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ORIGINAL RESEARCH

Informativeness of the federal reserve chair communication's sentiment on the monetary policy uncertainty

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Abstract

Can a single personal communication have a significant effect on the uncertainty of the monetary policy process? We estimate the personal communication risk profile of the U.S. Federal Reserve (Fed) Chair by using a new dataset of the sentiment revealed by their public statements during their tenure. We develop a new identification method using the implicit probability of change of the federal fund rate, and analyze the impact of the Fed communication's sentiment risk profile on the market price discovery process of interest rates, and the uncertainty of the monetary policy, in the aftermath of the release of Chair public statements. After controlling for the evolving state of the economy surrounding the meetings, we find that, based on the heterogeneity across Chairs and their personal traits, there is a significant statistical and economic difference in the communications' sentiment, which is likely to affect the market's reaction to monetary policy announcements. Specifically, the sentiment in the Chairs' communications plays an important 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.

Keywords Federal reserve · Monetary policy · Communications · Monetary policy uncertainty · Fed funds rate · Machine learning

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1 Introduction

> "The process is highly likely to involve some pain but the worst pain would be from failing to address this high inflation and allowing it to become persistent."– Jerome Powell, June 29, 2022. Sintra, Portugal
> (sentiment score of the sentence: non-neutral 80%, negative 90% – naïve Bayes NLTK)

> "ECB, Fed and BoE heads warn of painful shift after 'massive geopolitical shock' of Ukraine war and pandemic." (Quote extracted from the FT in reference to the Russia's Invasion to Ukraine)– Financial Times, June 29, 2022.
> (sentiment score of the sentence: non-neutral 40% – Naïve Bayes NLTK)

In the last two decades, there has been a proliferation of empirical and theoretical research that examines the dynamics of the interaction between monetary policymakers and other economic agents through the application of a continuous stream of communication (Bernanke et al., 1999; Bernanke & Gertler, 2000; Clarida et al., 2000; Bernanke & Gertler, 2001; Bernanke & Reinhart, 2004; Myatt & Wallace, 2014; Cieslak et al., 2019a). In that period, the literature has advanced our understanding of the underlying conditions and the spillover effects that the Federal Open Market Committee (FOMC) meeting triggers in certain assets: interest rates (Lucca & Trebbi, 2009), stocks (Lucca & Moench, 2015; Cieslak et al., 2019b; Bodilsen et al., 2021; Indriawan et al., 2021), and foreign exchange markets (Ahn & Melvin, 2007). In particular, there has been 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 & Apergis, 2016; Bordo & Istrefi, 2023; Harmon, 2018; Istrefi, 2019; Bennani & Romelli, 2021). In parallel, since Tetlock (2007); Tetlock et al. (2008), and Loughran and McDonald (2011) introduced sentiment analysis into the financial literature, a growing body of research has brought attention to the measurement of sentiment in the media and in communication and its effect on financial markets.[1]

Bridging the developments in monetary policy communication and sentiment analysis, the present study draws attention to one question: **What is the change in monetary policy uncertainty immediately following the release of the Federal Reserve Chair's personal**

[1] There is a growing body of research on central banks' communication 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. Horváth and Vaško (2016) and Correa et al. (2020) provide a textual analysis of the financial stability reports by central banks in a international finance setting. Horváth and Vaško (2016) find that central banks with higher transparency framework reflect higher transparency in their financial stability reports, but that there is an inverse relationship with transparency and financial stability, while Correa et al. (2020) find that financial stability sentiment is linked to banking events. Masciandaro and Romelli (2016) and Masciandaro et al. (2022) prove a survey of the evolving importance of communications in the central bank governance/political decision process and the connection with public through social media.

statement in relation to its sentiment content?
We seek an answer to this question by measuring the sentiment of Federal Reserve Chair communications, relying on a machine learning technique—Naïve Bayes classifier.

Our results show that there exists a significant difference in the sentiment of the Fed Chair statements,[2] sufficient to create a *textual sentiment profile* for every Chair, e.g. Ben Bernanke is more neutral (less sentimental) while Paul Volcker is more emotional (more sentimental). We also find that the sentiment in statements and speeches of the Chair of the Federal Reserve is correlated with the changes of the uncertainty of the monetary policy: an increase in sentiment is informative and reduces the monetary policy uncertainty.

Our contributions are threefold: first methodological, as we contribute to the uncertainty and asset pricing literature, by providing a new measure of monetary policy uncertainty. Our new measure, monetary policy entropy uncertainty (MPEU), is based on the arbitrage relationship between the interest rate futures and the Federal Reserve Target Rate (FFTR). With this new uncertainty indicator, We also contribute to the literature about sentiment analysis, in particular, uncertainty, and machine learning tools (Baker et al. (2016a), Saltzman and Yung (2018); Azqueta-Gavaldon et al. (2023), among the most relevant examples), providing a new indicator by using a novel approach, never applied in economics. We calibrate this new uncertainty measure (MPEU) 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 on reducing uncertainty. In our analysis, our sentiment indicator aligns with Knight (1921)'s definition of uncertainty, distinguishing between risk (where losses and probabilities are known) and uncertainty (where outcomes and their probabilities are unknown or incalculable).

Second, using a unique dataset of sentiment, we contribute to the central bank communications' management literature by providing a *textual sentiment profile* of the Chair—who in the case of the Federal Reserve plays a leading role in the implementation of monetary policy. Considering the sentiment profile of the FOMC Chair, the Federal Reserve can use 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. We also test the effects of the sentiment into the option market-based uncertainty measure of Bauer et al. (2021), defined as MPU, and we find that the Fed Chair statement sentiment increases the MPU, revealing a "complimentary" effect between MPEU and MPU. Our dataset of sentiment is unique as it is the longest spanning for Fed chair statements: it starts from January, 1971 when Arthur Burns was Chair of the Fed (all other datasets start from the mid-1990s).

Third, we contribute to the information design literature (see Bergemann and Morris, 2019), between behavioral economics and market equilibrium, as we found that personal characteristics influence the process of the Fed Chair communication, which then impacts the monetary policy transmission of information to the markets.

We extend the work of Bordo and Istrefi (2023) which 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

[2] In recent years, numerous studies that use recent advances in statistics and machine learning, try to disentangle and extract information from large informal datasets: Thelwall et al. (2010) developed a new methodology defined as 'SentiStrength' to predict the sentiment of informal messages in the social networks, then they use this prediction to identify the opinion of the retail consumers; Young and Soroka (2012) quantify the sentiment of news in a political communications context.

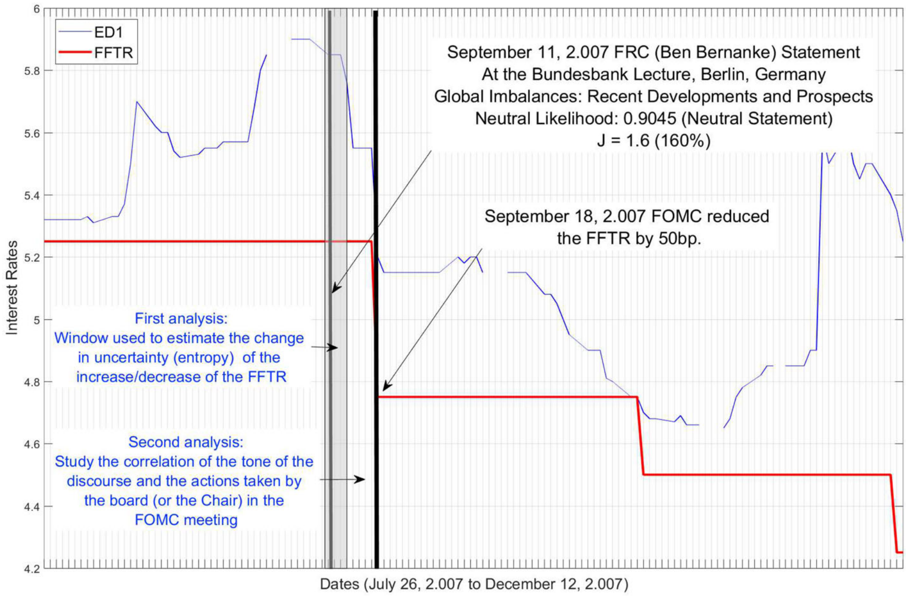


Fig. 1 Identification method—Uncertainty. The 1-month Eurodollar interest rate is in blue and FFTR is in red. The interest rates' sample is from July 26, 2007 to December 12, 2007. (Color figure online)

(2019).[3] In this regard, we find three main results: (i) the communication's 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) the Chair sentiment is rooted in personal characteristics: age, academic background, gender, and (iii) the existence of sentiment has an inverse effect during the market discovery process of its real value, uncertainty 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 results are in line with Bennani and Romelli (2021), where there is a difference between FOMC members in relation to the sentiment tone of the FOMC transcripts, which reveal a positive relationship with inflation projections.

To identify the relationships between the Fed Chair statements' sentiment we explore the uncertainty immediately after the statement is released (daily data—event study identification plus a structural VAR–SVAR–approach): Fig. 1 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 rate 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). The SVAR specifications used for identifying the "informativeness" (or "non-informativeness' given we address the neutrality of the sentiment) considers the 127 macroeconomic variables dataset of McCracken and Ng (2016), regularized by PCA and LASSO machine learning approaches.

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

In this identification method we assess the effects of the Fed Chair communications sentiment over a new measure of monetary policy uncertainty (MPEU). We construct MPEU 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. (2020a), and Bauer et al. (2021), among others, following the seminal papers on economic uncertainty identification approaches by Jurado et al. (2015) (macroeconomic variables based), Baker et al. (2016a) (news/media based), and Ederington and Lee (1996) (options volatility based). In particular, the Husted et al. (2020a) and Bauer et al. (2021) monetary policy uncertainty measures are related to ours but differ substiantially. Husted et al. (2020a) uncertainty measure is provided on a monthly, quarterly, and on a per FOMC meeting base. We need to measure the monetary policy uncertainty on a daily basis before and after the FOMC meeting, to track changes during Fed Chair speeches/statements, and as a result cannot compare our measure with Husted et al. (2020a) 's uncertainty 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) provides a market measure of monetary policy uncertainty (MPU) 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.

In the Online Appendix we provide a second identification method (see Fig. 1),[4] to establish a relationship between the interest rate discovery process and the communication's sentiment, 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.[5] To assess the effects of any type of communication after the FOMC meeting decision, we construct a surprise variable that is measured after the FOMC announcements, following Kuttner (2001).

Our work differs from that of Bordo and Istrefi (2023) as: (i) we focus only on the individual Fed Chair contribution to the FFTR change decision ((Bordo and Istrefi, 2023 considered a specification where the Fed Chair yields an 80% weight inside the board decision on the

[4] The surprise variable for the second identification method in the Online Appendix, is constructed to disentangle the reaction of interest rates to the communication's sentiment, uses the "surprise" of the interest rate market after the FOMC meeting decision release. 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 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. We analyze the impact of the Fed announcements (FOMC, Chair statements/press releases) by measuring the difference between the FFTR and the short-term/medium-term interest rates: 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 rates to eliminate the arbitrage possibility (Ahn & 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 & 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, 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.

[5] We find the Fed Chair statement sentiment averages the sentiment of the FOMC participants. This result is in line with Gertler and Horvath (2018) importance of the sentiment of the European Central Bank's (ECB) Governing Council key members versus sentiment of other members in the communication of the financial stability reports.

FFTR change), (ii) our main identification method is non-parametric/non-dependent on the specification in comparison to the Taylor parametric model used by Bordo and Istrefi (2023), (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% 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.[6] 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 effects of the sentiment of the communications with a daily uncertainty index—MPEU—in Sect. 2), and to just a few hours in the 2010s (see for example Nakamura and Steinsson, 2018, Gómez-Cram and Grotteria, 2022; ?): this is due to the advances of the market in processing the information faster. Still, the non-linear effects of the Fed Chair statement sentiment tone on the FFTR discovery process remains 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 arguments and their influence on institutional processes in the management literature. Our descriptive results and informational channel results on Fed Chair communication can be used jointly with Cieslak et al.'s (2019b) results on the asset prices around the FOMC meeting, to further our understanding of the role of the Fed Chair in the monetary policy communication process to the economy.

Our results are aligned with the Federal Reserve system of communication hypotheses, where the communication that is produced by the Chair plays a compelling role, and this role is not unusual in other governance structures. Our approach overcomes the inconsistent voting behavior described by Lähner (2018) in introducing an accurate analysis of the tone in the textual analysis, considering the influence of the sentiment of the Fed Chair communication. We find that the sentiment in statements and speeches by Fed Chairs is significantly influenced by their personal traits, even when controlling for the state of the economy and financial markets.

The paper is organized as follows: Sect. 2 develops the new measure of monetary policy entropic uncertainty (MPEU) based in arbitrage-free relationships. Section 3 describes the datasets and the textual sentiment analysis methodologies used. Section 4 describes the machine learning method used to measure the Fed Chair statement sentiment. Section 5 constructs the structural VAR will proxy the causal relationship between the Fed Chair announcements sentiment and monetary policy uncertainty (MPU and MPEU). Section 6 presents the results and Sect. 7 concludes.

2 Monetary policy entropic uncertainty (MPEU)

2.1 Arbitrage, market beliefs'—the FFTR rate discovery process between FOMC meetings

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

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

to identify which of the two agents reacted first; if the Federal Reserve by implementing a shock, following 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 by solving the identification puzzle, 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 Effective Federal Funds Rate $EFFR_t$, 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:

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

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

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

that implies

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

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 economic or market conditions, and in that case $T \leq 30$.[7]

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

$$f_t^{(1)} = \mathbb{P}_t(T < 30)\left(\frac{T}{30} FFTR_t + \frac{30 - T}{30} FFTR_{T+1}\right) + \left(1 - \mathbb{P}_t(T < 30)\right)\left(FFTR_t\right), \tag{2}$$

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 (1). 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:

[7] 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.

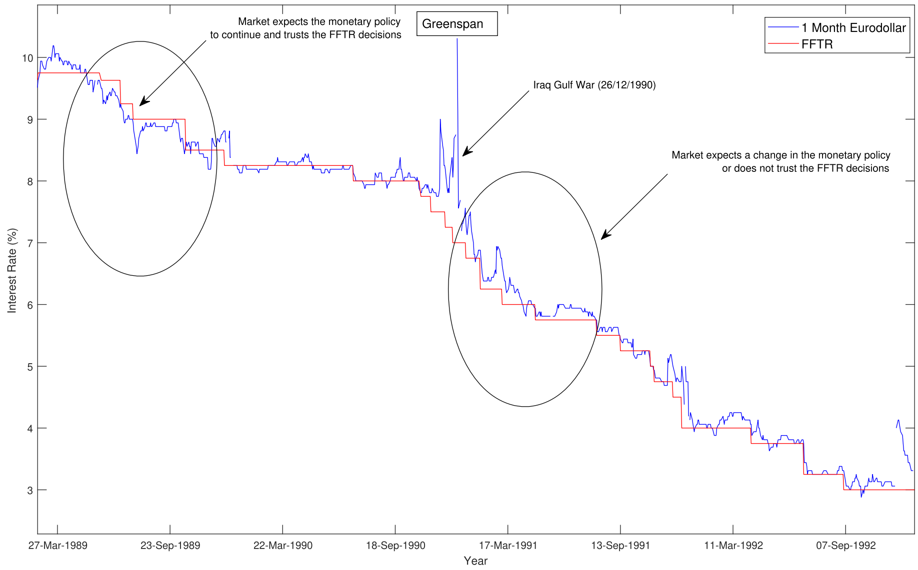


Fig. 2 Market expectations over decisions of the FFTR by the FOMC. The 1-month Eurodollar interest rate is in blue and FFTR is in red. The interest rates' sample is from February 26, 2007 to December 12, 2007. The interest rates' sample is from January 23, 1989 to December 26, 1992. (Color figure online)

(i) There is a policy shock and the market needs 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 becomes evident days after the FOMC policy decision, when the 1-month Eurodollar continues to decrease in the case when the market has detected a *Dovish* policy by the Fed, or when the 1-month Eurodollar rate continues to increase in the case when the market has detected a *Hawkish* policy (see Fig. 2).

In Equation (2), 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.

Following the "uninformed prior" probability grid method in Arismendi-Zambrano and Azevedo (2020), 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: $\left(\pi_{\delta_1}, \ldots, \pi_{\delta_N}\right)$. Then, $FFTR_t + \delta_1$ has a probability of occurring of $\mathbb{P}_{t,\delta_1}$.

Then, we define a new model of expectations that will consider two sets of probabilities: (i) a **"posterior implicit" agents' beliefs probability** $\mathbb{P}_{t,\delta_i}(\cdot)$ that represents the changes to the interest rate that will occur at certain future time (for example, $\mathbb{P}_{t,\delta_i}(T < 30)$ is the probability of the change to the FFTR occurring in less than 30 days), and (ii) a **"uninformed prior" probability** $\mathbb{Q}_t(\cdot)$ that the FOMC board is considering to set the FFTR based on only two options: 0 and δ_i. Given that $\mathbb{Q}_t(\cdot)$ is an "uninformed prior", we fix its value equal for all the scenarios of the grid. 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 (2), where every scenario has a probability of occurrence $\pi_{\delta_i}, i \in \{1, \dots, N\}$, where N is the number of different FFTR changes:

$$
\begin{aligned}
f_{1,t}^{(1)} &= \mathbb{P}_{t,\delta_1}(T < 30)\left(\frac{T}{30} FFTR_t + \frac{30-T}{30}\left(FFTR_t + \delta_1\right)\right) \\
&\quad + \left(1 - \mathbb{P}_{t,\delta_1}(T < 30)\right)\left(FFTR_t\right), \\
&\ \vdots \\
f_{N,t}^{(1)} &= \mathbb{P}_{t,\delta_N}(T < 30)\left(\frac{T}{30} FFTR_t + \frac{30-T}{30}\left(FFTR_t + \delta_N\right)\right) \\
&\quad + \left(1 - \mathbb{P}_{t,\delta_N}(T < 30)\right)\left(FFTR_t\right),
\end{aligned} \tag{3}
$$

where $\delta_i = \{-\max(change)bp, \dots, -12.5bp, +12.5bp, \dots, +\max(change)bp\}$. Setting all the δ changes on average yields the expected change implicit in the 1-month Eurodollar future; then, Equation (2) can be transformed into

$$
\begin{aligned}
f_{N+1,t}^{(1)} = \sum_{\delta_i} \mathbb{Q}_{N,t}\Bigg(&\mathbb{P}_{t,\delta_i}(T < 30)\left(\frac{T}{30} FFTR_t + \frac{30-T}{30}\left(FFTR_t + \delta_i\right)\right) \\
&+ \left(1 - \mathbb{P}_{\delta_i}(T < 30)\right)\left(FFTR_t\right)\Bigg).
\end{aligned} \tag{4}
$$

where $\mathbb{Q}_{N,t}$ is the probability that the rate for decision is δ_t. We use a Gaussian distribution as this $\mathbb{Q}_{N,t}$ prior. Additionally, we could assume, given the uninformed prior condition of $\mathbb{Q}_{N,t}$, that the N scenarios have the same probability in the initial setup (this is similar to assuming a prior distribution in a Bayesian framework). Then,

$$
\begin{aligned}
f_{N+1,t}^{(1)} = (1/N) \sum_{\delta_i} \Bigg(&\mathbb{P}_{t,\delta_i}(T < 30)\left(\frac{T}{30} FFTR_t + \frac{30-T}{30}\left(FFTR_t + \delta_i\right)\right) \\
&+ \left(1 - \mathbb{P}_{\delta_i}(T < 30)\right)\left(FFTR_t\right)\Bigg).
\end{aligned} \tag{5}
$$

The Equations (4) or (5) could be use jointly with the following arbitrage condition,

$$
f_{1,t}^{(1)} = f_{2,t}^{(1)} = \cdots = f_{N+1,t}^{(1)}. \tag{6}
$$

Equations (4) and (6), jointly with the N Equations in (3) for each δ_i will produce $N+2$ equations, with $N+1$ unknowns $(\mathbb{P}_{t,\delta_1}(T < 30), \mathbb{P}_{t,\delta_2}(T < 30), \dots, \mathbb{P}_{t,\delta_N}(T < 30), T)$, 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:

$$
\begin{aligned}
f_{i,t}^{(3)} &= \mathbb{P}_{t,\delta_i}(T < 90)\left(\frac{T}{90} FFTR_t + \frac{90-T}{90}\left(FFTR_t + \delta_i\right)\right) \\
&\quad + \left(1 - \mathbb{P}_{t,\delta_i}(T < 90)\right)\left(FFTR_t\right),
\end{aligned} \tag{7}
$$

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

$$f^{(3)}_{N+1,t} = \sum_{\delta_i} \mathbb{Q}_{N,t}\Bigg(\mathbb{P}_{t,\delta_i}(T < 90)\left(\frac{T}{30}FFTR_t + \frac{90-T}{90}(FFTR_t + \delta_i)\right) + \big(1 - \mathbb{P}_{t,\delta_i}(T < 90)\big)\,(FFTR_t)\Bigg). \tag{8}$$

but we restrict the effects of this 3-month Eurodollar rate to the extreme events (Only δ_1 and δ_N) to reduce the complexity of the model. Our set of Equations (3), (4), (6), (7), and (8) 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:

$$T \geq PriorNumberDaysNextChange/(DiffDaysLastChange_t + 2), \tag{9}$$

where $PriorNumberDaysNextChange_t$, is a variable that represents the number of days the FOMC board can take for deciding on changes to the FFTR (an average of every 30 business days), and $DiffDaysLastChange_t$ is the number of days at time t since the last interest rate change (we set initially 5 business days—one week—as the minimum amount for a FFTR change). We select Equation (9) between several other candidates, given that (i) the optimization problem to solve Equations (3), (4), (6), (7), and (8) 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 (9) restriction on T is reduced, and the probability on FFTR is allowed to increase.[8] 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 Reserve Economic Data (FRED) repository, from January, 1971 to December, 2015.

Figure 3 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.

2.2 Monetary policy entropic uncertainty (MPU): 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?, or in explaining the impact of the Fed Chair statements' sentiment on the monetary policy uncertainty? (our 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.

[8] The number selected is close to the average days between FFTR changes: in Table 1 in Sect. 3 we observe some descriptive statistics of the FFTR changes from which we estimate this number.

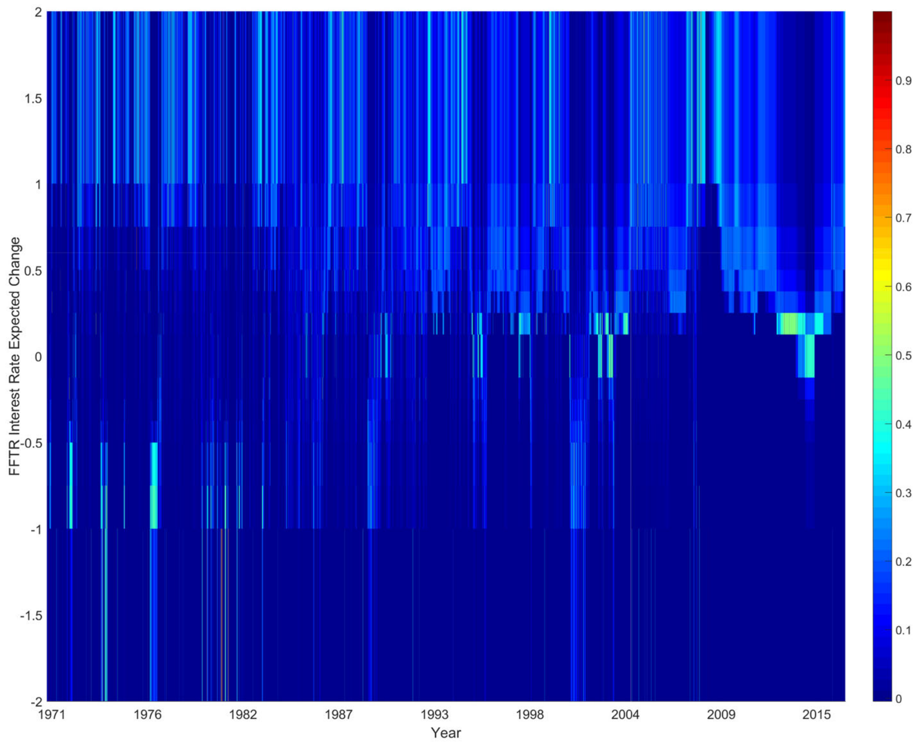


Fig. 3 Implicit probability of the FFTR changes expected by the market for the next FOMC meeting. The implicit probabilities are calculated by solving Equations (3) (4), and (7), with the restrictions in (6). The 1-Month Eurodollar, 3-Month Eurodollar, and FFTR interest rates' sample is from January 01, 1971 to December 31, 2015

Let $\mathbb{P}_{t,\text{Hawkish}} = \mathbb{P}_{t,\delta_1}(T < 30) + \ldots \mathbb{P}_{t,\delta_i}(T < 30)$ with $\delta_1, \ldots, \delta_i < 0$, be the probability at date t of a *Hawkish* decision in the next FOMC meeting occurring in less than 30 days, and $\mathbb{P}_{t,\text{Dovish}} = \mathbb{P}_{t,\delta_{i+1}}(T < 30) + \ldots \mathbb{P}_{t,\delta_N}(T < 30)$ with $\delta_{i+1}, \ldots, \delta_N > 0$ be the probability at date t of a *Dovish* decision in the next FOMC meeting occurring in less than 30 days. We define, following an approach similar to Backus et al. (2014), the entropy in the market expectations between *Hawkish* and *Dovish* decisions at time t as,

$$E_t = \left|\mathbb{P}_{t,\text{Hawkish}} - \mathbb{P}_{t,\text{Dovish}}\right| \tag{10}$$

the sample differential (absolute growth) Entropy between dates $t_1, t_2, t_1 \leq t_2$ as,

$$\Delta E_{t_1,t_2} = E_{t_1} - E_{t_2}, \tag{11}$$

our measure of **monetary policy entropic uncertainty (MPEU)** as,

$$MPEU_t = E_t, \tag{12}$$

and its **differential (time aggregate) change** between dates t_1 and t_2 as,

$$\Delta MPEU_{t_1,t_2} = \Delta E_{t_1,t_2}\sqrt{\Delta t}, \tag{13}$$

where $\Delta t = t_2 - t_1$. The sample differential (absolute growth) entropy number $\Delta E_{t_1,t_2}$ 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.

Our measure of monetary policy uncertainty, is closely related to another measure of market-based monetary policy uncertainty, the Bauer et al.'s (2021), defined as,

$$MPU_t = Variance(L_t)^{1/2}, \tag{14}$$

and its time aggregate change as,

$$\Delta MPU_{t_1,t_2} = MPU_{t_2} - MPU_{t_1}, \tag{15}$$

with $Variance(L_t)$ the option market implicit variance of the LIBOR rate L_t, calculated in a similar manner to the VIX measure. We will use the monetary policy uncertainty measure (14) as a reference for our analysis, to compare the type of "uncertainty" that our MPEU measure reveals, and as robustness measure to test the effects of the Fed chair statement sentiment into this type of uncertainty.

The next step is to measure the sentiment of the Federal Reserve communication, and associate that sentiment to the MPEU and MPU measures.

3 Data and textual analysis

3.1 Data description

Two types of Federal Reserve documents are used to estimate the sentiment contained in communication 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 base the *personality*-driven contents of other Fed Chair's communication: 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 instead spans 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.

Table 1 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

Table 1 Federal reserve communications

	Number	(%)	Average Number of Words	Average Days Between Statements
Panel A: FOMC 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)

	Number	(%)	Average Number of Words	Average Days Between Statements	Average Days Before FFTR Change (N = 244)
Panel B: Fed Chair Statements					
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)

Table 1 continued

	Number	(%)	Average of Words	Number	Average Between ments	Days State-	Average Before Change	Days FFTR (N = 244)
Janet Yellen	32	2.82%	2442.41		21.29		13.00	
			(303.74)		(4.04)		(0.00)	

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 hours 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

statement before 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 1 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 communication, 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.

In our analysis we use the 1-month Eurodollar interest rates, as proposed by Cochrane and Piazzesi (2002), to study the effects of any communication by the Fed's Chairpersons on interest rates and their volatility. Specifically, 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 underwent a change 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 consistency, 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 Fig. 4 we show a time series of the interest rate (1-month Eurodollar) and the FFTR. We can observe the volatility 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.

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 Fig. 4 (Before and after 1994). In line with the 1980s–1990s reforms, Taylor (1993) proposed a reduced form equation for the estimation of the response

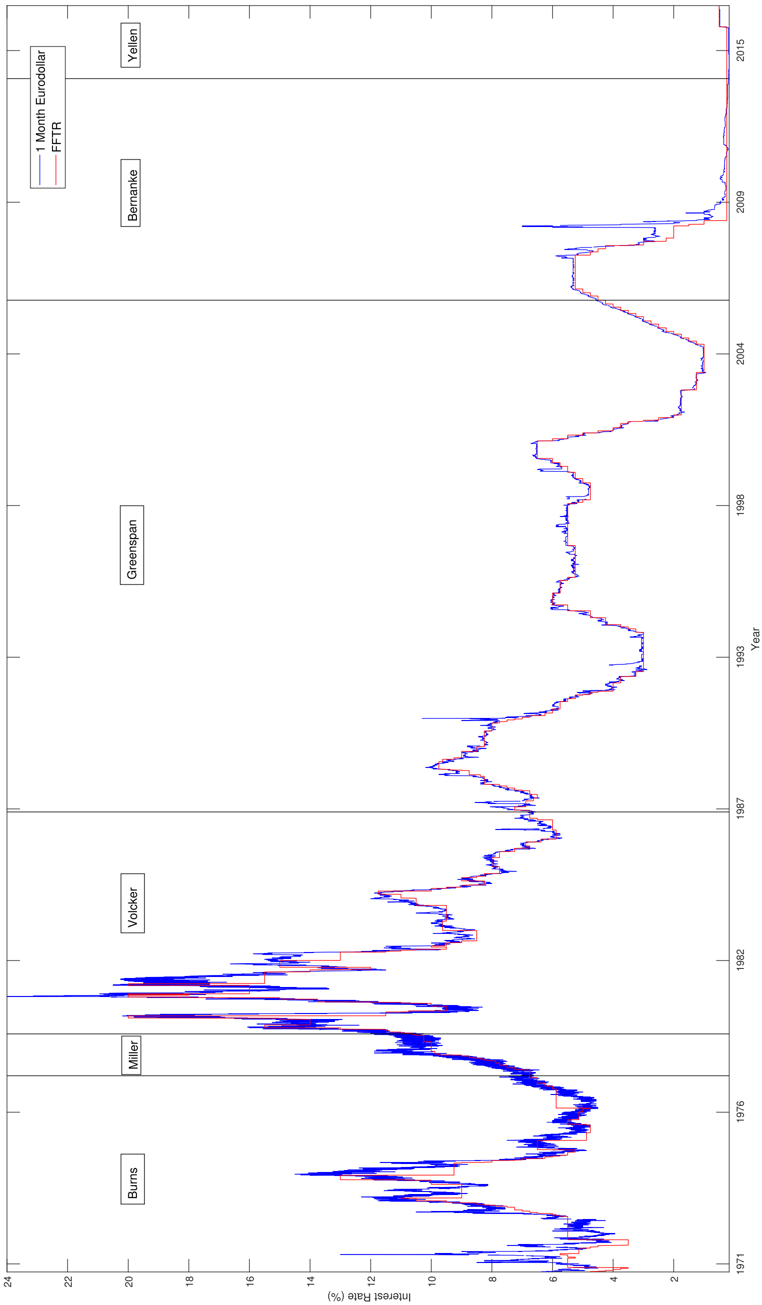


Fig. 4 Interest rates (1-month Eurodollar—blue) and FFTR (red). The interest rates' sample is from January 01, 1971 to December 31, 2015. The graph is split by regions with the tenures of the different Fed Chairs. (Color figure online)

of interest rates to changes in the macroeconomic variables:

$$i_t = \pi_t + r_t^* + a_\pi \left(\pi_t - \pi_t^*\right) + a_y \left(y_t - \bar{y}_t\right), \tag{16}$$

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 in 1994.

Table 2 presents some descriptive statistics on the interest rates' environment for our sample period. To allow our analysis to reflect the remarkable changes implemented in the FOMC meetings mentioned earlier, we divide the sample into two sub-periods, 1971–1993 and 1994–2015. Table 2 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).

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

As for the macroeconomic state variables, according to the Taylor rule in Equation (16), 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 react 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's 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).

Table 2 Interest rates and FOMC decisions

	1971–1993		1994–2015	
	Mean Value	Volatility	Mean	Volatility
Panel A: Interest Rates				
Federal Reserve				
FFTR	7.96	3.28	2.76	2.28
EFFR	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

	# FFTR Changes	Average Abs FFTR Change (%)	1-Month Eurodollar Average Jump
Panel B: FOMC Decisions			
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		

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

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).[9]

4 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 social sciences, "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 interpersonal 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 (with bigrams), trained with two widely used datasets (see Pang et al., 2002, with more than +11,000 citations) for sentiment measurement: a sentiment database (including positive/negative tone), and a subjectivity database (neutral/not-neutral tone).[10] 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.

4.1 The Naïve Bayes of NLTK sentiment methodology

Following Pang et al. (2002), two sentiment databases (Polarity 2.0, and 3.0) were built by training a Naïve Bayes classifier on a database of 2000 movie critic reviews. Define the features as f_i, the Naïve Bayes training method consist of the estimation of the probability (prior and conditional) of the feature f_i of being classified in the category c, $P(f_i|c)$, using the fact that:

$$P_{NB}(c|d) = \frac{P(c)\left(\prod_{i=1}^{m} P(f_i|c)^{n_i(d)}\right)}{P(d)}, \tag{17}$$

where d is the document containing the text being processed, f_i for $i = \{1, 2\}$ is the set of defining features, i.e., in this case the positive versus negative or the neutral versus non-neutral words, and $n_i(d)$ is the number of times f_i occurs in the document. Each document d will be represented by $d = (n_1(d), \ldots, n_3(d))$. The distinction among neutral and non-neutral words (the latter positive or negative) represents a key step in our research design: we are measuring the emotional effects that the markets may perceive from the Fed's official communications and one cannot rule out as a plausible outcome the fact that no such emotions are stirred by Fed's communications. As a result, the final tagging procedure encompasses two hierarchical steps: we first test the neutrality of a document; only if the document were to

9 Source: https://www.federalreservehistory.org.

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

be classified as non-neutral, then the probability of a positive or negative tone of the document is estimated and recorded. Therefore our sentiment indicator may take three potential values:

- Neutral, when the sentiment of the document contains a mix of emotions (or lack of them), and the effective polarity of the document cannot be estimated,
- Not-neutral and Positive, when the set of expressions in the official communication is estimated to produce a positive emotion in the reader, and
- Not-neutral and Negative, when the set of expressions in the document is inferred to deliver negative feelings.

In this paper, we are mainly interested in analyzing the empirical effects of the neutrality of the Federal Reserve Chairpersons' statements: we therefore focus our attention on the existence or non-existence of sentiment as this represents the first stage of the hierarchical process of measurement illustrated above.

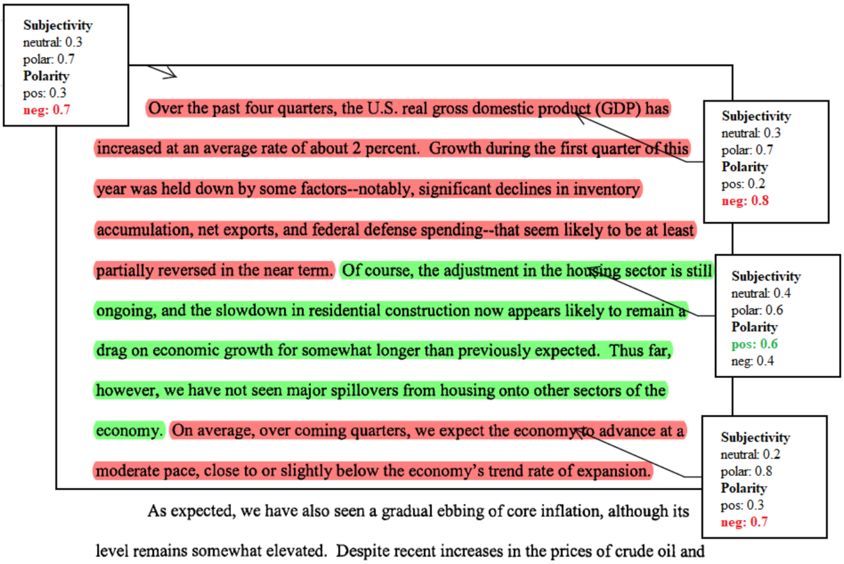
Figure 5 shows an example of the Naïve Bayes sentiment measure derived from two introductory sections of two different Fed Chair statements: the top Panel 5a concerns the sentiment inferred from a section of Chair Bernanke's "*Remarks on the Housing Market and Subprime Lending*" from the *2007 International Monetary Conference* in Cape Town, South Africa, delivered on June 5, 2007. The bottom Panel 5b illustrates the same methodology with reference to Janet Yellen's remarks titled "*Women's History Month Reception*" delivered in Washington D.C., U.S., on March 25, 2014. Interestingly, June 2007 was the year that preceded the great financial crisis, when the Federal Reserve started to raise the alarm for the possibly critical conditions of the US credit markets and this is noticeable from the introduction of the document that in fact receives a non-neutral, negative polarity tone classification with a likelihood of 0.7. In contrast, Yellen's remarks in June 2014 are classified as more neutral or even positive. As such Chair Yellen's statement is classified by our algorithm (with a likelihood of 0.8). It is plausible that as the financial crisis eased after 2010, there was decreasing pressure for the media to gain access to the Fed's opinions about the future outlook of the economy, and as a result considerable more space for the Chairperson at that time to speak about the peculiar details of the public event she had been invited to.

4.2 Other neutral sentiment proxies based on the Harvard IV (Tetlock et al., 2008) and Loughran and McDonald (2011)'s dictionary

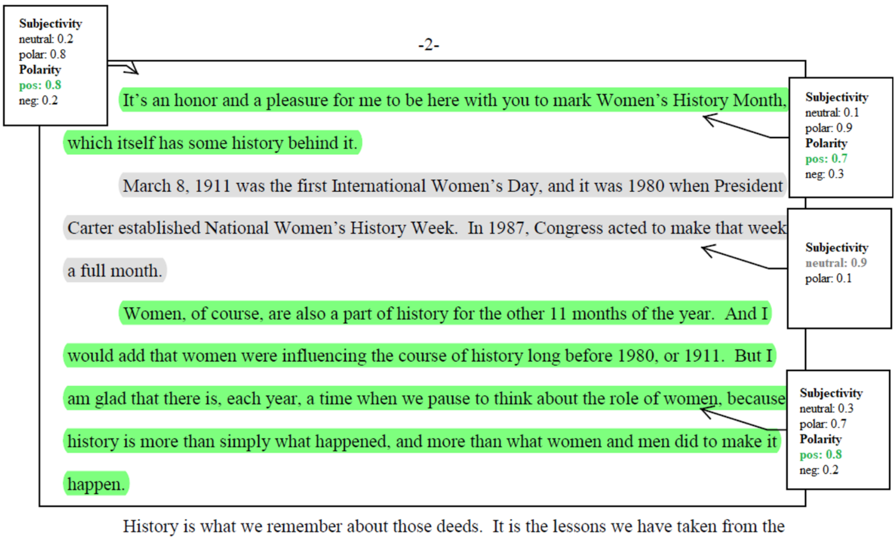
The measure of neutral sentiment selected for the baseline empirical analysis in this paper is based on a supervised machine learning method, a Naïve Bayes classifier. Although results obtained from this measure have been used before in finance (Li, 2010) and extensively in other areas of applied sentiment analysis, we also consider simpler, more traditional measures, with the objective of testing the robustness of our findings. The two proxy measures of neutral sentiment tone that we use are the percentage of neutral words in a statement, where neutrality is established counting the proportion of neutral words (not negative, and not positive) using the Harvard IV dictionary as in Tetlock et al. (2008), and using the Loughran and McDonald (2011)'s dictionary (see the Online Appendix for a full definition).

4.3 Analytical versus emotional communications

An important debate in the behavioral social sciences concerns the *rational* contribution of *sentiment* to the economy. Angeletos and La'O (2013) develop a rigorous theoretical treatment and incorporate "*sentiment*" into a rational expectations model. Because our study is



(a) Sentiment of a Fed Chair statement extract (Remarks) from June 05, 2007.



(b) Sentiment of a Fed Chair statement extract (Remarks) from March 25, 2014.

Fig. 5 The Fed Chair Statements' Sentiment. The figure shows two examples of the Naïve Bayes (NLTK) classifier output. Sub-sections of the extracts were analyzed separately, and the output reported in the left-side box. Sections of the text classified as Neutral are highlighted in gray, Positive in green, and Negative in red. A text classified as Neutral will get the "Neutral" likelihood over 0.5. A text classified as "Not-Neutral" will get a "Positive" or "Negative" tag. The sentiment of the full extract (the three paragraphs) is in the left-side box. (Color figure online)

not committed to link the Fed Chairpersons' communications to departures from a rational expectations framework, we also incorporate additional measures of sentiment that may be considered *near-rational* or, as Angeletos and La'O (2013) define them, "extrinsic shocks".

This second type of "sentiment" is defined as "analytical sentiment" as opposed to the "emotional sentiment" we have defined in Sect. 4. Analytical sentiment is supposed to capture a different dimension of a central bank's communications, one that has been associated before to decisions in a rational expectations framework—or a policymaker "rational" framework (See for example, Gardner et al.'s (2022) sentiment dictionary). In practice, it will consist of simple measure of the communications' bias towards an increase in interest rates—a "*Hawkish*" stance, or of a bias towards a decrease in the interest rate—a "*Dovish*" stance.

This second type of "rational" sentiment is built using Tetlock et al.'s (2008) and Loughran and McDonald's (2011) BoW methods: we use dictionaries of two opposite, near-rational tones, collecting words associated with a *Hawkish* monetary policy stance in one sub-set and with a *Dovish* monetary policy stance in the other. The *Hawkish* dictionary is built by looking into all synonyms of *tight* and *tightening*, and the *Dovish* set of words by synonyms of *ease* and *easing*. Table C1 in the Online Appendix displays the structure of the dictionary: a total of 63 words are expressions of a *Hawkish* stance, while 75 words match a *Dovish* tone.

In addition to helping assess the robustness of our empirical results, this additional *Hawkish* versus *Dovish* sentiment analysis may be revealing in comparison to the *Neutral* versus *Not-neutral* exercise to test whether the channel of neutral/not-neutral and positive/negative sentiment in Fed Chairpersons' communications may provide an additional "emotional" content that significantly contributes to explaining the impact of Fed sentiment in the prediction of interest rate movements over and above the classical dynamics of the sentiment of the Federal Reserve regarding the *Hawkish* and *Dovish* states over the business cycle.[11]

4.4 Other sentiment measures

$$P_{\text{TETLOCK}} = \frac{\text{number of neutral words as classified by Harvard IV}}{\text{total number of words in a statement}}, \tag{18}$$

where the neutral words are simply all words that do not belong in the Harvard IV positive/negative list. We also use the percentage of neutral words in a statement, where neutrality is established using Loughran and McDonald (2011)'s dictionary:

$$P_{\text{L\&M}} = \frac{\text{number of neutral words as classified by Loughran}-\text{McDonald dictionary}}{\text{total number of words of the statement}}. \tag{19}$$

4.5 The common features in different sentiment measurement methods

Table 3 shows the proportion of common words in the intersection of words by using the different sentiment methods. The proportion is normalized by including only positive or negative words in the counting process. We can observe that there are common words in the statements, that will be tagged as positive for both dictionaries.

We observe in Table 3 that the three methods used (one main method and the two proxies) to measure the neutral sentiment converge in the words that define the positive/negative (emotion) tone of a document.

[11] One may think that the majority of the *Dovish* communications ought to come after a crisis, and that the *Hawkish* ones ought to predominate after a boom or expansion period, therefore associating *Dovish* (*Hawkish*) sentiment with non-neutral negative (positive) sentiment, in the sense of Sect. 2.2.

Table 3 Most frequent positive and negative words in the statements

Panel A: Positive							
FOMC Statements				Federal Reserve Statements			
Harvard IV (Tetlock)	Cumulative %	Loughran & McDonald	Cumulative %	Harvard IV (Tetlock)	Cumulative %	Loughran & McDonald	Cumulative %
STABILITY	7.62%	STABILITY	17.40%	IMPORTANT	1.33%	GREATER	3%
SUPPORT	12.86%	STABLE	24.63%	EVEN	2.64%	STABILITY	5%
MODERATE	17.83%	IMPROVED	31.12%	INTEREST	3.87%	BETTER	7%
FOSTER	22.61%	PROGRESS	37.32%	SIGNIFICANT	5.01%	STRONG	10%
HELP	26.81%	IMPROVEMENT	43.51%	CREDIT	6.13%	GOOD	12%
CONSISTENT	30.49%	EXCEPTIONALLY	49.56%	STABILITY	7.16%	ABLE	14%
PRODUCTIVITY	33.98%	STRONGER	54.28%	SUPPORT	8.17%	EFFECTIVE	15%
ACCOMMODATION	37.34%	IMPROVE	58.55%	LIKE	9.13%	BEST	17%
STABLE	40.50%	ATTAINMENT	62.39%	EXPERIENCE	10.04%	PROGRESS	19%
UTILIZATION	43.60%	GAINS	65.93%	VALUE	10.92%	GREAT	21%
INTEREST	46.58%	STRENGTHENS	68.88%	ABILITY	11.79%	OPPORTUNITY	23%
IMPROVEMENT	49.29%	STRENGTH	71.24%	HELP	12.66%	DESPITE	25%
CREDIT	51.94%	DESPITE	73.30%	KNOW	13.50%	GAINS	26%
OBJECTIVE	54.20%	STRENGTHEN	75.22%	ABLE	14.31%	IMPROVE	28%
ENSURE	56.27%	STRENGTHENING	77.14%	BEST	15.12%	IMPROVED	29%
APPROACH	58.27%	EFFECTIVE	79.06%	EFFECTIVE	15.92%	ACHIEVE	31%
EVEN	60.21%	STRONG	80.83%	MEET	16.67%	STABLE	32%
ASSET	62.14%	FAVORABLE	82.45%	OPPORTUNITY	17.41%	PLEASED	34%
IMPROVE	64.02%	IMPROVING	84.07%	CONSISTENT	18.14%	IMPROVEMEN	35%
ROBUST	65.70%	BEST	85.40%	PRODUCTIVITY	18.86%	OPPORTUNITIES	36%
UPSIDE	67.38%	STRENGTHENED	86.73%	SHARE	19.56%	SUCCESS	38%
ATTAINMENT	69.06%	IMPROVES	87.91%	HOME	20.25%	STRENGTH	39%
GENERATE	70.67%	STABILIZE	88.94%	APPROACH	20.91%	EFFICIENCY	40%
RETURN	72.22%	STABILIZING	89.97%	IMPROVE	21.56%	BENEFIT	41%
BLOOM	73.71%	CONFIDENT	91.00%	RETURN	22.20%	ENCOURAGING	42%
SIGNIFICANT	75.06%	ADVANCES	92.04%	IMPORTANCE	22.84%	IMPROVING	43%
MODEST	76.29%	ADVANCING	92.92%	ACHIEVE	23.47%	ACHIEVING	44%
COMPENSATION	77.39%	SMOOTH	93.81%	SAVINGS	24.09%	STRONGER	45%
EFFICACY	78.49%	BETTER	94.69%	STABLE	24.70%	SUCCESSFUL	46%
NORMAL	79.46%	ACHIEVED	95.28%	EQUITY	25.29%	IMPROVEMENTS	47%
Panel B: Negative							
FOMC Statements				Federal Reserve Statements			
Harvard IV (Tetlock)	Cumulative %	Loughran & McDonald	Cumulative %	Harvard IV (Tetlock)	Cumulative %	Loughran & McDonald	Cumulative %
INFLATION	30.24%	UNEMPLOYMENT	7.39%	DIFFICULT	2.44%	DIFFICULT	1.35%
LOW	47.46%	DECLINE	11.96%	INFLATION	4.37%	PROBLEMS	2.65%
DECLINE	54.30%	SLOWED	15.81%	COST	6.21%	DECLINE	3.77%
STERN	59.60%	WEAK	19.65%	LOW	8.02%	PROBLEM	4.83%
EXCESS	63.13%	SLOW	22.90%	TURN	9.76%	CONCERN	5.85%
DECREASE	66.00%	DECLINES	26.14%	DECLINE	11.43%	LATE	6.84%
COST	68.65%	DIMINISHING	29.39%	FOREIGN	13.02%	CRITICAL	7.84%
RELUCTANT	70.64%	DEPRESSED	32.64%	PROBLEM	14.59%	CONCERNS	8.81%
TURN	72.63%	DOWNWARD	35.89%	COMPETITIVE	16.10%	UNEMPLOYMENT	9.69%
LIMIT	74.39%	DECLINED	38.85%	DEAL	17.41%	QUESTION	10.52%
UNDERMINE	76.16%	WEAKNESS	41.80%	COMPLEX	18.69%	SHARPLY	11.32%
EXECUTE	77.70%	IMBALANCES	44.61%	FORCE	19.84%	FORCE	12.12%
STRESS	79.25%	STRAINS	47.42%	RECESSION	20.98%	RECESSION	12.92%
ORDER	80.57%	CONCERNED	50.07%	AVOID	22.11%	DIFFICULTIES	13.71%
CRUDE	81.90%	EASING	52.44%	DEFICIT	23.23%	SERIOUS	14.49%
FOREIGN	83.00%	SLOWING	54.51%	ORDER	24.34%	DEFICIT	15.27%
ADVERSE	84.11%	UNDERUTILIZAT	56.43%	COMPETITION	25.43%	CRISIS	16.01%
ABATE	85.21%	SLOWER	58.35%	CRISIS	26.51%	DECLINED	16.73%
NEED	86.09%	LATE	59.97%	EXCESSIVE	27.56%	LOSSES	17.44%
FAIL	86.98%	PERSISTENTLY	61.60%	DOUBT	28.56%	EXCESSIVE	18.15%
TRAGIC	87.86%	DISRUPTIONS	63.07%	HARD	29.56%	DECLINES	18.86%
CRISIS	88.52%	CONCERN	64.55%	ADVERSE	30.54%	DOUBT	19.56%
TURMOIL	89.18%	DIMINISHING	65.88%	WAR	31.50%	QUESTIONS	20.25%
TEMPORARILY	89.85%	CONTRACTION	67.21%	SEVERE	32.44%	CHALLENGES	20.92%
OMIT	90.51%	RELUCTANT	68.54%	FAILURE	33.35%	ADVERSE	21.59%
SLUGGISH	91.17%	UNWELCOME	69.72%	LIMIT	34.25%	DEFICITS	22.26%
DEPENDENT	91.61%	WEAKENED	70.90%	EXCESS	35.14%	SLOW	22.93%
BIT	92.05%	DECLINING	72.08%	LOSS	36.00%	CONCERNED	23.57%
SPOT	92.49%	SHORTFALL	73.26%	SERVE	36.81%	SEVERE	24.21%
EROSION	92.94%	UNDERMINE	74.45%		37.61%	FAILURE	24.84%

The table shows the most sentiments' significant words extracted from 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. The words are extracted by cross-checking the words of every document with the Harvard IV (Tetlock et al., 2008) and Loughran and McDonald (2011) dictionaries and counting the repetitions. The cumulative percentage is relative to the total words recognized by the dictionary (conditional frequency). Positive and common extracted words from both dictionaries are highlighted in **bold**, negative and common extracted words from both dictionaries are highlighted in *italics*

4.6 Fed chairs' statements sentiment drivers

In this sub-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' communication in the aftermath of FOMC decisions. We have one main research questions: (i) What is the change in monetary policy uncertainty immediately after the release of a personal statement by the Federal Reserve Chair, in relation to its sentiment content?. Before answering that question, we analyze the drivers of the sentiment of the statements, with the purpose to isolate the most important endogenous variables.

We measure the effects of the personal characteristics on the communication sentiment to check the sentiment heterogeneity across Chairs, estimating a linear mixed effects (LME) model (following Huang et al., 2013; Loughran and McDonald, 2011, 2013), controlling for the state of the economy and the financial market.[12] We regress the sentiment of the Fed Chair statement by macroeconomic variables, financial variables and personal characteristics, to understand which variables might "initially" be associated with this "sentiment":

$$\begin{aligned} NeutSentFRC_t = \beta_0 + MacroVariables_{t-1} + FinancialVariables_{t-1} \\ + PersonalCharacteristics_{t-1}, \end{aligned} \tag{20}$$

where

$$\begin{aligned} MacroVariables_{t-1} &= \beta_1 BC_{t-1} + \beta_2 \Delta PCE_{t-1} + \beta_3 \Delta IP_{t-1} \\ &\quad + \beta_4 \Delta M1_{t-1} + \beta_5 \Delta UR_{t-1}, \\ FinancialVariables_{t-1} &= \beta_6 \Delta SP500_{t-1} + \beta_7 Baa10YT_{t-1}, \\ PersonalCharacteristics_{t-1} &= \beta_8 CHAIR_{t-1} + \beta_9 AGE_{t-1} \\ &\quad + \beta_1 0 EDUC_{t-1} + \beta_1 1 GEND_{t-1}, \end{aligned}$$

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 Sect. 3.1.[13] 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.

5 Identification: structural vector autoregressive (SVAR) model

To respond to our main question (*What is the change in monetary policy uncertainty immediately following the release of the Federal Reserve Chair's personal statement in relation to its sentiment content?*), we estimate an SVAR model with zero short-run restrictions (Cholesky) as follows:

(i) First, we set the uncertainty variables considered in the SVAR: the Monetary Policy Uncertainty (MPU) and the Monetary Policy Entropic Uncertainty ($MPEU$).

[12] In the Online Appendix, we add an additional analysis to support to answer the main question by constructing a variable that recovers the "jump surprise effect" (a new indicator of uncertainty of the unexpected change in FFTR). 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.

[13] The Personal Characteristics variables are calculated as follows: **Age:** is the number of years between the statement release, and the year when the Fed Chair was born, **Education:** represents the number of years of education is US, considering 12 years of primary and post-primary school, 4 years of bachelor, 2 years of masters, and 5 years for PhD degrees[14]; and **Gender:** a dummy variable equals to 1 for male and equals to 0 for female. In regards to the amount of variables, given that Chair Yellen made several decisions the sample is larger than 1.

(ii) Second, we introduce our 'policy' variable: the informativeness of the Fed chair's statements. Given that we consider the sentiment of the Fed chair statement as information, and the absence of such sentiment as non-information, we define the *Fed-chair-information* shock as Non-Informativeness ($NonInform$) to be aligned with the neutral sentiment ($NeutSent$) variable that proxies the shock.

(iii) Then, to reduce the potential misspecification, we include variables from the large database of macroeconomic variables of McCracken and Ng (2016). As there are 127 variables (see the Online Appendix D for the definition of the variables), we apply two types of projection methods to reduce the dimensionality of the problem following a "machine learning" regularization approach:

   (a) A principal component analysis (PCA) method where we select the first four principal components (naming the factor variable i as $MacroPCAf_i$) that explain 92.5% of the covariance matrix variation, and
   (b) A least absolute shrinkage and selection operator (LASSO) method, that considers a sparse reduced set with the first 10 most important variables. The LASSO regularization considers as the explained variable (endogenous) the entropic uncertainty (MPEU) and uses as explanatory variables the 127 macroeconomic variables (McCracken & Ng, 2016).

(iv) Finally, we consider in our identification that the policy "shocks" (unobserved, but proxied by MPU and MPEU) affect all the variables contemporaneously, and that the *Fed-chair-information* shock does not affect any variable contemporaneously (the neutral sentiment of the statement). In between those extremes, the macro variables are ordered in contemporaneous effect by the order of importance of the regularization methods (PCA factor importance, of the order of the variable in the LASSO regularization).

The frequency of the macroeconomic variables is monthly. To improve the identification quality, we have produced a daily variable of the monetary policy entropic uncertainty ($MPEU_t$ with t being daily), to match the daily frequency of the sentiment of the statement of the Fed chair ($NeutSent_t$) to which we have access once it is publicly read (or announced/published). To fix this misalignment in frequencies, we might use methods such as MIDAS. Nevertheless, considering this is an initial exploratory study of the effects of sentiment in monetary policy uncertainty, we create the following time series matrix, conditional to the observation of a Fed chair statement (the time-frequency of the SVAR is conditional on a statement release date):

Let $MPEU_{t_1}$ be the $MPEU$ observed the day of the release (or read/publication) of the Fed chair statement, and MPU_{t_1} the corresponding observed Bauer et al.'s (2021) MPU index. Define as $NeutSent_{t_1}$ the neutral sentiment of the Fed chair statement observed that day. Let the McCracken and Ng's (2016) i-th macro variable observation in month τ be defined as $m_{i,\tau}$. Define the future relative change (return) of the macro variable between the current month observation ($\tau_1 = 0$) to the next month observation ($\tau_2 = 1$) as $\Delta_{\tau_1,\tau_2,t_2} m_i = (m_{i,\tau_2} - m_{i,\tau_1})/m_{i,\tau_1}$. In the SVAR time series matrix, we associate the $MPEU_{t_1}$, MPU_{t_1}, and $NeutSent_{t_1}$ observations, to the future relative change (return) of the macro variable $\Delta_{\tau_1,\tau_2,t_1} m_i$. Given that in the SVAR assumptions we considered that the *Fed-chair-information* shock ($NeutSent_{t_2}$) is not contemporaneous to any variable, we are exploring how the sentiment observed during the current month, can explain "contemporaneously" the future changes of the macroeconomic variables. We consider four (4) lags, that represent the information revealed in the last four statements (equivalent to a two-month period approximately that will include at least one full FOMC meeting cycle).

In addition, as a robustness check, we estimate an SVAR specification where we associate the $MPEU_{t_1}$, MPU_{t_1}, and $NeutSent_{t_1}$ observations, to the past relative change (return) of the macro variable $\Delta_{\tau_{-1},\tau_1,t_1} m_i$; these additional results are provided in the Online Appendix.

Our final SVAR specification, in the case where PCA is applied, is,

$$\begin{bmatrix} MPU_{t_1} \\ MPEU_{t_1} \\ \Delta_{\tau_1,\tau_2} MacroPCAf_1 \\ \Delta_{\tau_1,\tau_2} MacroPCAf_2 \\ \Delta_{\tau_1,\tau_2} MacroPCAf_3 \\ \Delta_{\tau_1,\tau_2} MacroPCAf_4 \\ NeutSent_{t_1} \end{bmatrix} = \sum_{p=1}^{4} \Phi_p X_{t-p} + \mathbf{B}_{PCA} \begin{bmatrix} \varepsilon_t^{\text{monPolUnc}} \\ \varepsilon_t^{\text{monPolEntUnc}} \\ \varepsilon_t^{\text{MacroPCAf1}} \\ \varepsilon_t^{\text{MacroPCAf2}} \\ \varepsilon_t^{\text{MacroPCAf3}} \\ \varepsilon_t^{\text{MacroPCAf4}} \\ \varepsilon_t^{\text{NonInform}} \end{bmatrix}, \tag{21}$$

where X_t is the matrix with the data observations and in the case when LASSO is applied is,

$$\begin{bmatrix} MPU_{t_1} \\ MPEU_{t_1} \\ \Delta_{\tau_1,\tau_2} MacroLASSO_1 \\ \vdots \\ \Delta_{\tau_1,\tau_2} MacroLASSO_{10} \\ NeutSent_{t_1} \end{bmatrix} = \sum_{p=1}^{4} \Phi_p X_{t-p} + \mathbf{B}_{LASSO} \begin{bmatrix} \varepsilon_t^{\text{monPolUnc}} \\ \varepsilon_t^{\text{monPolEntUnc}} \\ \varepsilon_t^{\text{MacroLASSO1}} \\ \vdots \\ \varepsilon_t^{\text{MacroLASSO10}} \\ \varepsilon_t^{\text{NonInform}} \end{bmatrix}, \tag{22}$$

with $\mathbf{B}_{method}$ defined as,

$$B_{method} = \begin{bmatrix} b_{11} & 0 & 0 & \cdots & 0 \\ b_{21} & b_{22} & 0 & \cdots & 0 \\ b_{31} & b_{32} & b_{33} & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ b_{n1} & b_{n2} & b_{n3} & \cdots & b_{nn} \end{bmatrix}$$

for n the number of variables in the specification. We define these specifications as SVAR_PCA1 and SVAR_LASSO1. Two additional SVAR specifications are tested: one similar to the SVAR in Equation (21), but locating the $MPEU_{t_1}$ and $\varepsilon_t^{\text{NonInform}}$ at the last row, and one similar to the SVAR in Equation (22) in the last row. These two additional specifications address the effects of the two measures of monetary policy uncertainty. We define these specifications as SVAR_PCA3 and SVAR_LASSO3. The additional specification in the Online Appendix where we associate $MPEU_{t_1}$, MPU_{t_1}, and $NeutSent_{t_1}$ observations, to the past relative change (return) of the macro variable $\Delta_{\tau_{-1},\tau_1,t_1} m_i$ is named SVAR_PCA_B1.

6 Results

This section discusses the results of the textual sentiment profile related to the 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.

Table 4 Federal reserve communications' sentiment—type of communication

	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	10.97	3.56	94.27	2.76	2.97
				(0.27)	(0.25)	(0.16)	(0.19)	(0.11)	(0.15)
Meeting	49.67	47.71	2.61	85.16	11.19	3.65	94.15	2.89	2.96
				(0.27)	(0.25)	(0.17)	(0.19)	(0.11)	(0.15)
Telephone Conference	63.64	27.27	9.09	89.72	7.98	2.29	95.94	0.97	3.09
				(1.10)	(0.78)	(0.65)	(0.88)	(0.32)	(0.76)
Fed Chair Statements	51.50	46.65	1.85	77.82	14.91	7.27	90.37	3.68	5.95
				(0.09)	(0.07)	(0.06)	(0.05)	(0.03)	(0.05)
Testimony before the	41.99	56.28	1.73	78.08	14.55	7.37	90.23	3.43	6.34
House of Representatives				(0.18)	(0.13)	(0.11)	(0.11)	(0.06)	(0.10)
Testimony before the Senate	50.00	48.98	1.02	78.09	14.58	7.33	90.10	3.59	6.31
				(0.19)	(0.15)	(0.12)	(0.12)	(0.06)	(0.11)
Testimony before a Joint	55.26	42.11	2.63	79.21	13.47	7.32	89.80	3.61	6.59
Committee				(0.34)	(0.24)	(0.20)	(0.20)	(0.10)	(0.18)
Remarks before an	55.09	43.52	1.38	77.35	15.38	7.28	90.50	3.83	5.67
Institution				(0.12)	(0.11)	(0.09)	(0.08)	(0.05)	(0.08)
Other (Press Briefing	53.85	36.54	9.62	78.84	14.63	6.53	91.50	3.51	5.00
Dedication, Interview)				(0.48)	(0.46)	(0.35)	(0.29)	(0.16)	(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	66.36	33.03	86.46	72.67	27.33	89.13	43.27	56.73
	(2.19)	(0.95)	(0.88)	(0.26)	(1.14)	(1.14)	(0.43)	(2.18)	(2.18)
Meeting	50.95	66.71	33.29	86.16	72.55	27.45	88.99	44.67	55.33
	(2.25)	(0.89)	(0.89)	(0.25)	(1.14)	(1.14)	(0.44)	(2.23)	(2.23)
Telephone Conference	59.32	61.46	29.45	90.54	74.44	25.56	91.04	19.89	80.11
	(9.54)	(6.85)	(4.23)	(1.17)	(6.47)	(6.47)	(1.99)	(6.95)	(6.95)
Fed Chair Statements	51.51	72.76	26.98	76.55	63.94	36.06	86.86	30.40	69.60
	(0.87)	(0.41)	(0.39)	(0.10)	(0.25)	(0.25)	(0.10)	(0.37)	(0.37)
Testimony before the	45.87	70.03	29.11	76.91	62.94	37.06	86.09	26.75	73.25
House of Representatives	(1.93)	(0.93)	(0.84)	(0.20)	(0.45)	(0.45)	(0.16)	(0.54)	(0.54)
Testimony before the Senate	50.04	71.65	28.35	77.04	63.13	36.87	85.82	27.94	72.06
	(2.08)	(0.88)	(0.88)	(0.22)	(0.51)	(0.51)	(0.18)	(0.66)	(0.66)
Testimony before a Joint	53.82	70.00	30.00	78.06	61.97	38.03	85.60	27.66	72.34
Committee	(3.36)	(1.57)	(1.57)	(0.37)	(0.81)	(0.81)	(0.31)	(0.95)	(0.95)
Remarks before an	53.79	75.32	24.68	75.92	64.72	35.28	87.54	32.71	67.29

Table 4 continued

	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
Institution	(1.21)	(0.53)	(0.53)	(0.14)	(0.38)	(0.38)	(0.17)	(0.58)	(0.58)
Other (Press Briefing	53.45	64.60	33.48	77.83	65.63	34.37	88.32	34.19	65.81
Dedication, Interview)	(4.15)	(2.54)	(2.30)	(0.59)	(1.94)	(1.94)	(0.41)	(2.51)	(2.51)

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

6.1 Sentiment of FOMC and fed chair statements

Table 4 displays 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 show 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 Congress, it seems to have a bias for being more emotional and positive, than when presenting in other circumstances.

In the next step, we study the connection with the main question of this research: Can Fed Chairs be tagged by their statements' sentiment, in the sense that we can create a textual risk-profile style? If that is the case, we should observe their statements' sentiment cluster, and we will need every cluster to have a statistically significant difference from each other. Table 5 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.

We investigate the differences among Chairs by providing the Kolmogorov–Smirnov test of sample differences in Table 6. The results show that there is a statistically significant

Table 5 Federal reserve chair statements' sentiment

	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)

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 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 versus 353 words in their positive base.

We still need to check if the textual sentiment profile differences are due to the macroeconomic environment, or due to other personal characteristics. This is thoroughly addressed in Sect. 6.2, but by looking into the interest rate levels (see Fig. 4), and the macroeconomic situation during the two different regimes observed (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, a combination of high inflation and a high unemployment rate. Nevertheless, the sentiment in their documents, on average, is quite the opposite: while Burns has a very neutral position, Volcker was quite emotional and positive. This is the first important contribution to the monetary policy analysis 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.

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.[15] Table B1 in the Online Appendix shows the results and we can observe that the different sentiment methodologies can extract similar features, and this intersection is consistent in the different analyses we explore in this study.

6.2 Federal reserve chair statements' sentiment and personal characteristics

Table 7 displays the results that confirm our conjecture on our first question: the sentiment of the Fed Chair's public statements reflects a personal tone, that is recognizable given the personal characteristics, controlling 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).

The sub-panels in columns (1), (3), and (5) show the fixed-effects regressions of the model in Equation (20) without the personal characteristics, and columns (2), (4), and (6) show model in Equation (20) 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

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

Table 6 Federal reserve chair statements' neutral sentiment—Kolmogorov–Smirnov test

Panel A: All Statements

Panel A.1: Naïve Bayes (NLTK)—Neutral Sentiment Sorting

	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—Neutral Sentiment Sorting

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		–	(≮)	(<) ***	(<) *

Table 6 continued

Panel B: Only Last Statement Before FFTR Change—Neutral Sentiment Sorting					
	Panel B.1: Naïve Bayes (NLTK)—				
	Volcker	Greenspan	Miller	Burns	Bernanke
Miller			–	($\nless$)	($\nless$)
Greenspan				–	($\nless$)

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)

Table 7 Federal reserve chair statements' neutral sentiment and personal characteristics

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	−19.7	42.5	−4.0***	9.8	−3.1***	−1.9
Production	(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)

Table 7 continued

Panel A: $NeutSentFRC_t$ Regressed by Macroeconomic and Personal Characteristics						
	Naïve Bayes		Harvard IV (Tetlock)		Loughran & McDonald	
Model	(1)	(2)	(3)	(4)	(5)	(6)
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		−0.95		0.60***		0.15**
Background		(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

The table shows the fixed-effects regressions of the Fed Chair statement neutral sentiment as in baseline model Equation (20). The Fed Chair statements' sample is from January 01, 1971 to December 31, 2015. Panel A shows the nested model in Equation (20): 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 (20) 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

the Chair.[16] 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.[17]

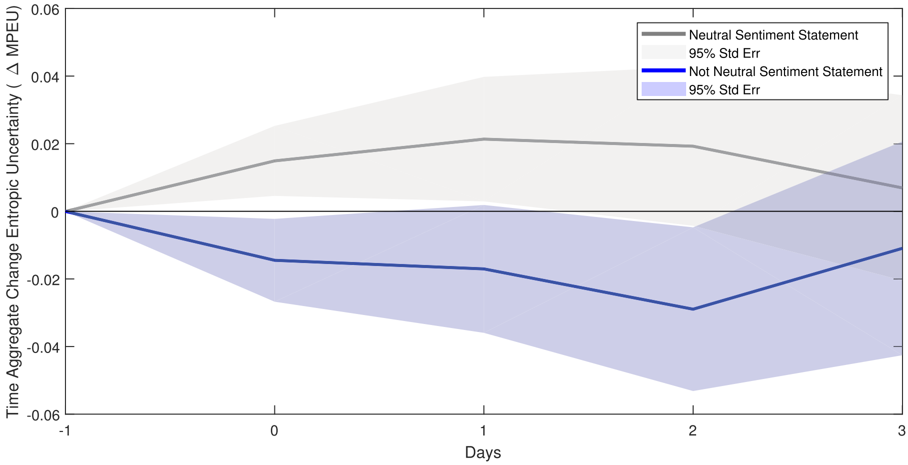
6.3 Empirical results

Figure 6 shows the resulting mean time aggregate.[18] change of uncertainty in monetary policy: Panel A shows the change in monetary policy entropic uncertainty ($MPEU$) of the market beliefs, as in Equation (13), and Panel B the change in market-based monetary policy uncertainty (MPU), both conditional on the sentiment of the Fed Chair statement released (day=0), *neutral* in the gray line, and *non-neutral* (emotional) in the blue line, with

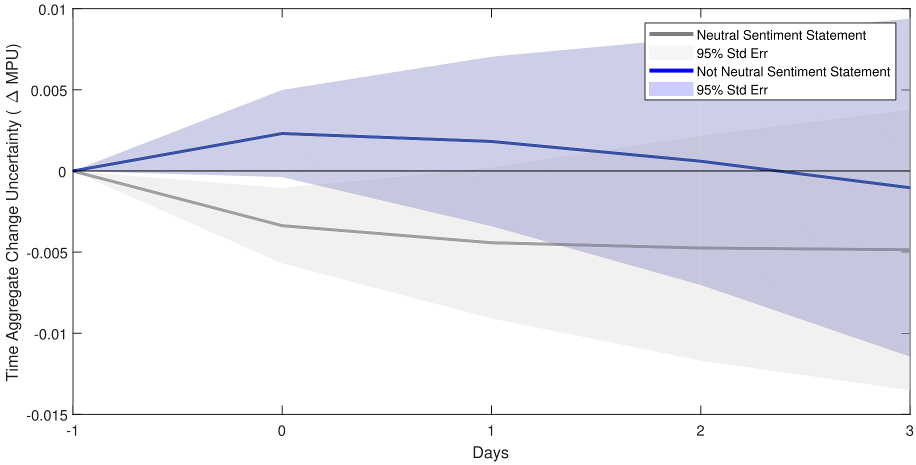
[16] These results are aligned with Malmendier et al. (2021), which finds that inflation affects the tone of the FOMC members.

[17] It is important to note that the sign of the parameter for the change in M1 (ΔM1) is influenced by the choice of sentiment dictionary. This highlights the sensitivity of sentiment analysis results to the specific characteristics and domain alignment of the dictionaries used.

[18] In the Online Appendix E we show time change $MPEU_{t_1}$ and MPU_{t_1} results per Fed chair period, finding that Volcker and Greenspan periods (the least neutral and more sentimental) is where the difference between the impact of the neutral and non-neutral sentiment of statements/speeches is more distinguishable; while the patterns of the more neutral Fed chairs might be associated to a different personality—as revealed by Table 7, we have to consider that their behavior might be inconsistent as well (Lähner, 2017) In unreported results we found that the sentiment of Ben Bernanke, went from more sentimental before his tenure as chair, to neutral (statistically significant) during his tenure, indicating potential changes to profile during tenure.



(a) Monetary Policy Entropic Uncertainty (MPEU)



(b) Monetary Policy Uncertainty (MPU – Bauer et al., 2021)

Fig. 6 Time aggregate change in monetary policy entropic uncertainty (MPEU) of the FFTR changes expected by the market for the next FOMC meeting after a Fed Chair statement release, Monetary Policy Uncertainty (MPU—Bauer et al., 2021), and Neutral sentiment of the Fed Chair statement. MPEU 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 (3) (4), (7), and (8) with the restrictions in Equation (6) and (9). MPU is provided by Bauer et al. (2021) (https://www.michaeldbauer.com/research/).Neutral Sentiment of the Fed chair statement is calculated as in Sect. 4.1. The 1-Month Eurodollar, 3-Month Eurodollar, and FFTR interest rates' sample is from January 01, 1971 to December 31, 2015

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 time aggregate change in $MPEU$, $\Delta MPEU_{t_1,t_2}$ 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 ($t_2 = 0$), and the next three days after the statement release ($t_2 \in \{1, 2, 3\}$). For the day of the statement release, $MPEU$ growth, $\Delta MPEU_{t_1,t_2}$, has a value different to zero (it is not the starting point of observation), given that we consider daily closing prices, and during that day the interest rate closing prices had already been affected. The results show that the sentiment of the Fed chair statement has an effect in both types of uncertainty: (i) in the case of $MPEU$, the neutral sentiment of the Fed chair statement (non-informativeness), is associated with an increase, while non-neutral (emotional) statements are associated with a decrease of the uncertainty, and (ii) in the case of the MPU, the neutral sentiment statement has an effect on decreasing uncertainty, while non-neutral sentiment has an effect of increasing the uncertainty.

In both cases, the neutral sentiment effect is significant, while the non-neutral case is significant only in the $MPEU$ case, but still reveals an opposite direction in the $\Delta MPU_{t_1,t_2}$ similar to the case of $\Delta MPEU_{t_1,t_2}$. These differences in the impact of uncertainty might be related to changes in the monetary policy stance of the Fed chair statement, an "analytical" sentiment that is usually more relevant for policymakers. Then, using the dictionary of monetary policy stance as in Sect. 4.3, similar to Gardner et al. (2022) "analytical" sentiment dictionary, we estimate the same time aggregate change in $MPEU$ and MPU, $\Delta MPEU_{t_1,t_2}$ and $\Delta MPU_{t_1,t_2}$, but with the monetary policy stance instead of neutral sentiment as condition, where the *Fed chair stance* that maintains the same stance of the Fed program in the gray line, and the *Fed chair stance* that changes the *stance of the Fed program* in the blue line, with 95% confidence intervals in the shaded gray and the shaded blue, respectively. Figure 7b shows the results. We can observe that there is no significant change in the $\Delta MPEU_{t_1,t_2}$ nor in $\Delta MPU_{t_1,t_2}$, strengthening the relevance of the emotions in the statement (neutral sentiment).

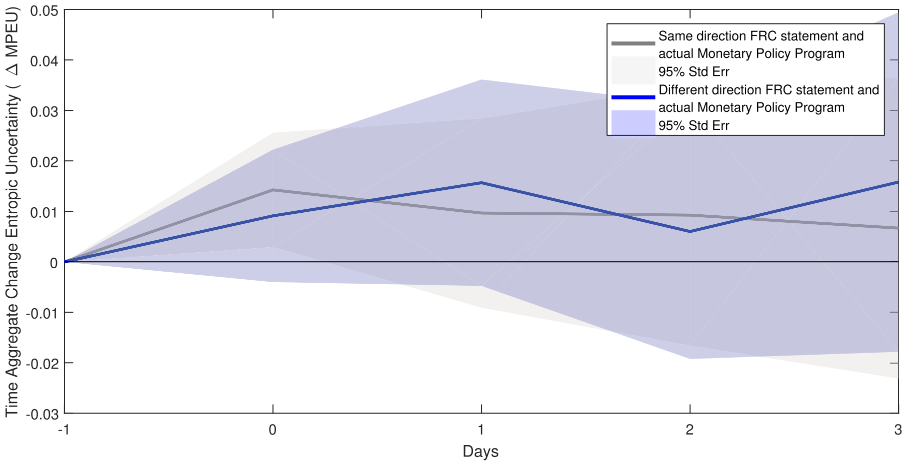
This initial analysis reveals the "*complementary*" effects of the Fed chair statement sentiment: while it reduces the market-based (option implicit—risk-neutral measure based) MPU, it increases the (market beliefs—physical measure) $MPEU$. These two effects, imply a reduction in the uncertainty premium, offering a potential response to Fed information channel puzzle (Cochrane & Piazzesi, 2002) during Fed chair statement releases.

To analyze further this "*complimentary*" effect between $MPEU$ and MPU, we analyze the time aggregate change that occurs during the FOMC statement announcement day. Figure 8 shows that the MPU is reduced (as in Bauer et al. (2021) Fig. 3) during the FOMC days,[19] while the $MPEU$ is relatively controlled before the FOMC statement is announced, but increases immediately after (given the market starts to analyze what will be the FFTR that the FOMC will set in the next meeting).[20]

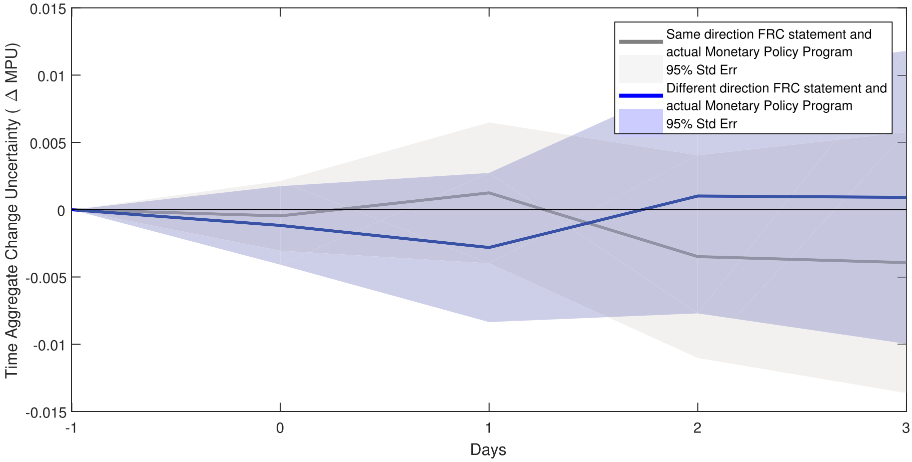
These analyses (Figs. 6 and 8) are initial exploratory investigations; then, we need to check the SVAR results to identify the effect of the shock on the macroeconomic variables. Figures 9, 10, and 11 show the partial results of the impulse response (IR) functions (see the Online Appendix for the full IR plots) of the SVAR specifications SVAR_PCA1, SVAR_LASSO1, and SVAR_LASSO2 (See Equations (21) and (22) in Sect. 5), for the effects of the Non-Informativeness *Fed-chair-information* shock (proxied by $NeutSent_{t_1}$) over the market-based monetary policy uncertainty (MPU_{t_1}) and the monetary policy entropic uncertainty ($MPEU_{t_1}$). For the SVAR specification with PCA regularization (SVAR_PCA1—Fig. 9), we observe that the initial results are confirmed: an increase in Non-informativeness ($NeutSent_t$) reveals an increase in $MPEU_{t_1}$ and a decrease of MPU_{t_1}, and the increase in $MPEU_{t_1}$ is signification after 2 lags (2 statements releases). In the SVAR specification with LASSO regularization (SVAR_LASSO1—Fig. 10), we find the

[19] Our plot differs from Bauer et al. (2021) as we consider the starting point 5 days before the FOMC statement announcement day, but our plot is consistent with Fig. 3 of Bauer et al. (2021) as there is an incremental reduction of MPU around the FOMC day.

[20] The FFTR change occurs the same day of the FOMC statement announcement day.



(a) $\Delta MPEU_{t_1,t_2}$ Change – Full Period – Hawkish/Dovish Sentiment Direction

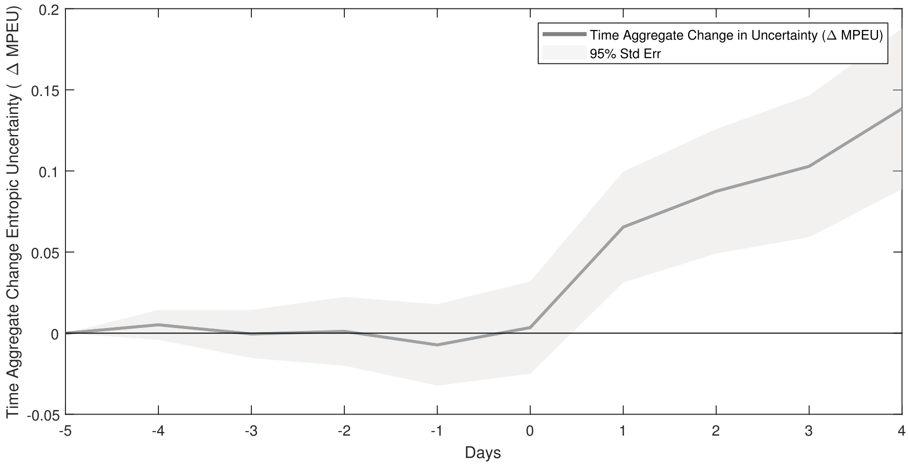


(b) $\Delta MPU_{t_1,t_2}$ Change – Full Period – Hawkish/Dovish Sentiment Direction

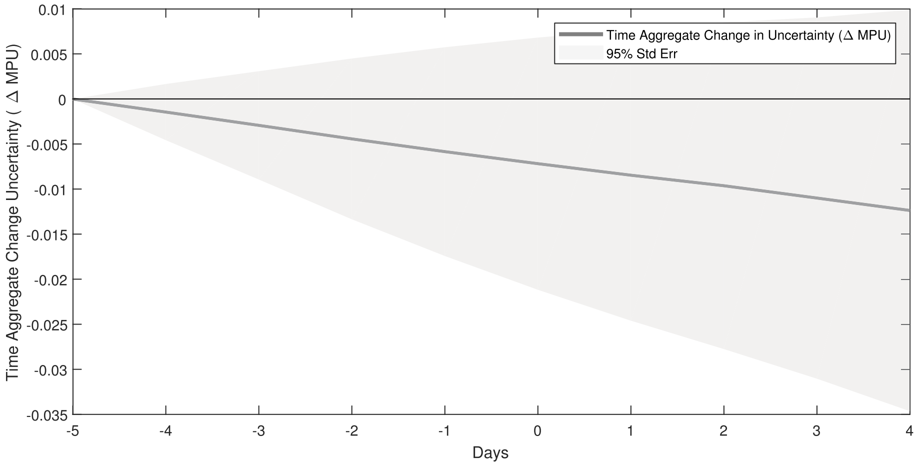
Fig. 7 Time aggregate change in monetary policy entropic uncertainty (MPEU) of the FFTR changes expected by the market for the next FOMC meeting after a Fed Chair statement release, Monetary Policy Uncertainty (MPU—Bauer et al., 2021), and monetary policy stance of the Fed Chair statement. MPEU is calculated 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 (3) (4), (7), and (8) with the restrictions in Equation (6) and (9). MPU is provided by Bauer et al. (2021) (https://www.michaeldbauer.com/research/). Direction of the monetary policy stance of the Fed chair statement versus monetary policy stance program of the Fed is calculated as in Sect. 4.3. The 1-Month Eurodollar, 3-Month Eurodollar, and FFTR interest rates' sample is from January 01, 1971 to December 31, 2015

same results, but less statistically significant than with PCA regularization. These results confirm the importance of the Non-informativeness shock (proxied by $NeutSent_{t_1}$) in the monetary policy uncertainty dynamics.

Figure 11 shows the partial results (see full results in the Online Appendix) of the SVAR response function of the MPU_{t_1} reaction to the monetary policy entropic uncertainty shock ($MPEU_{t_1}$). This specification was defined as SVAR_PCA3. Figure 11 confirms the inverse



(a) Monetary Policy Entropic Uncertainty (MPEU)

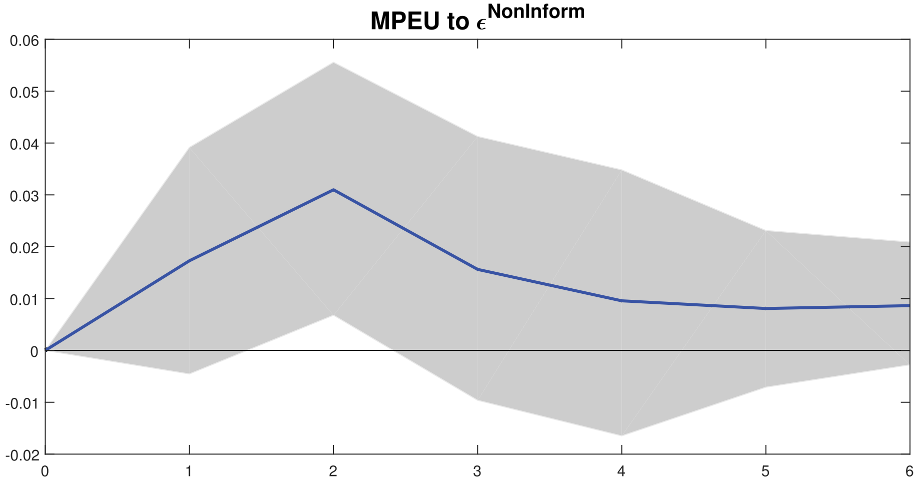


(b) Monetary Policy Uncertainty (MPU – Bauer et al., 2021)

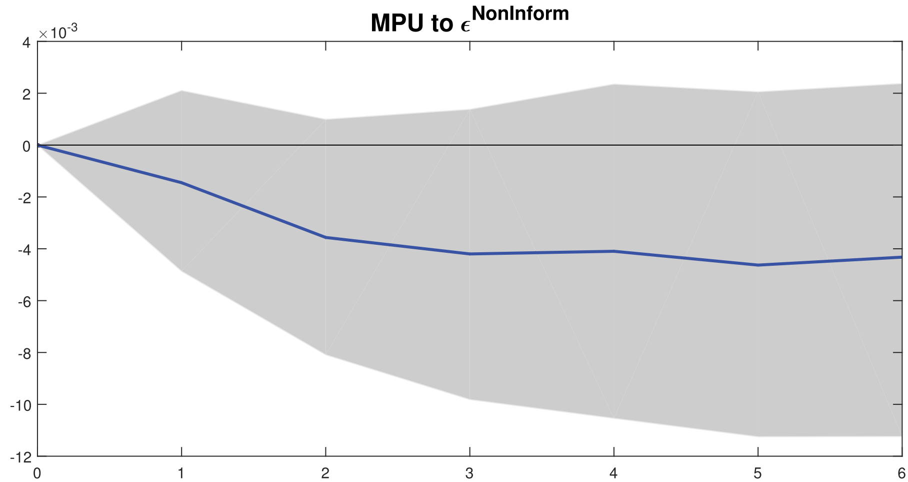
Fig. 8 FOMC Announcement Days—Aggregate Change in Monetary Policy Entropic Uncertainty (MPEU) and Monetary Policy Uncertainty (MPU—Bauer et al., 2021). Uncertainty variables are calculated as the average time aggregated difference against 5 days before the FOMC announcement day (Day=0). MPEU is calculated 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 (3) (4), (7), and (8) with the restrictions in Equation (6) and (9). MPU is provided by Bauer et al. (2021) (https://www.michaeldbauer.com/research/). Neutral Sentiment of the Fed chair statement is calculated as in Sect. 4.1. The 1-Month Eurodollar, 3-Month Eurodollar, and FFTR interest rates' sample is from January 01, 1971 to December 31, 2015

relationship between MPU_{t_1} and $MPEU_{t_1}$ changes during the release day of the Fed chair statement.

An event study assessment of the $MPEU$ changes during other macroeconomic variables announcements is another robustness check. Only four (4) macroeconomic variables have daily datasets with their original announcement dates (ALFRED St. Louis Fed database) for the period covered in this study (1971–2015): CPI, Industrial Production, M1, and Unemployment rate, defined in Sect. 3.1. Figure 12 shows the results, indicating that no other



(a) Monetary Policy Entropic Uncertainty (MPEU)



(b) Monetary Policy Uncertainty (MPU – Bauer et al., 2021)

Fig. 9 SVAR response of Monetary Policy Entropic Uncertainty (MPEU) and Monetary Policy Uncertainty (MPU—Bauer et al., 2021) to Non-Informativeness Shock Using PCA Regularization. SVAR is identified with the SVAR_PCA1 specification in Equation (21). MPEU 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 (3) (4), (7), and (8) with the restrictions in Equation (6) and (9). MPU is provided by Bauer et al. (2021) (https://www.michaeldbauer.com/research/). Neutral Sentiment of the Fed chair statement is calculated as in Sect. 4.1. The 1-Month Eurodollar, 3-Month Eurodollar, and FFTR interest rates' sample is from January 01, 1971 to December 31, 2015

macroeconomic variable announcement day is clearly significant for changes in the MPEU uncertainty in regards to the jointly increase/decrease relationship (gray shaded area non-overlapping the blue shaded area). Nevertheless, when the 1-period (1-month) lagged changes on the macroeconomic variables are less than two (2) standard deviations, the MPEU tends to be reduced the next day. For the case of the effects of macroeconomic variables in MPU

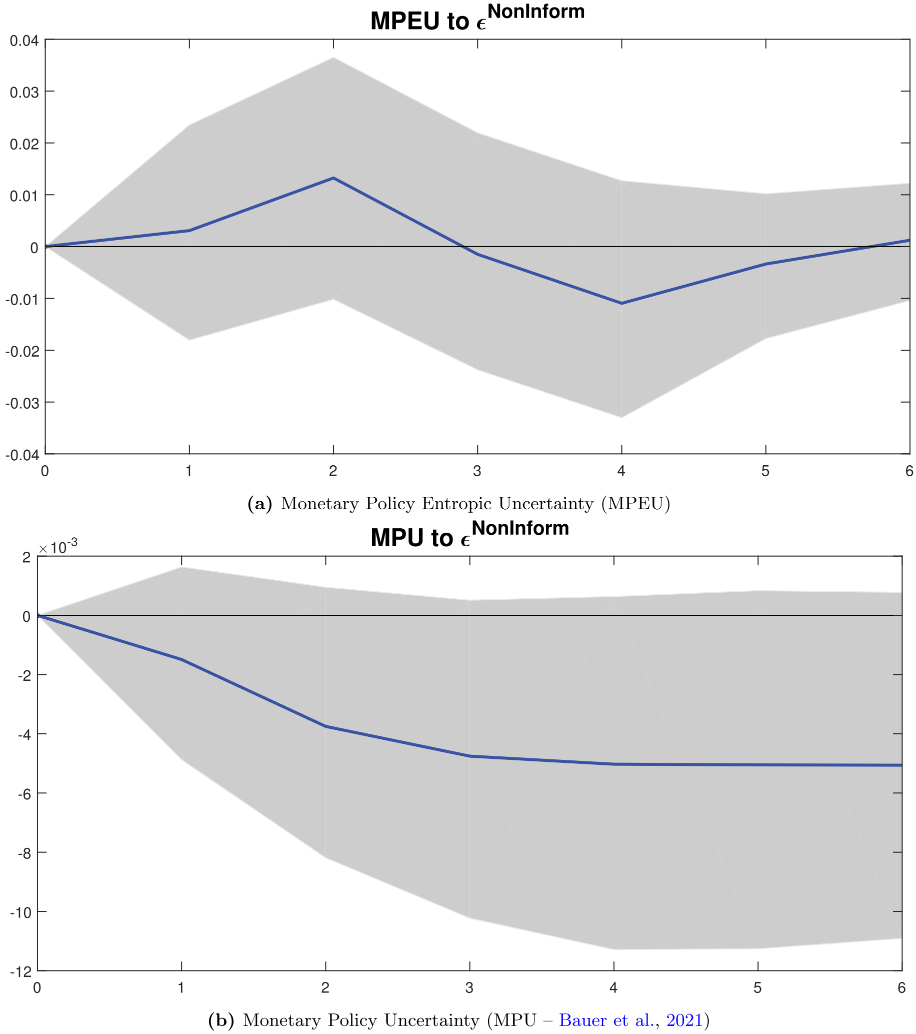


Fig. 10 SVAR response of Monetary Policy Entropic Uncertainty (MPEU) and Monetary Policy Uncertainty (MPU—Bauer et al., 2021) to Non-Informativeness Shock Using LASSO Regularization. SVAR is identified with the SVAR_LASSO1 specification in Equation (22). MPEU is calculated as the difference of the probability of and increase minus the probability of a decrease of the FFTR. The implicit probabilities are calculated by solving Equations (3) (4), (7), and (8) with the restrictions in Equation (6) and (9). MPU is provided by Bauer et al. (2021) (https://www.michaeldbauer.com/research/). Neutral Sentiment of the Fed chair statement is calculated as in Sect. 4.1. The 1-Month Eurodollar, 3-Month Eurodollar, and FFTR interest rates' sample is from January 01, 1971 to December 31, 2015

(see Online Appendix) we observe no significant joint increase/decrease relationship for announcements with changes of more/less than two (2) standard deviations.

A concern with monetary policy and SVAR analyses is the possibility of structural breaks. In Section J of the Online Appendix we have implemented Lütkepohl and Netšunajev (2013) Smooth Transition SVAR (ST-SVAR) and we observe a transition appears around 1994. Then, we explore the SVAR results on the sentiment effects on uncertainty (MPEU and MPU) for

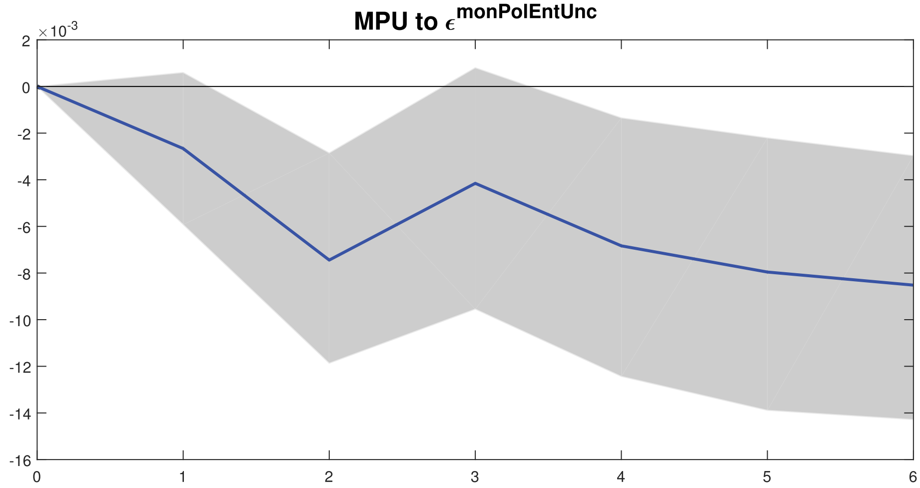
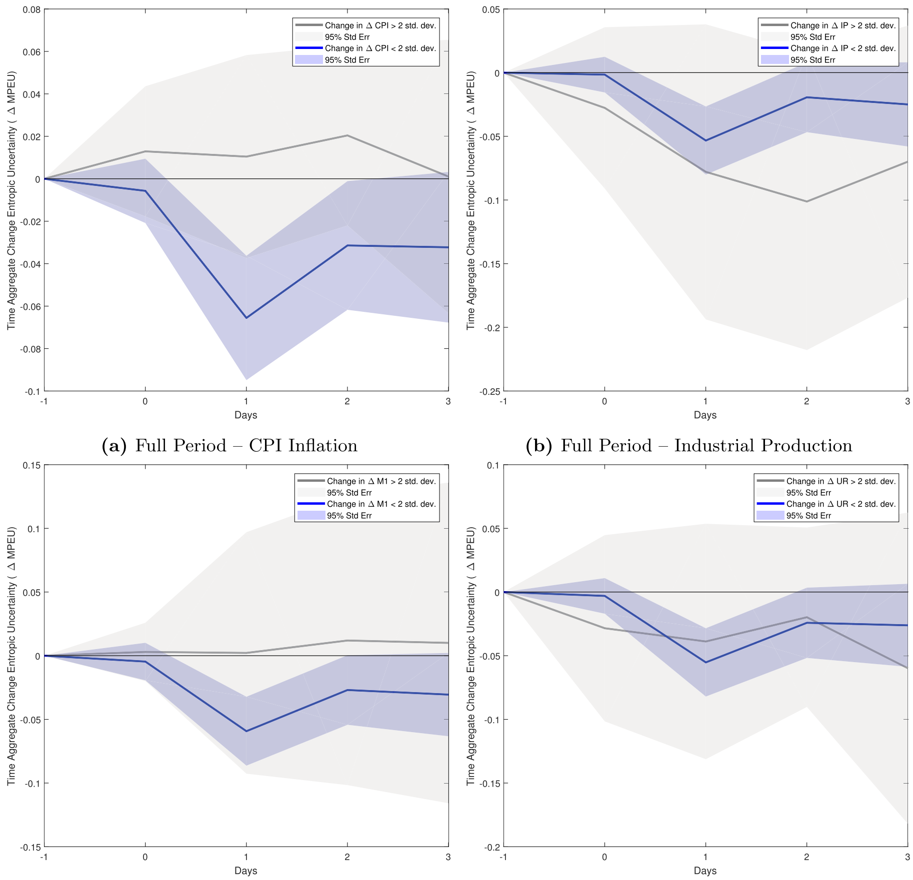


Fig. 11 SVAR response of Monetary Policy Entropic Uncertainty (MPEU) and Monetary Policy Uncertainty (MPU—Bauer et al., 2021) to Non-Informativeness Shock—SVAR_LASSO2. SVAR is identified with the SVAR_LASSO2 specification. MPEU is calculated as the difference of the probability of and increase minus the probability of a decrease of the FFTR. The implicit probabilities are calculated by solving Equations (3) (4), (7), and (8) with the restrictions in Equation (6) and (9). MPU is provided by Bauer et al. (2021) (https://www.michaeldbauer.com/research/). Neutral Sentiment of the Fed chair statement is calculated as in Sect. 4.1. The 1-Month Eurodollar, 3-Month Eurodollar, and FFTR interest rates' sample is from January 01, 1971 to December 31, 2015

two sets: one with the period before 1994, and the other with the period after 1994, finding that results are stronger after 1994.

6.4 Forward guidance implications

When we talk about monetary policy, we need to include the Forward guidance practice that played a crucial role for the Federal Reserve Chairs during the Zero Lower Bound (ZLB) period (2009–2015) (Campbell et al., 2019; Andrade et al., 2019; Lunsford, 2020; Swanson, 2021; Sutherland, 2023). Our measure of uncertainty (MPEU) also reveals that the market expectations on the future rate changes can be used as an input, see Fig. 2, to measure the level of agreement or disagreement (uncertainty) of the market with future actions of the Chair. Moreover, we can discuss how the MPEU can be implemented to study the dynamics of the monetary policy in the long-term horizon (see Online Appendix G). The SVAR results in Figs. 9 and 10 show that the "informativeness" effect correspond not only to one particular statement but to a set of statements. In addition, Table 3 reveals that the wordings the Fed Chair uses in their statements, associated with the sentiment of the statement, such as "stability", "improve", and "challenges", aim to establish a path to provide information about the future monetary policy intentions. The machine learning-based sentiment indicators have the advantage of providing an indicator that exploits text analysis and big data powers to describe the future path of the dynamics of the monetary policy.



(a) Full Period – CPI Inflation

(b) Full Period – Industrial Production

(c) Full Period – M1

(d) Full Period – Unemployment Rate

Fig. 12 Time aggregate change in monetary policy entropic uncertainty (MPEU) of the FFTR changes expected by the market for the next FOMC meeting after a Fed Chair statement release, During Macroeconomic Variables Announcement Days. MPEU 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 (3) (4), (7), and (8) with the restrictions in Equation (6) and (9). The macroeconomic days are split in two groups: (i) days selected for announcements where the change is greater than two (2) standard deviations, and (ii) days selected for announcements where the change is less than two (2) standard deviations (the complement set). The 1-Month Eurodollar, 3-Month Eurodollar, and FFTR interest rates' sample is from January 01, 1971 to December 31, 2015

7 Conclusions

The Federal Reserve communication process is a delicate mechanism that the monetary policy institution uses to control the dynamics of the monetary policy. We find that there is sentiment present in the Federal Open Market Committee (FOMC) and the Federal Reserve Chair statements, where we find a textual sentiment profile of the Fed Chairs that is produced by personal choice over the macroeconomic circumstances and personal characteristics. Thanks to machine learning tools, we provide novel empirical evidence with ad-hoc indicators that represent the monetary policy uncertainty (MPEU and MPU) and that affect 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 for 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 communication mechanisms. The reduction of effects of the Fed Chair statements' sentiment is associated with greater effectiveness in the implementation of the monetary shock, by reducing the sentiment and increasing the "*market uncertainty*". Our results provide a novel 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.

7.1 Future research

Future research may investigate how Federal Reserve Chairpersons modify their communication strategies in reaction to market responses, and whether financial market participants demonstrate a learning curve in interpreting these communications over time. Our findings indicate significant differences in communication patterns among Chairmen, with sentiment tones growing less neutral as FOMC meetings approach, reflecting an adaptive communication strategy.

It is possible that future research will investigate the additional effects that other members of the FOMC board have on the formation of interest rates and asset prices or the relationship between the sentiment expressed by the Fed Chair and an unconventional monetary policy scheme. This is particularly relevant in light of the fact that the most important central banks, including the Federal Reserve, have adopted this system in recent years. Additional sentiment analysis using other sources of non-digital information, such as audio and video recordings of the Fed Chair's press releases, would be an intriguing subject for further investigation. This could be a potential avenue for research in both monetary policy and machine learning tools applied to macroeconomics.

Future research should explore the impact of advanced econometric methods and central bank communication on improving the accuracy of economic forecasting (Brubakk et al., 2021 and Moschella and Romelli, 2022, among others), and as a further investigation, we can rely on our approach, considering forward-looking agents, to predict future interest rates in an out-of-sample exercise by estimating both univariate (i.e. ARMA, Lasso or Ridge regressions) and multivariate models (Bayesian VAR). This will improve our understanding of how these factors contribute to reducing market uncertainty and improving the predictability of monetary policy (Blinder et al., 2008 and Couppey-Soubeyran, 2020, among others).

Similarly, future research can explore the adaptability of our methodology to analyze various types of uncertainty in economic policy (following the EPU introduced by Baker et al. (2016b)), such as monetary policy (Husted et al., 2020b), trade policy (Caldara et al., 2020), geopolitical risk (Caldara & Iacoviello, 2022), environmental policy (Wossink & Gardebroek, 2006), financial regulation policy (Nodari, 2014), and fiscal policy (Anzuini et al., 2020). Investigating these applications will help determine the broader applicability and robustness, in particular, of text-based sentiment indicators to capture nuanced economic signals across different policy domains. However, none of these other indicators captures the importance of the tone of central bank governors as effectively as our sentiment indicator.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s10479-024-06414-6.

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