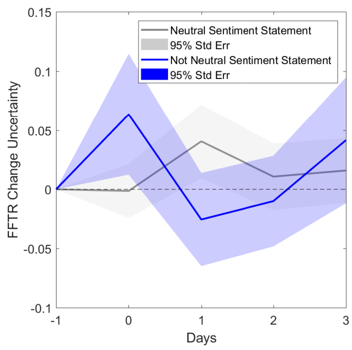


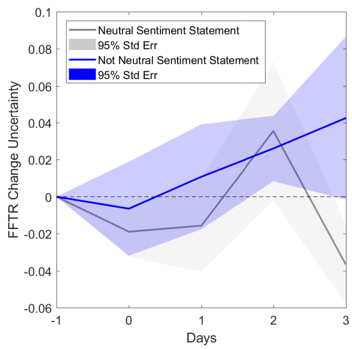
Figure 11. Implicit probability of the FFTR changes expected by the market for the next FOMC meeting . The implicit probabilities are calculated by solving Equations (9) (10), and (12), with the restrictions in (11). The 1-Month Eurodollar, 3-Month Eurodollar, and FFTR interest rates' sample is from January 01, 1971 to December 31, 2015.



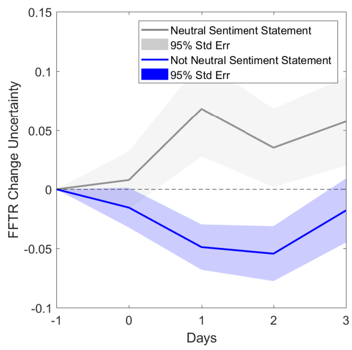
(a) Full Period



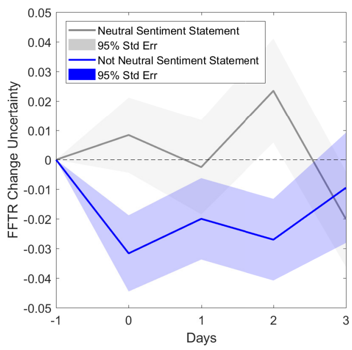
(b) Burns



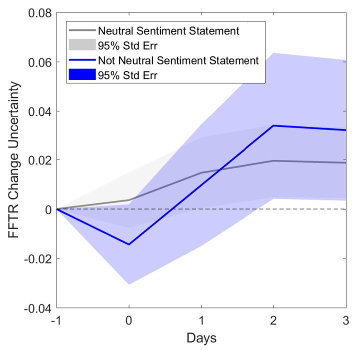
(c) Miller



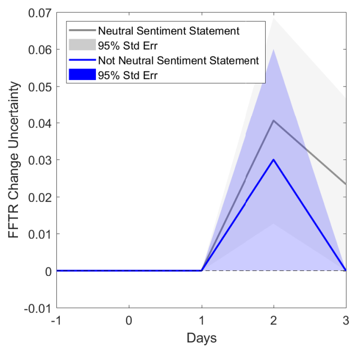
(d) Volcker



(e) Greenspan



(f) Bernanke



(g) Yellen

Figure 12. Uncertainty of the FFTR changes expected by the market for the next FOMC meeting after a Fed Chair statement release and Neutral sentiment of the Fed Chair statement. Uncertainty is calculated as the difference of the probability of and increase minus the probability of a decrease of the FFTR. The implicit probabilities are calculated by solving Equations (9) (10), and (12), with the restrictions in (11). The 1-Month Eurodollar, 3-Month Eurodollar, and FFTR interest rates' sample is from January 01, 1971 to December 31, 2015.