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Central bank sentiment and policy expectations

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Abstract

We explore empirically the theoretical prediction that optimism or pessimism have aggregate effects, in the context of monetary policy. First, we quantify the tone conveyed by FOMC policymakers in their statements using computational linguistics. Second, we identify sentiment as the unpredictable component of tone, orthogonal to fundamentals, expectations, monetary shocks and investors' sentiment. Third, we estimate the impact of FOMC sentiment on the term structure of private interest rate expectations using a high-frequency methodology and an ARCH model. Optimistic FOMC sentiment increases policy expectations primarily at the one-year maturity. We also find that sentiment affects inflation and industrial production beyond monetary shocks.

Key words: Animal spirits, optimism, confidence, FOMC, interest rate expectations, central bank communication, ECB, aggregate effects.

JEL classification: E43, E52, E58.

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1. Introduction

Cyclical fluctuations in macroeconomic activity and asset markets depend on beliefs about future outcomes. Pigou (1927) believed that business cycle fluctuations are driven by expectations and that entrepreneurs' errors of optimism and pessimism are crucial determinants of these fluctuations. Keynes (1936) highlighted the importance of changes in expectations that are not necessarily driven by rational probabilistic calculations, but by what he labeled "animal spirits". More recently, Angeletos and La'O (2013), Angeletos, Collard and Dellas (2015) and Benhabib, Wang and Wen (2015) have analysed how "sentiments" or "confidence" may drive business cycle fluctuations. Quantifying these unobservable concepts is important to understand how financial markets' participants, firms and households form their expectations and make their decisions.

This paper aims first to quantify these concepts of animal spirits, confidence, market sentiment or waves of optimism and pessimism in central bank communication, and second to explore empirically the theoretical prediction that sentiments, that are orthogonal to fundamentals, beliefs about fundamentals, may have aggregate effects, in the context of the US monetary policy.[1] Specifically, we investigate whether the sentiment conveyed by policymakers at the Federal Open Market Committee (FOMC) in their statements, quantified using computational linguistic methods, affect the term structure of private agents' short-term interest rate expectations. We also assess whether this effect is non-linear and depends on the state of the economy. Beyond this direct channel, we examine whether this central bank sentiment is transmitted to inflation expectations, inflation and industrial production.

Because long-term interest rates – a key determinant of private investment and consumption decisions – depend on expected short-term interest rates plus a term premium, central banks over the last decades have enhanced transparency of their actions and communication to the public in order to better signal future policy decisions, shape private expectations and optimise their policy outcomes (see e.g. Geraats, 2002; Woodford, 2005; King, Lu and Pasten, 2008, Reis, 2013). The question of whether central bank communication has been successful in affecting financial markets or helping predict policy decisions has given rise to

[1] The question of the effect of the policymakers' sentiment may also be raised in other contexts such as fiscal policy. For example, Frankel (2011) suggests that the over-optimism of official GDP and budget balance forecasts could be explained by the will of governments to boost consumer and business confidence.

an abundant literature surveyed by Blinder et al. (2008). However, the question of its transmission mechanism and why central bank communication affects private beliefs remains a much more open question. Gürkaynak, Sack and Swanson (2005) have shown the importance of information about the future policy path embedded in FOMC statements. Two usual candidates for the information revealed to private agents by central bank communication are signals about policymakers' views about the current and future state of the economy and signals about their reaction function (which would include, for instance, the forward guidance policy and the commitment to deviate from a given policy rule). This paper explores another specific dimension: the sentiment conveyed by central bank communication, orthogonal to current or future policy and macroeconomic developments and standard monetary shocks.

The first empirical challenge for investigating central bank communication and for measuring such an intangible concept as *central bank sentiment* is to convert the policy statements into quantities that we can systematically analyse. The first contribution of this paper is to quantify the tone conveyed by FOMC statements using computational linguistic methods and more precisely dictionary methods.[2] Their main advantages are automation and replicability. We use three different dictionaries that cover central banking, everyday and financial contexts, respectively the Apel and Blix-Grimaldi (2012)'s dictionary, the General Inquirer's Harvard dictionary and the one developed by Loughran and McDonald (2011). Using dictionary methods, we also compute a measure that captures the signal precision conveyed in policy statements. Many studies have coded indicators of the monetary policy stance conveyed by central bank communications (see e.g. Ehrmann and Fratzscher, 2007, Hayo and Neuenkirch, 2010, or Hubert, 2016) and many studies in finance have computed market sentiment measures (see e.g. Tetlock, 2007, and Tetlock et al., 2008), but none has quantified the sentiment conveyed by monetary policymakers.[3] The closest papers to ours are Lucca and Trebbi (2011), Hansen, McMahon and Prat (2015) and Hansen and McMahon (2016). The first paper uses computational linguistics to obtain semantic orientation between hawkish and dovish FOMC

[2] This central bank sentiment could potentially stem from policymakers' subjective probabilities, non-nested information sets, risk aversion, cognitive bias, or even the central bank press office. This sentiment could also be intentional or not, and so used strategically. These questions however are beyond the scope of this paper, which objective is to investigate whether such sentiment does exist and affects private interest rate expectations.

[3] In sociology, Fligstein, Brundage and Schultz (2014) use computational linguistics on FOMC transcripts to measure sense-making of deliberations, while Acosta (2015) also uses computational linguistics on FOMC transcripts and minutes to analyze the FOMC's responses to calls for transparency.

communications. However, while they focus on the policy stance of central bank communication, sentiment is by definition orthogonal to communication about the current and future policy stance. The second paper uses probabilistic topic modelling that decomposes documents in terms of the fraction of time spent covering a variety of topics. They analyse how the internal deliberations during FOMC meetings have been affected by the release of FOMC transcripts after 1994. The third paper evaluates the tone associated to the different topics contained in FOMC statements and measures their effects on market and real economic variables.

This paper aims to quantify whether there are such "waves of optimism and pessimism" independent from topics and fundamentals conveyed to the public by monetary policymakers; said differently, whether the choice and use of some specific words rather than some others to formulate a given message matters. In that respect, sentiment may be viewed as soft information conveyed through the *tone* of policymakers' communication beyond traditional quantitative and qualitative information conveyed through the *content* of their communication.

Our second contribution to the literature is to investigate whether this policymakers' sentiment affects the term structure of private interest rate expectations. It requires overcoming a second empirical challenge. Our computed tone measure is endogenous to the business cycle, because the quantitative output of the computational linguistic method captures a combination of beliefs about the current and future state of the economy and sentiments. To correct for that endogeneity and comply with the main assumption of Angeletos and La'O (2013), we identify the unpredictable component of central bank tone such that central bank sentiment shocks are orthogonal to fundamentals, expectations of future fundamentals, standard monetary shocks (be it a Federal Funds rate shock à la Kuttner, 2001, or a communication shock à la Gürkaynak, Sack and Swanson, 2005) and investors' sentiment. This identification strategy follows Romer and Romer (2004) and augments it in two ways. First, exogenous sentiment shocks are not only orthogonal to the central bank's information set but also to the private agents' information set. Second, following insights from the information frictions literature, the contribution of past sentiment shocks is stripped out.

We then use a high-frequency identification approach to isolate the effects of sentiment shocks from other-days events, controlling for the monetary shock happening the same day. We estimate the effect of sentiment on revisions in private beliefs about future policy, i.e. changes in private short-term interest rate expectations at maturities from 1 month to 10 years ahead, measured with Overnight Indexed Swaps (OIS). As common with financial variables and because of evidence of "volatility clustering" (Mandelbrot, 1963), we use an autoregressive conditional heteroskedasticity (ARCH) model developed by Engle (1982) to properly account for the presence of heteroskedasticity. We also estimate the dynamic effects of sentiment using the local projections method of Jorda (2005). Moreover, because the precision of the signal conveyed to the public would matter in a Bayesian updating model or because the position in the business cycle, the level of inflation or the level of financial stress could also potentially matter, we assess the non-linear effects of sentiment shocks. Finally, we test whether the effect of sentiment shocks on private interest rate expectations is transmitted to aggregate variables and therefore has a macroeconomic relevance. We examine the impact of sentiment on inflation expectations, whether it helps predict the next policy decision, and whether it impacts inflation and industrial production.

The main message of this paper is that central bank sentiment conveyed through the tone of central bank communication has effects on private interest rate expectations beyond monetary shocks, central bank projections and private sentiment. More specifically, we find that positive shocks to FOMC sentiment increase private short-term interest rate expectations. The peak effect in terms of magnitude and significance is around the 1-year maturity. This effect is robust to the dictionary used for the quantification of tone measures, to various alternative identification strategies of sentiment shocks, to alternatives estimation methods. In addition, we find a similar result when assessing the effect of the European Central Bank (ECB) sentiment. We also show that this effect is persistent and that the effect of sentiment is stronger when the precision of the signal conveyed is high (i.e. the ambiguity of central bank statements is low). The effect of sentiment shocks on private interest rate expectations is state-dependent and depends on the level of inflation, the business cycle and the level of financial stress measured with the VIX. Finally, we find that the effect of sentiment shocks is transmitted to other variables: they negatively influence 10-year inflation expectations, help predict the next policy decision and positively affect both inflation and industrial production.

These results give policymakers some insights on how private agents interpret and respond to the sentiment conveyed by central bank communication, which should be interpreted as optimism or pessimism signals beyond policy decisions and standard forms of communication. Our results suggest that sentiment shocks matter for shaping private interest rate expectations and that the characteristics of sentiment and the timing when it is conveyed matters in that respect.

The rest of this paper is organized as follows. We present the framework in Section 2 and the automated lexicographic methodology in Section 3. Section 4 introduces the financial and macro data. Section 5 is focused on the identification of exogenous sentiment shocks. In Section 6 we investigate the effect of sentiment on interest rate expectations and Section 7 assesses some further effects of sentiment. Section 8 concludes.

2. Sentiments in a Theoretical Framework

This section presents an existing theoretical framework from which predictions can be derived about how private interest rate expectations might react to shocks to the sentiment conveyed by central bank statements. Angeletos and La'O (2013) develop a unique-equilibrium, rational-expectations, macroeconomic model which features "animal spirits", labelled sentiments. In standard macro models, these phenomena would be modelled as exogenous random shocks to preferences, endowments, technology or other fundamentals. However, shifts in sentiments or aggregate demand seem to appear without innovations in people's preferences and abilities, or firms' technologies. The literature has also analysed aggregate fluctuations as the result of "animal spirits" in models with multiple equilibria (see Farmer, 2012, or Benhabib, Wang and Wen, 2015) or as departures from rationality with a learning process (see Milani, 2014).

Angeletos and La'O (2013) show that as long as information frictions prevent agents from reaching exactly the same expectations about economic activity, aggregate fluctuations in these expectations may be driven by a certain type of shocks which they call sentiments. These shocks are similar to sunspots but in unique-equilibrium economies, are modelled as shifts in expectations of economic activity without shifts in the underlying preferences and technologies, and refer to any residual, payoff irrelevant, random variable. Angeletos and La'O (2013) split the economy into different "islands" following Lucas (1972) and "sentiment shocks" impact the information that is available to each island, without however affecting first-order beliefs about the aggregate fundamentals (which are fixed) or about the idiosyncratic fundamentals of its trading partner (which are random). These shocks impact equilibrium expectations, because they modify the equilibrium belief that each island forms about the decisions of other islands. A positive sentiment shock can be considered as a shock that rationalizes the optimism of one island by making this island receive a signal that other islands are themselves optimistic.[4] The sentiment shock ξ_t is modelled as an exogenous random variable that affects information sets without affecting the true aggregate fundamentals or any agent's first-order beliefs about fundamentals (for the latter being fixed and common knowledge).[5] The sentiment shock ξ_t adds an aggregate noise component in the private signal that one island receives about another island's information about its own characteristics, but ξ_t does not affect beliefs of either fundamentals. The main result is that aggregate output and the average expectation can vary with the sentiment shock ξ_t and are increasing linear functions of ξ_t if and only if information is imperfect.

Angeletos, Collard and Dellas (2015) have then quantified the importance of the variations in sentiment (or confidence) in macroeconomic DSGE models. They find that sentiment shocks lead to strong co-movement between employment, output, consumption and investment and that they account for around one half of GDP variance and one third of the nominal interest rate variance at business-cycle frequencies.

We bring the issue of sentiment shocks to the data, by focusing on a specific fundamental: the expected short-term interest rate $r^E{}_t$ and the associated sentiment shocks ξ_t provided by a specific agent: the central bank, using computational linguistic models to quantify this unobservable variable. We acknowledge that this paper departs from the above-mentioned framework in two ways. First, the sentiment we consider emanates from a specific island, the central bank, that could affect all other islands. However, because the sentiment in Angeletos and La'O (2013) is about a signal that each island receives that other islands are themselves optimistic, we assume that the central bank

[4] These shocks can also be understood as shocks to higher-order beliefs. By introducing trading frictions and imperfect communication, there can be higher-order uncertainty at the micro level: when two islands are matched together, they are uncertain, not only about each other's productivities, but also about each other's beliefs of their productivities, each other's beliefs of their beliefs and so on. However, the authors prefer to interpret these sentiment shocks as shocks to first-order beliefs of endogenous economic outcomes, because agents only need to form first-order beliefs of the relevant equilibrium allocations and prices.

[5] This game-theoretic interpretation reveals an important connection between our micro-founded business-cycle economy and the class of more abstract coordination games studied by Morris and Shin (2002) and Angeletos and Pavan (2007): it is as if the islands were trying to coordinate their production choices.

sentiment could work in a similar fashion and affect the signal that islands receive. In that dimension, the central bank sentiment, though different in nature, spreads to private agents like animal spirits or investor sentiment would. Second, while the signal is about productivity in Angeletos and La'O (2013), it is related to the monetary policy stance in our specification because we focus on central bank sentiment.

Finally, in order to identify sentiment shocks from the central bank tone, two crucial assumptions of Angeletos and La'O (2013) must be fulfilled. We need to take information frictions into account and sentiment shocks must be orthogonal to beliefs about fundamentals or "news shocks", and so to private agents' and policymakers' macroeconomic information sets.

3. Quantifying Central Bank Tone

3.1. Central Bank Statements as a Source of Central Bank Tone

Quantifying central bank sentiment requires measuring central bank tone. We first need to identify the main source through which central bank sentiment may occur and be disclosed to the public. In that respect, central bank statements that follow monetary policy decision meetings seem to be the most relevant candidate for three reasons. First, they announce the policy decisions. Second, these statements act as a focal point for financial market participants, media, banks, monetary policy watchers and economists at the time when they are released, so these statements are made available to a large audience. They provide a detailed analysis of the central bank evaluation of the economic situation and of its assessment of risks to price and financial stability, and gives insights about the future likely policy path. These statements are cautiously prepared in advance, so their content is directly attributed to policymakers (see e.g. the analysis by Jansen and De Haan, 2009, about the use of the word "vigilance" by the former ECB Governor Jean-Claude Trichet). Third, the schedule and timing of these meetings are extremely precise, making it possible to accurately identify their effects on our variables of interest.

FOMC statements are released at the end of the two-day FOMC meetings that are scheduled eight times a year. For comparison, ECB statements are released just before the monthly press conference explaining monetary policy decisions taken during the Governing Council meetings that happened earlier the same day. The FOMC publishes statements since 1996 with a frequency of eight statements a year since January 2000. Because of data availability constraints on our dependent variable – OIS – across maturities, our sample starts in August 2005 so estimates are comparable across the term structure. Table 1 provides descriptive statistics for FOMC statements. Since August 2005, the FOMC published 85 statements while the ECB released 119 ones. On average, the FOMC statements are 278 words long. For comparison, the ECB statements are three times longer (858 words).[6]

Other types of communication could also reveal central bank sentiment such as the minutes of the policy meetings published by the FOMC. Nevertheless, the FOMC minutes are available three weeks after the monetary policy meeting and their circulation is not as large and their objective is more about the accountability of decisions than to communicate with the public. Other interventions in the press and speeches at conferences or events like the testimony to the US Congress may also convey central bank sentiment. However, because of their publicity, frequency, speaker, audience and context, the attention given by market participants to these infrequent communications is more difficult to control for.[7] Given these considerations, we focus on central bank statements to capture central bank sentiment.[8]

3.2. Measuring Tone with Dictionary Methods

The development of machine learning algorithms by computer scientists for natural language processing opens up the possibility of handling large unstructured text databases so as quantify the content of raw text data (see for instance Blei et al., 2003). One advantage of the methods of this field is to be fully automated and replicable, which remove the subjectivity of human-reading coded indices. One major challenge for the analysis of central bank communication and for measuring such an intangible concept as central bank "waves of optimism and pessimism" is to convert the raw policy statements into quantities that we can systematically analyse. We compute three measures

[6] The FOMC introduced press conferences in April 2011 and only for meetings when publishing the Summary of Economic Projections, so text data would not be comparable between FOMC meetings over our sample. We therefore limit our investigation to statements. In addition, whether the tone is consciously or unconsciously conveyed in these statements is beyond the scope of this paper and left for future research. This paper aims to quantify central bank tone and whether central bank sentiment affects private beliefs.
[7] The question of whether more or less attention is given to the sentiment conveyed by speeches versus statements is an interesting question and we leave that for future research.
[8] This choice means that, in the case of the ECB for instance, we would leave out Mario Draghi's "Whatever it takes" speech. One could however argue that this speech given on July 26th 2012 is an outlier in the ECB communication and constitutes the upper bound of the most scrutinized speeches.

from each statement: the first, our benchmark, is the tone; the second is a clarity-weighted tone measure; and the third is the precision of the tone signal conveyed to the public.

Before running any lexicographic analysis on a document, we perform a series of transformations on the original text. The text is first split into a sequence of substrings (tokens) whose characters are all transformed into lower case. We remove English stop words and stem English words using the Porter stemming algorithm, which is an iterative, rule-based replacement procedure of word suffixes (see Hansen, McMahon and Prat, 2015, or Hansen and McMahon, 2016, for details).

To measure the tone of a document, we use "directional" word lists measuring words associated with positive and negative tone as proposed by three different dictionaries, each one capturing positive and negative tone in different environments. First, we use the dictionary proposed by Apel and Blix-Grimaldi (2012), which has been specifically developed for central bank communication, and is therefore the most relevant for the present question. Second, Loughran and McDonald (2011) have developed a list of words that reflect the tone in a financial context. Third, we also use the seminal positive and negative categories of the General Inquirer's Harvard IV-4 psychosocial dictionary.[9] These categories reflect Osgood et al. (1957)'s basic and everyday language universals. Interestingly, almost three-quarters of negative words in the Harvard dictionary are not negative in a financial context according to the dictionary of Loughran and McDonald (2011). These three dictionaries comprise very different numbers of positive and negative words, from around 25, 300 and 2000 respectively (see Table A in the Appendix).

These three dictionaries have different characteristics and are complementary. Our preferred dictionary -that we use as a benchmark- is the one of Apel and Blix-Grimaldi (2012) and we provide results for all three dictionaries to give a comprehensive assessment of central bank tone. For illustration purposes, Table A in the Appendix shows the most illustrative positive and negative words identified in statements. One would naturally note that policymakers could use a combination of positive and negative words together as "*solid decline*" for instance, that they could phrase a given message in opposite terms as "*increasing growth*" versus "*decreasing unemployment*", or that they could use a

[9] The 182 General Inquirer categories were developed for social-science content-analysis research applications. The Harvard-IV-4 dictionary lists positive and negative words: http://www.wjh.harvard.edu/~inquirer/.

negation to convey an opposite message such as with "*not improving*" versus "*worsening*". These cases do not weaken our empirical strategy and, on the contrary, even constitute the substance of this analysis. Our research question is exactly about these language choices and whether the use of some specific words rather than some others matters to convey an equivalent content.

Once negative and positive words are identified with each dictionary, we construct a tone variable based on the balance between the number of positive and negative words that appear in a given document divided by the total number of words included in the document.

$$\Xi_t = \frac{\text{PositiveWords}_t - \text{NegativeWords}_t}{\text{TotalWords}_t} \tag{1}$$

We therefore obtain three measures of tone, bounded between [-1; 1], using the three different dictionaries. The first is labelled Tone_AB based on the dictionary of Apel and Blix-Grimaldi (2012), the second is labelled Tone_LM, based on the dictionary of Loughran and McDonald (2011), and the third is labelled Tone_Harv identified with the General Inquirer's Harvard dictionary. A positive value of these tone variables for a given statement reflects some optimism in the language used, whereas a negative value reflects some pessimism. The descriptive statistics and evolution of the tone variables are shown in Table 1 and Figure 1.[10] The tone variables appear correlated to the business cycle over our sample.

Second, we compute a robustness measure of tone weighted by the clarity of the tone measure. A statement of 100 words with 5 positive words and 0 negative word and another statement of 100 words with 55 positive words and 50 negative words would have the same tone score (0.05) based on equation (1), while the signal conveyed by the former may appear clearer than the latter because no negative word were used. A robustness measure (Tone_AB2), which would yield a score of 1 for the former statement and of 0.048 for the latter, is therefore computed using the sum of positive and negative words such as:

$$\Xi_t' = \frac{\text{PositiveWords}_t - \text{NegativeWords}_t}{\text{PositiveWords}_t + \text{NegativeWords}_t} \tag{2}$$

Third, we compute a variable that captures the precision of the signal conveyed. Because Ξ_t' captures the clarity of the tone measure and whether the message is equivocal (Ξ_t' around 0) or unequivocal (Ξ_t' close to -1 or 1), the absolute value of

[10] For comparison purposes over a similar scale in Figure 1 and later in the empirical analysis (the number of positive and negative words being different in the three dictionaries with a factor of 1 to 100), the three measures have been standardized to a normal distribution with a mean of 0 and a standard deviation of 1.

Ξ_t', defined between 0 and 1 and labelled Abs_Tone_AB2, can be considered as a proxy for the precision of the tone signal conveyed by a given statement.

4. Financial and Macroeconomic Data

This section describes the financial and macroeconomic data used to identify exogenous sentiment shocks to the tone variable Ξ_t and to estimate their effects. Our dependent variables are the different maturities of the OIS rate, from 1-month to 10-year forward.[11] The OIS rate being the average effective federal funds rate expected at a given maturity, these instruments are good proxies of expectations of future short-term interest rates. OIS allow financial institutions to swap the interest rates they are paying without having to refinance or change the terms of loans they have taken from other financial institutions. Typically, when two financial institutions create an OIS, one of the institutions is swapping a floating interest rate and the other institution is swapping a fixed short-term interest rate at a given maturity. The transaction involves only marginal counterparty risk since the principal amount is not exchanged between the parties.[12] Under absence of arbitrage, OIS rates reflect risk-adjusted financial market participants' expectations of the average policy rate over the horizon corresponding to the maturity of the swap (see Christensen and Rudebusch, 2012). Our database has a daily frequency and spans from May 2005 to June 2015.

Because monetary policy decisions are taken the same day as sentiment is conveyed to the public through statements, our analysis requires controlling for the effect of monetary shocks.[13] We use several monetary shocks measures. We follow Kuttner (2001)'s high frequency methodology to identify monetary policy shocks. For a monetary policy event on day d of the month m, the monetary shock can be derived from the variation in the rate implied by current-month fed funds futures contracts on that day. The price of the future being computed as the average monthly rate, the change in the futures rate must be augmented by a factor related to the number of days in the month affected by the change:

$$MP_{kutt,t} = \frac{D}{D-d}\left(f_{m,d}^{0} - f_{m,d-1}^{0}\right) \tag{3}$$

[11] They are made public by the Federal Reserve, which obtains them from the ICE Benchmark Administration, at https://www.federalreserve.gov/releases/h15/default.htm.
[12] OIS rates are then free of default or liquidity risks, but they might still incorporate a so-called term premium.
[13] In addition, the monetary shock may also convey policy and macro signals as analyzed by Baeriswyl and Cornand (2010), Melosi (2016) and Hubert and Maule (2016).

$MP_{k,t}$ is the unexpected policy decision constituting the monetary shock, $f^0_{m,d}$ is the current-month futures rate and D is the number of days in the month and d the day of the decision.

One issue with the Kuttner measure is that it focuses on futures contracts about interest rates only. However, monetary policy has taken many different dimensions over the last years and we ought to consider shocks to unconventional instruments and communication policies (about the future policy path, for instance) in addition to shocks to the conventional instrument. One way to measure these different dimensions of monetary policy is to use shadow rates as proposed by Krippner (2013, 2014) and Wu and Xia (2016) that translate these various dimensions in a single variable expressed in interest rate space.[14] The Krippner series, SSR_t, is estimated at the daily frequency and it therefore enables to apply the concept of Kuttner's high frequency event-study identification of monetary surprises to the daily variation in SSR_t on the policy announcement day: $MP_{kripp,t} = SSR_t - SSR_{t-1}$.[15] These Krippner shocks rely on the financial market participants' interpretation of the overall monetary news disclosed that day, and include private reactions to central bank conventional or unconventional decisions, and central bank communication (about the state of the economy or the likely future policy path) released at the same time. Because these Krippner shocks encompass most of the dimensions of monetary policy, they may as well capture some of the private reaction to central bank sentiment conveyed the same day.

Another way to measure monetary shocks is to decompose them into two types of monetary shocks in the vein of Gürkaynak, Sack and Swanson (2005). Such measures are provided by Nakamura and Steinsson (2016). One of them measures the shock to the policy rate while the other measures the shock to the monetary policy news contained in FOMC announcements and so captures policy communication in general and "forward guidance" more specifically. This is crucial as central bank sentiment is conveyed through statements and we need to single out that component from other types of central bank communication.

We use different macroeconomic and financial variables as explanatory variables. Our dataset includes daily returns of the Standard and Poor's 500

14 Wu and Xia's series is available at the monthly frequency only. Both shadow rates have a correlation of 0.91.

15 Because shadow rate measures are not calendar-based instruments like fed funds futures, there is no need for an adjustment for the remaining number of days.

(SP500) price index which could potentially correlate with changes in private interest rate expectations. In the same vein, changes in commodity prices and financial instability can also explain changes in our dependent variables. We thus include in our specification changes in WTI oil prices and a variable capturing investors' sentiment and financial stress (the VIX). Finally, we control that changes in our dependent variable are not driven by changes in private sentiment by including the ISM Report on Business Survey index for the US (ISMBS). Table C in the Appendix presents the descriptive statistics of the data series used in this paper.

For the identification of sentiment shocks, we use macroeconomic forecasts from central banks (the FOMC projections) and private agents (the US Survey of Professional Forecasters, SPF). The FOMC publishes forecasts for key macroeconomic variables – inflation, real and nominal GDP growth, and unemployment – twice each year in the Monetary Policy Report to the Congress since 1979. Since October 2007, the publication of these FOMC forecasts has become quarterly and its horizon extended by one additional year. FOMC forecasts for current and next year was released each year in late January/early February and late June/early July until 2007Q3, then in January, April, June and October until 2012Q4, and since then in March, June, September and December. We consider forecasts of the Personal Consumption Expenditures (PCE) measure of inflation and real GDP. These forecasts are published as two ranges encompassing each individual FOMC member's forecasts: the "full range" includes the highest and the lowest forecasts while the "central tendency" removes the three highest and three lowest forecasts. As standard in the literature, we use the midpoint of the full range. The US SPF is collected from approximately 40 panellists and published by the Federal Reserve Bank of Philadelphia. SPF forecasts are also published in February, May, August, and November, and CPI forecasts are provided as year-over-year percent changes. We consider the median of individual responses as the SPF inflation forecast in our analysis.[16] The specification also includes the year-over-year CPI inflation rate, real GDP growth rate and the policy rate as measured by the shadow rate estimated by Wu and Xia (2016) as an overall measure of monetary policy since our sample period encompasses periods when monetary policy makes use of

[16] There may be agency problems between professional forecasters and their clients that would cause forecasters not to report their true expectations and perform strategic revisions. Models of agency problems suggest that forecasters are concerned about the accuracy of their forecasts and about their forecasts relative to others' forecasts. This implies that forecasters' predictions are centered on their true expectations, and so median forecasts reflect forecasters' true expectations (Lamont, 1995).

both conventional and unconventional tools. Data sources are presented in Table B in the Appendix.

5. Identifying Sentiment Shocks

After having quantified the tone conveyed by FOMC statements, we face a second empirical challenge. Our computed tone variables are correlated to the business cycle and other macroeconomic and financial market variables, because the quantitative output of the computational linguistic method captures a combination of central bank sentiment and of beliefs about the current and future states of the economy and policy. Thus, it is necessary to isolate exogenous sentiment shocks in order to be able to identify causal effects of policymakers' sentiment on private interest rate expectations. This econometric requirement about sentiment shocks follows the main assumption of Angeletos and La'O (2013).

5.1. The concept of central bank sentiment shocks

Let equation (4) represent the central bank reaction function as a Taylor rule linking the overall stance S_t of monetary policy, stemming from either conventional or unconventional instruments and from central bank communication, to the policymakers' information set Ω_t, encompassing economic fundamentals and/or any variable policymakers link their policy to. The f function captures the systematic response of monetary policy whereas the residuals $\varepsilon^s{}_t$ capture policymakers' deviations from their policy rule.

$$S_t = f(\Omega_t) + \varepsilon^s{}_t \tag{4}$$

In its simplest form, S_t is the central bank interest rate and $\varepsilon^s{}_t$ is the standard monetary shock. A more elaborate version of equation (4) following Gürkaynak, Sack and Swanson (2005) would have S_t containing central bank communication together with central bank actions and $\varepsilon^s{}_t$ including their "path factor" and "target factor". Nakamura and Steinsson (2016) propose a similar decomposition between the standard "Fed Funds Rate shock" and a "policy news shock". Their original measure is set to capture the effects of forward guidance in a broad sense. Forward guidance refers to central bank announcements that convey information about medium to long-term expected changes in the likely future policy path (see Barakchian and Crowe, 2010, and

Zeev, Gunn and Khan, 2015).[17] This communication shock has been shown to reinforce the stance of monetary policy and positively affect interest rates and expected short-term interest rates at different maturities. With the recent recourse to unconventional policies during the financial crisis, S_t would be augmented to be a combination of the central bank interest rate, central bank announcements and unconventional instruments. In that set-up, a shadow rate capturing in the interest rate space conventional and unconventional policies may be considered to be a proxy for an empirical representation of S_t. Finally, S_t could be augmented to include another dimension: the optimism and pessimism conveyed to the public through central bank statements, i.e. the central bank tone Ξ_t. In this set-up, $\varepsilon^s{}_t$ would be a combination of a standard monetary shock, a communication shock, an unconventional policy shock and the sentiment shock ξ_t. The sentiment shock is then by definition the component of tone orthogonal to fundamentals and other types of monetary shocks encompassed in MP_t and it could be defined as:

$$\Xi_t = f(\Omega_t) + MP_t + \xi_t \tag{5}$$

The sentiment shock embedded in the tone of policy statements may be thought of as soft information reflected by positive and negative words beyond more traditional quantitative information conveyed by projections or usual forms of communication like forward guidance. For that reason, it is particularly important to differentiate the communication shock (the "path factor" or "policy news shock"), whether it be about the future policy path or about economic fundamentals, which arises from the *content* of central bank communication from the sentiment shock which arises from the *language and tone* of central bank communication.

We test the null hypothesis that these central bank sentiment shocks positively impact interest rate expectations, in the same way as other monetary shocks. To identify these sentiment shocks, we need to make some assumptions on how to measure the central bank information set and monetary shocks to conventional and unconventional instruments and to communication about the future likely policy path. We assume that the information set can be captured by central bank projections and monetary shocks are measured using different methodologies proposed in the literature.

[17] Campbell et al. (2012) introduced the distinction between Delphic and Odyssean forward guidance. The former describes the central bank communication about future macroeconomic fundamentals while the latter consists of statements that bind policymakers to future courses of action. This distinction is beyond the scope of this paper.

5.2. Identification strategy

The choice of the most relevant identification strategy for taking care of endogeneity issues is an open question. Timing assumptions in recursive identifications –reasonable for real variables and their sluggish reaction to shocks and low sampling frequency– are not relevant when applied to financial variables or fast-moving variables. The two leading alternatives, proposed by Romer and Romer (2004) and Gertler and Karadi (2015), have also proven problematic. Because information sets may be different (Romer and Romer 2000, Blinder et al. 2008, Hubert 2015), the Romer and Romer (2004)'s identification approach may underestimate the extent to which market participants are able to predict future interest rate decisions. Ramey (2015) notes that Gertler and Karadi (2015)'s proxies may be predictable by Greenbook forecasts, while Miranda-Agrippino (2015) shows that market participants' past information, prior to the date of the announcement, also predicts these future "surprises".

As discussed in Blanchard et al. (2013) and Ricco (2015), the presence of information frictions significantly modifies the identification problem. We therefore propose an identification that combines insights from the work of Romer and Romer (2004) and from the information frictions literature, also following the assumption of Angeletos and La'O (2013) that information is imperfect. We thus require the estimated shocks (labelled Sent_xx, xx being AB, LM or Harvard depending on the dictionary considered) to be orthogonal to both central bank's and private agents' information sets, to other monetary shocks and to macro and financial market variables for the identification of sentiment shocks to be achieved. Finally, in a context of imperfect information, the new information is only partially absorbed over time and, estimated surprises are likely to be a combination of both current and past shocks.

We estimate the following equations (6)-(7) on statement days (so on 84 observations) using the last quarterly, monthly and daily figure available at the date of each statement. The dependent variable is the central bank tone. We consider as the exogenous sentiment shock the residuals ξ_t of such a model:

$$\Xi_t = \beta_0 + \beta_1 \Xi_{t-j} + \beta_2 \Omega_t + \beta_3 MP_t + \beta_4 \Psi_t + \beta_5 X_{t-1} + \beta_6 Z_t + \xi'_t \tag{6}$$

$$\xi'_t = \beta_6 + \beta_7 \xi'_{t-j} + \xi_t \tag{7}$$

where j is the number of days between each policy statement, so Ξ_{t-j} is the tone of the previous FOMC policy statement. We assume in equation (6) that the sentiment variable ξ'_t must be orthogonal to the contemporaneous policymakers' information set Ω_t, to other monetary shocks MP_t, to the private agents' information set Ψ_t, to a day-lag of financial market variables embedded in X_{t-1}, and to a vector Z_t of contemporaneous and t-j macroeconomic variables (their past values at the date of the previous policy statement). Then, following insights from the information frictions literature and because ξ'_t is likely to be a combination of current and past sentiment shocks, we estimate equation (7) so as to remove its AR(1) contribution. The error term ξ_t reflects exogenous shocks to the tone variable and is interpreted as a sentiment shock. In our benchmark analysis, we consider the Tone_AB measure to extract sentiment shocks (labelled Sent_AB). In this benchmark case, MP_t encompasses Krippner shocks (Kuttner shocks or both FFR shocks and Policy News shocks are used in in alternative estimations). The policymakers' information set Ω_t comprises FOMC inflation and output projections for current and next calendar years, Ψ_t includes the US SPF inflation forecasts for next quarter, next year and 10 years ahead, X_{t-1} contains the VIX, SP500 daily returns, the oil price growth rate and the ISMBS index, and Z_t comprises the inflation rate, real GDP growth rate and the level of the overall policy stance measured by the shadow rate of Wu and Xia (2016). Figure 2 plots the time series and distribution of the estimated sentiment shocks with the AB, LM and Harvard dictionaries. Table D in the Appendix shows the estimated parameters of equations (6)-(7) for our benchmark sentiment shocks (Sent_AB).

A consequence of the timing of the right-hand-side vectors in equation (4) is that sentiment shocks can have contemporaneous effects on financial market variables, but do not affect contemporaneously central bank's and private agents' information sets or macroeconomic variables. We believe that the opposite assumptions that central bank sentiment is only based on past data or that central banks do not move financial markets in real-time are fragile.[18]

When extracting exogenous sentiment shocks, the inclusion of both private and central bank forecasts in the regression model enables us to deal with three concerns. First, private agents and policymakers' information sets include a large number of variables. Forecasts present the advantage of encompassing rich information sets. Bernanke et al. (2005) show that a data-rich environment

[18] One could argue that there may also be information frictions in financial markets and that financial variables in t-1 do not incorporate information news from t-2, t-3, etc. We control for this by estimating equation (4) with two additional lags. The correlation coefficient between this alternative shock series and the benchmark is 0.99 so that our identification strategy is not affected by this. These estimates are available from the authors upon request.

approach modifies the identification of monetary shocks. Forecasts work as a FAVAR model as they summarise a large variety of macroeconomic variables as well as their expected evolutions. Second, forecasts are real-time data. Private agents and policymakers base their decisions on their information set in real-time, not on ex-post revised data. Orphanides (2001, 2003) show that Taylor rule-type reaction functions estimated on revised data produce different outcomes when using real-time data. Third, private agents and policymakers are mechanically incorporating information about the current state of the economy and anticipate future macroeconomic conditions in their forecasts and we need to correct for their forward-looking information set.

5.3. Robustness tests

We assess the internal validity of our identification strategy for extracting the sentiment shocks in three ways. First, we assess the robustness of our choice of Krippner shocks for representing other types of monetary shocks. We identify sentiment shocks by estimating equations (6)-(7) with *(a)* Kuttner shocks, *(b)* the FFR and Policy News shocks of Nakamura and Steinsson, *(c)* all monetary shocks together (Kuttner, Krippner and Nakamura and Steinsson ones), and *(d)* no monetary shocks. Another alternative *(e)* is to represent, as denoted in equation (4), the central bank tone and Krippner series as a system of simultaneous joint data generating processes estimated with Seemingly Unrelated Regressions (SUR). These alternative sentiment shocks all have a correlation comprised between 0.95 and 0.99 with the baseline sentiment shocks (see Table 2). Table 2 also provides the correlation –non-significant– of the different sentiment shocks with the various monetary shocks. Figure 2 plots the time series and distribution of these alternative sentiment shocks.

Second, the central bank projections that we use to capture the information set of policymakers (Ω_t) could be a function of the sentiment of policymakers. So if central bank projections are influenced by the policymakers' sentiment, then equation (6) may suffer an endogeneity bias and the sentiment shock ξ_t may be misspecified. We correct for this potential bias by using Greenbook forecasts as an instrument for FOMC forecasts. Greenbook forecasts are staff model-based forecasts, formed and provided to the FOMC members before FOMC meetings. Therefore, Greenbook forecasts cannot be correlated to policymakers' sentiment. We estimate the following equation: $\Omega_t = f'(\Phi_t) + \nu_t$, where Φ_t encompasses Greenbook forecasts, and we use the fitted values of Ω_t in equation (6) so as to ensure that our identification of sentiment shocks is not biased by endogeneity (see estimates in section 6.3). The fact that the correlation between ν_t and ξ_t is non-significant suggests that FOMC projections are not influenced by the policymakers' sentiment. The correlation between our benchmark sentiment shock, Sent_AB, and this alternative one, Sent_AB_GB, is 0.74.

Third, one may argue that the midpoint of the range of central bank projections does not capture the full information set of policymakers and in particular the dispersion of macroeconomic outcomes or the balance of risks foreseen by policymakers, and that our sentiment shock suffers from another type of omitted variable bias. We therefore include in Ω_t a measure of the dispersion of FOMC forecasts (the distance between the upper and lower bound of the full range) and a measure of the skewness of FOMC forecasts (the difference between *(i)* the distance between the upper band of the full range and the upper band of the central tendency and *(ii)* the distance between the lower bound of the central tendency and the lower bound of the full range). The correlation between our benchmark sentiment shock and this alternative sentiment shock, labelled Sent_AB_UnSkew, is 0.89 and suggests that the estimated sentiment shock are not biased by our representation of the information set of policymakers.

We assess the external validity of our identification strategy for extracting the sentiment shock in three ways. First, we estimate sentiment shocks using a VAR at a daily frequency with financial market variables such as the VIX, the Saint-Louis Fed Financial Stress Index, SP500 returns, oil price variations, the Krippner series and the Tone_AB measure ordered last in the vector of endogenous variables. The sentiment shock (labelled Sent_VAR) is obtained from the standard Cholesky decomposition. The correlation between this alternative sentiment shock and the benchmark sentiment shock is 0.60.

Second, while the benchmark identification is performed only on statement days, we estimate equations (6)-(7) on all days (so 2576 observations) with monthly and quarterly data constant-interpolated to daily frequency. This alternative estimation does not add variation in the data series at low frequency, but enables to consider information in the data series at the daily frequency. This alternative sentiment shock (labelled Sent_AB_AllDays) has a 0.87 correlation with the baseline sentiment shock.

Third, we assess the autocorrelation and predictability of sentiment shocks. Our estimated series of sentiment shocks, if relevant, should not be auto-correlated and predictable from movements in data. Table 2 shows their autocorrelation coefficient as well as descriptive statistics and the correlation of sentiment shocks together and with monetary shocks. Except with Kuttner shocks (because they capture only one dimension of monetary policy over the recent sample), sentiment shocks are not correlated with other monetary shocks. Table 2 also shows the adjusted R^2 and F-stats of an OLS estimation that aims to test the null hypothesis that our estimated series of exogenous shocks are unpredictable. We assess the predictability of the estimated shock series with Granger-causality type tests using 22 macroeconomic and financial variables, including lagged sentiment. It suggests that the sentiment shock series are relevant to be used in our second-stage estimations so as to assess their effects on private interest rate expectations.

6. The Effect of Sentiment on Policy Expectations

6.1. The empirical methodology

We use a high-frequency methodology to estimate the effects of sentiment, which consists in focusing on movements in some asset prices in a narrow window around FOMC policy meetings. This approach was initiated by Cook and Hahn (1989), Kuttner (2001), and Cochrane and Piazzesi (2002). The key assumption is that the reaction of interest rate expectations that are continually affected by various factors can be specifically attributed to monetary news on the day of the policy announcement, or said differently that there is no other macroeconomic news during that window. Since interest rate expectations adjust in real-time to news about the macroeconomy, movements in interest rate expectations during the window of a policy announcement only reflect the effect of news about monetary policy. This is crucial for identification since it strips out the endogenous variation in interest rate expectations associated with other shocks than monetary news.[19]

We focus our empirical analysis on a narrow window (from the day before, close of business, to the day of the announcement, close of business) around

[19] For example, a positive employment announcement that systematically occurs the day before a policy announcement will already have been factored into interest rate expectations when the central bank makes its announcement. A central assumption of these high-frequency methodologies is that all information flows happening before the window of the event at date *t* have been incorporated in prices in *t-1*. Nakamura and Steinsson (2016) use a similar approach focusing on the increased volatility generated by monetary news.

FOMC policy announcements. On these days, policymakers do not only provide the decision about the level of key interest rates but also publish statements about the rationale for their decisions and their view about the current and future state of the economy which would be informative of the future path of its monetary policy. The informational content of these policy announcements can be decomposed in two components: the policy decision and signals about the state of the economy and the future likely policy path. However, the signals themselves can be decomposed between the central bank beliefs about fundamentals and sentiments. In line with the theoretical framework described in section 2, our analysis requires to identify exogenous sentiment shock so we can single out the causal effect of the central bank sentiment on revisions of private interest rate expectations.

There are two other issues that we need to overcome. First, as is common with financial variables, the variance of our dependent variables changes over time. We therefore use an ARCH (autoregressive conditional heteroskedasticity) model to treat heteroskedasticity as a variance to be properly modelled and take into account this "volatility clustering". Second, because the estimated sentiment shocks from equations (6)-(7) are generated regressors that might cause biased standard errors; we compute standard errors robust to misspecification using the Huber-White-sandwich estimator.[20] The ARCH model is estimated at the daily frequency (so on 2575 observations) and the estimated equations are the following:

$$\Delta r^E_{t,m} = \beta_0 + \beta_1\, \xi_t + \beta_2\, MP_t + \beta_3\, C_t + \varepsilon_t\,,\ \varepsilon_t \sim (0, \sigma^2_t) \tag{8}$$

$$\sigma^2_t = \gamma_0 + \sum_{i=1}^{p} \gamma_i\, \varepsilon^2_{t-i} \tag{9}$$

where $\Delta r^E_{t,h}$ is the change between t and t-1 in US interest rate expectations for horizon m, ξ_t is the sentiment shock estimated through equations (6)-(7), MP_t comprises the monetary shocks (either Krippner, Kuttner or NS ones), and C_t is a vector of controls that includes the VIX, SP500 daily returns, oil price variations and the ISMBS index. The number of lags $p=1$ in the variance equation is determined by their significance. While sentiment shocks are orthogonal to monetary shocks by construction from equation (6), we include the latter in equation (8) to further control for this orthogonality condition as well as to provide estimates of the effect of monetary shocks -β_2- for comparison purposes. In addition, using Krippner shocks that encompass most of the

[20] This issue is common to all empirical studies estimating exogenous shocks in a first step as in Romer and Romer (2004), but is more acute when the generated regressors are not normally distributed.

dimensions of monetary policy provide conservative estimates of the effect of central bank sentiment.

6.2. Benchmark estimates

We test the hypothesis that central bank sentiment affects interest rate expectations by estimating equations (8)-(9) with an ARCH specification. Our baseline analysis is performed with the sentiment measure (Sent_AB) generated in equations (6) and (7) with the dictionary of Apel and Blix Grimaldi (2012) and with Krippner monetary shocks. We estimate nine different regressions for interest rate expectations at 1, 3, 6 and 9-month, and 1, 2, 3, 5 and 10-year horizons. Our estimation sample starts in August 2005 so we have 2576 observations for each maturity. Table 3 shows the benchmark results. The β_1 coefficient associated with sentiment shocks is positive and significant for the 1-month, and 1 and 2-year horizons. The information conveyed by the sentiment expressed in FOMC statements appears to be interpreted by private agents to provide some information at the horizon of the next policy decision and for similar horizons to the transmission lags of monetary policy, estimated to be between 12 and 24 months in Bernanke and Blinder (1992) or Bernanke and Mihov (1998).[21]

The second and third panels of Table 3 show estimates when using other monetary shocks than the Krippner one in the identification and estimation steps, so in equations (6) and (8). When using Kuttner shocks or Nakamura and Steinsson (NS) shocks, the β_1 coefficient remains positive and significant for the 1-year maturity at minimum. It is noteworthy that the effect of sentiment is stronger when controlling for the simplest form of monetary shock, i.e. Kuttner ones, than when controlling for a combination of a standard monetary shock and a communication shock about policy news, i.e. NS shocks. This is consistent with the idea that central bank sentiment corresponds to some soft information conveyed through communication together with the content of the given communication.

The bottom panels of Table 3 show estimates when using tone measures from alternative dictionaries: the Loughran and McDonald (2011)'s and Harvard's

[21] A complementary possibility for explaining the effect of sentiment is that it may transmit to private agents through another channel of monetary policy –the risk-taking channel– and may affect the risk aversion of market participants and so the term premium. Because the term premium can be proxied by financial indicators like the VIX, controlling in equation (8) for such variables that predict the term premia enables to isolate the effect on policy expectations (see Piazzesi and Swanson, 2008).

word lists and the alternative measure capturing the clarity of the tone conveyed (Tone_AB2). Estimates from these measures show different results both in term of magnitude and significance. The effect of sentiment derived from the Tone_AB2 is stronger than the baseline result whereas the effect of sentiment derived from the LM and Harvard dictionaries is smaller. This may be explained by the very objective of each tone measure. When the Loughran and McDonald (2011)'s dictionary is relevant for the financial context, the Harvard's dictionary is dedicated to all social sciences and everyday language. At the opposite, the dictionary by Apel and Blix Grimaldi (2012) has been specifically developed to analyse central bank communication and is more relevant to capture central bank tone. Despite their differences in terms of purpose and number of words, these alternative measures all confirm that sentiment increases interest rate expectations with a peak effect at the 1-year horizon.

Because they all happen on the same day, the effect of sentiment shocks is estimated simultaneously with the one of monetary shocks. In all specifications tested, the β_2 coefficient, associated with monetary shocks, is positive and significant, as expected. Krippner shocks are strongly significant for almost all maturities. The coefficients associated with Kuttner shocks are only significant for maturities of 1, 6 and 9-month ahead. The NS policy news shocks are positive and significant for maturities between 1 and 9-month while the shock to the policy rate is positive and significant for maturities between 1-month and 1-year and negative at 5 and 10-year ahead. These estimates show how much the effect of monetary shocks may be different in magnitude over the recent sample when considering only one dimension of the monetary policy stance (the interest rate) or many (balance sheet policies and/or communication).

6.3. Alternative estimates

In this subsection, we test the strength and potential for generalisation of our benchmark estimates along several dimensions. First, we apply the same analysis to another central bank: the ECB. Second, we assess the stability of our results when modifying the identification strategy to extract sentiment shocks. Third, we evaluate whether our benchmark estimates are affected by the econometric specification of equations (8)-(9).

We estimate the effects of the sentiment conveyed by another central bank using the same method as for the FOMC. We assess the impact of ECB sentiment on policy expectations in the euro area. Tone is quantified from the ECB statements provided on a monthly basis after each Governing Council.[22] For the identification of sentiment shocks, we use ECB/Eurosystem projections and the ECB's SPF.[23] Monetary shocks are identified using the Krippner shadow rate for the euro area. In equations (8) and (9), the dependent variables are Eonia OIS for the same maturities as in the US and we control for the CISS, daily returns of the Eurostoxx 50 and the Economic Sentiment Indicator (ESI) of the European Commission. The number of lags, determined by their significance, in the ARCH specification is p=4. We estimate the effect of sentiment from the four measures of central bank tone described in section 3. Table 4 presents the results for the ECB. The sentiment based on the dictionary of Apel and Blix Grimaldi (2012) (Sent_AB) has a positive and significant impact in the euro area for horizons of 9-month and from 1 to 3-year. This effect is confirmed with other dictionaries (Sent_LM or Sent_Harv) and the clarity-weighted alternative tone measure (Sent_AB2). The Harvard dictionary gives less significant results but confirms that ECB sentiment is significant and positive at least at the 1-year horizon. We acknowledge that we are not able to control for a potential endogeneity bias in the identification of sentiment, contrary to the FOMC case, because the ECB does not differentiate the staff forecasts (Greenbook) from the policymaker ones (FOMC). Since the ECB does not publish dispersion and skewness measures of its projections, we cannot test whether we are able to capture the full information set of policymakers. Our estimates indicate that ECB sentiment affects policy expectations in the euro area in a similar fashion than in the US.

We gauge the sensitivity of our benchmark estimates when modifying the identification procedure of sentiment shocks. First, because which monetary shocks we consider in equation (6) affect the estimation of our sentiment shocks, we test the effect of sentiment shocks estimated in two extreme cases: including all monetary shocks together in equation (6) and including any monetary shocks. Second, we identify sentiment shocks by instrumenting

[22] ECB statements are followed by press conference including a Questions & Answers session. We do not consider this Q&A text data since it would make the text data analyzed from the ECB and the FOMC structurally different and their tone would not be comparable. Contrary to the statements, Q&A text data are not prepared in advance and polished. Q&A text data could reflect the tone used by a journalist more than the policymakers' one.

[23] The ECB/Eurosystem staff macroeconomic projections for the euro area are produced quarterly since June 2004. They are published during the first week of March, June, September and December and are presented as ranges for annual percentage changes in both HICP (the Harmonized Index for Consumer Prices) and real GDP. The ECB's SPF is a quarterly survey of expectations for the rates of inflation, real GDP growth and unemployment in the euro area. Participants are experts affiliated with financial or non-financial institutions in the European Union. SPF forecasts are produced in February, May, August and November. HICP is measured as average annual percentage change for current and next years.

FOMC forecasts with Greenbook forecasts or by augmenting the policymakers' information set with dispersion and skewness measures of FOMC forecasts. Third, because the monetary shock and the sentiment shock happen simultaneously, we control that this potential simultaneity bias does not affect our results by estimating equation (6) with Seemingly Unrelated Regressions (SUR). Fourth, we identify sentiment shocks by estimating equation (6) not only on announcement days but on all days in our sample. Tone and monetary shocks series take the value zero during days when no statement occur.[24] Fifth, we consider sentiment shocks identified with a VAR based on the following vector of endogenous variables: [VIX, STLFSI, SP500, Oil, Krippner monetary shocks, Tone_AB]' putting tone last in the vector to have the most conservative estimates of sentiment shocks. Sixth, because Forward Guidance (FG) is a policy using communication and statements as a tool to manage policy expectations, we estimate the effect of sentiment in equation (8) by controlling for the FG announcements (using dummies for the days FG has been introduced or modified). Seventh, we include in equation (6) another potential measure of monetary shocks: the variation in the shadow rate of Wu and Xia (2016). This shadow rate being available at a monthly frequency only, it cannot be used to estimate monetary shocks in an high-frequency event-study fashion but it might still contain some information that would influence the identification of sentiment shocks. Results are shown in Table 5. These robustness tests confirm the positive effect of sentiment shocks on interest rate expectations, primarily at work around the 1-year maturity.

We also run some alternative estimations related to the model and specification estimated.[25] First, we allow the coefficients associated to the control variables in the daily ARCH specification of equation (8) to vary on statements days compared to non-statement days. Second, we include a lag of the dependent variable in equation (8). Third, we estimate equation (8) without the C_t vector of controls to examine potential over-identification issues and further verify the orthogonality condition of our estimated shocks. Fourth, we estimate the effects of sentiment during normal times, so before the implementation of the FG policy and before the conventional tool of monetary policy has reached its Effective Lower Bound (ELB). Fifth, we estimate a Threshold ARCH model

[24] Weekly, monthly and quarterly data have been constant-interpolated to daily frequency to respect the information structure. The assumption is that the information set at date *t* includes the last data point published, whereas a linear interpolation would assume that they already know the next data point to be published.

[25] One may suggest using OLS on event days. But this option would require introducing another assumption to evaluate the OIS "abnormal variation" on event days. Moreover, OLS do not allow treating properly heteroskedasticity problems.

which enables to take into account the asymmetric nature of positive and negative innovations: a positive shock will have a different effect on volatility than will a negative shock. On financial markets, downward movements ("bad news") are followed by higher market volatility than upward movements ("good news"). Sixth, we modify the number of lags in the variance equation of the ARCH specification. Estimates are presented in Table 6. They confirm that sentiment shocks have a positive and significant effect on interest rate expectations at the 1-year maturity. Interestingly, the fact that the effect of sentiment is significant at longer maturities (3 and 5-year) when we do not include controls in equation (8) suggests that the effect of sentiment on OIS at these maturities may go through the term premium.

6.4. Dynamic estimates

This section investigates the dynamic effects of sentiment and assesses how persistent is the contemporaneous effect evidenced in section 6.2. More specifically, we test the null hypothesis that the effect of FOMC sentiment is offset during the following days. Our preferred approach is to use the local projections method of Jorda (2005). Impulse response functions obtained from VARs may be imposing excessive restrictions on the endogenous dynamics, so that estimates derived from local projections, more flexible approaches, might be preferable. Another advantage is the robustness of local projections to model misspecification to estimate dynamic responses to exogenous shocks.[26]

Considering that exogenous shocks have been identified beforehand, Jorda (2005) suggests estimating a set of h regressions representing the impulse response of the dependent variable at the horizon h to a given exogenous shock ϵ_t at time t:

$$y_{t+h} = \alpha_h + \beta_h \epsilon_t + \phi_h(L) X_t + \eta_{t+h} \tag{10}$$

where y_{t+h} is the dependent variable at the horizon h, ϵ_t represents the given exogenous shock, $\phi_h(L)$ is a polynomial lag operator, and X_t is a vector of control variables. In our case, rather than estimating equation (8) with OLS, we estimate the ARCH model of equations (8)-(9) so that the variable of interest is $\Delta r^E_{t,h}$ the daily change in US interest rate expectations for horizon h, the exogenous shock ϵ_t is the sentiment shock ξ_t, and the vector X_t encompasses the vectors MP_t and C_t from equation (8).

[26] Another alternative is to estimate the effect of sentiment shocks in a simple autoregressive distributed lag (ADL) model. One potential drawback of this approach for our specification is the differencing of the dependent variable over the long run, which goes against the high-frequency identification.

Figure 3 plots the results from estimating the dynamic effects, over the following 20 business days, of sentiment shocks on 1-year OIS (the main maturity for which we find a significant effect).[27] The upper panel shows the dynamic estimation of our benchmark estimates, i.e. the effects of sentiment shocks using Tone_AB and Krippner shocks for the identification in equation (6) and for the estimation in equation (8). We observe that the positive effect measured on the day of the announcement is not offset during the 20 following days. There is no negative significant effect on the following days of the size of the contemporaneous effect that would offset it. The cumulated local projection effect shows that the impact of FOMC sentiment on 1-year OIS is not offset and even tends to increase in the following 20 days. The middle and lower panel of Figure 3 shows dynamic estimates of sentiment shocks identified and estimated with NS or Kuttner shocks in equation (6) and (8). Estimates show a similar pattern and suggest that the effect of sentiment is not offset.

6.5. State-dependent estimates

A further step in our analysis is to investigate whether private agents process sentiment shocks differently conditional on the characteristics of the sentiment shock or according to the state of the economy. For instance, the effect of sentiment could depend on the precision of the sentiment signal conveyed through policy statements. In a Bayesian updating model of beliefs, the weight given to a signal (the sentiment shock) should depend on the precision of this signal and so whether this signal is informative for the formation of beliefs. We use the measure of signal precision (Abs_Tone_AB2) discussed in section 3.2 to capture the precision of the message conveyed in central bank statements. We expect the effect of sentiment shocks to be stronger if the signal is more precise and vice versa. We augment equation (8) with an interaction term between sentiment shocks and the signal precision (that we also include in isolation in equation 8). Table 7 shows the results. As expected, the effect of sentiment shocks is stronger when the signal is more precise. The non-linear effect of sentiment shocks conditional on the precision of the signal is particularly at work at the 2-year maturity whereas the marginal non–linear effect is not significant at the 1-year maturity, for which sentiment is always very significant whatever the signal precision.

[27] The cumulated local projections are provided without confidence bands since they come from different estimations and their standard-errors from different variance-covariance matrices. These cumulated local projections are only indicative.

The strength of the effect of sentiment on interest rate expectations could also depend on the economic environment in which private agents form their beliefs. We thus test first whether the effect of sentiment is different according to the position in the economic cycle. Sentiment shocks are interacted with a HP-filter measure of the output gap. Results in Table 7 show that the interaction term between sentiment and the output gap is negative and significant for the two maturities considered (1 and 2-year). More precisely, when differentiating the effect of sentiment between expansion and recession periods, it appears that the FOMC sentiment has more effect during recessions than expansions. It suggests that private agents put more weight on sentiment for the formation of their beliefs about the expected future policy rate when the economy is below its potential. One interpretation is that private agents may seek for additional soft information about the policymakers' reaction function and/or the state of the economy (beyond forward guidance and projections) during recessions, and therefore put more weight on the sentiment signal. Second, we examine how the effect of sentiment varies with the level of inflation. The interaction term of sentiment shocks with the CPI inflation rate is positive and significant for both maturities. FOMC sentiment shocks have more effect when inflation is 1 standard-deviation above its mean. Again, this suggests that private agents may have a less clear view of the policymakers' reaction function when inflation is high. Except in the case of demand-driven inflationary pressures, central bankers may face a trade-off and tolerate higher inflation to reach another objective (full employment for instance) according to their mandate. It makes their future decisions not easily predictable. During these periods, private agents may then put more weight on sentiment to form their beliefs about the future policy rate. Third, the effect of central bank sentiment may be different depending on the level of the investors' sentiment, their risk aversion or the financial stress in the economy. We assess the non-linear effect of sentiment shocks conditional on financial stress using the VIX. The interaction term is significant and positive for both maturities, so the FOMC sentiment has a stronger positive effect when financial stress is high. Private agents tend to put more weight on central bank sentiment during uncertain times, consistent with the results about the interaction with the output gap.

These estimates suggest that the reaction of private agents to the sentiment conveyed by policymakers is state-dependent. More precisely, private agents put more weight on central bank sentiment to form their beliefs about future policy when inflation and financial stress are above their mean, and when the output gap is negative, characterizing periods of uncertain times when central bank actions are under more scrutiny.

7. Some Further Effects of Sentiment

In addition, we test whether the effect of sentiment on private interest rate expectations is transmitted to macroeconomic variables. Said differently, does central bank sentiment affect beliefs about policy only or does it matter for the economy in general? We examine three types of potential additional effects of sentiment. Focusing on macroeconomic variables from the highest to the lowest frequency, we study if sentiment affects inflation expectations, helps predict the next monetary decision, and influences industrial production and inflation.

First, we assess the impact of sentiment on inflation expectations using the same ARCH specification than for the benchmark estimates with interest rate expectations. We focus our analysis on daily changes in inflation expectations at the 3, 4, 5 and 10-year horizons measured with inflation swaps or Break-Even Inflation Rates (BEIR). Results are presented in the upper panel of Table 8. They show that FOMC sentiment has a negative and significant effect on 10-year inflation expectations, but is not significant for inflation expectations at 3, 4 and 5-year. Whereas inflation expectations in the medium-run are likely to be affected by macroeconomic and policy developments, long-term inflation expectations are more likely to be influenced by private agents' perceptions of the central bank's long-run inflation objective or by the price investors attach to long-run inflation risks. This result suggests that a positive central bank sentiment shocks reduces one of these two dimensions or both together.

Second, we investigate whether central bank sentiment helps predict the next monetary policy decision. We test whether sentiment shocks from a given statement at date t add some relevant information to predict the level of the effective Federal Funds Rate (FFR) of the next policy decision beyond the information contained in the level of the FFR and in the FOMC inflation and output next year projections at date t. Because the FFR is at its ELB during a significant part of our sample, we perform the same prediction test with the shadow rate computed by Wu and Xia (2016) or by Krippner (2013, 2014), which measures the overall stance of monetary policy. One could also argue that predicting the next policy decision does not consist in predicting the level but whether there will be a change and in which direction. The left-hand side variable therefore becomes a ternary variable that takes the value 1 for a FFR hike, -1 for a FFR decrease and zero otherwise. This specification is estimated with a probit model to account for the discrete nature of target rate decisions. We also test the sensitivity of the analysis to the right hand-side variables. We test the predictive power of sentiment shocks measured with the clarity-weighted tone measure (Sent_AB2) of the tone measure (Tone_AB), when augmenting the model with private forecasts (SPF), or with policy expectations measured with Fed Funds futures, 1-month OIS or 1-year OIS. The middle panel of Table 8 shows the estimates of the predictive power of sentiment (or tone). The coefficient is positive and significant and suggests that sentiment (and tone) help predict the next policy decision.

Third, we aim to estimate the effects of sentiment on inflation and industrial production. We estimate a standard monetary VAR model augmented with sentiment shocks. The identification is obtained through a Cholesky decomposition with industrial production, inflation, the shadow rate computed by Krippner (2013, 2014) and our sentiment shock series as endogenous variables ordered that way. Putting sentiment last means that the identification of the causal effects of sentiment is therefore the most conservative one. By construction, sentiment reacts contemporaneously to monetary shocks whereas macroeconomic variables react with a lag to monetary and sentiment shocks. Oil prices, the VIX and daily returns of the SP500 index are also included as exogenous variables. The frequency of this dataset corresponds to statement dates (8 observations a year, 85 observations overall) so the vector of the sentiment series does not contain zeros. The VAR model is estimated with 6 lags. All eigenvalues lie inside the unit circle, so the VAR model satisfies the stability condition to interpret impulse response functions. Figure 4 plots impulse responses of inflation and industrial production over 10 periods to a positive sentiment shock (bold black circled line) and to a positive monetary shock (thin blue line). Sentiment shocks positively affect inflation one period ahead while industrial production positively reacts from 3 to 7 periods ahead. In the meantime, monetary shocks have the expected effects on inflation and industrial production. A restrictive monetary shock has a negative effect on inflation 5 periods ahead and on industrial production 3 periods ahead.
Beyond the statistical significance of the effect of sentiment shocks on inflation and industrial production, it is also interesting to compare the contribution of both sentiment and monetary shocks to the dynamics of these macroeconomic variables. The lower panel of Table 8 shows the forecast error variance decomposition of each shock. Sentiment shocks account for 3.5% of the industrial production variance, whereas the monetary shock explain 1%.

Conversely, sentiment shocks explain 1.3% of the variance of inflation while monetary shocks explain 3.7% of it. This suggests that sentiment shocks explain as much variance as monetary shocks over that sample and that the effect of central bank sentiment goes beyond its effect on private beliefs about the future policy path.

8. Conclusion and Interpretations

This paper tests in the context of monetary policy the theoretical prediction of Angeletos and La'O (2013) that sentiment may have aggregate effects. We quantify the concept of central bank sentiment and test its potential importance in economic decisions. Using computational linguistic methods, we quantify the tone from which we identify sentiment shocks conveyed by FOMC statements. We are then able to assess whether this central bank sentiment affects private interest rate expectations and macroeconomic dynamics. We find that positive shocks to sentiment (i.e. optimism shocks) increase private interest rate expectations mainly at 1-year maturity. The effect of sentiment shocks is state-dependent and varies conditional to the level of inflation, the business cycle and financial stress. Moreover, we find that sentiment shocks affect inflation expectations, help predict the next policy decision, and have an effect on inflation and industrial production.

The fact that central bank sentiment has some effect on macroeconomic variables shed some light on potential interpretations about its nature. Is central bank sentiment some soft information about the future likely policy path or about the state of the economy? These two possibilities rely on our main result that sentiment positively affects interest rate expectations. The first hypothesis is that sentiment shocks convey a (complementary) signal about future policy, so optimism shocks positively affect interest rate expectations which in turn negatively affect inflation and output. They would then work as a standard monetary shock. An alternative hypothesis is that sentiment conveys signals about fundamentals, so optimism shocks positively affect inflation and output, which in turn positively affect interest rate expectations. VAR estimates provide some tentative evidence to reject the first hypothesis given that sentiment shocks positively affect inflation and industrial production. State-dependant estimates of sentiment shocks with the output gap go in a similar direction. Private agents put a positive weight on the relative FOMC optimism during recessions whereas no weight during expansions, and therefore expect future rate hikes. One may then understand FOMC sentiment rather as a signal about future economic fundamentals.

These results give policymakers some insights on how private agents interpret and respond to the sentiment conveyed by central bank communication. Our results suggest that sentiment shocks matter for shaping private interest rate expectations. The coordination of the sentiment conveyed by central bank communication and policy decisions thus appears important for managing interest rate expectations.

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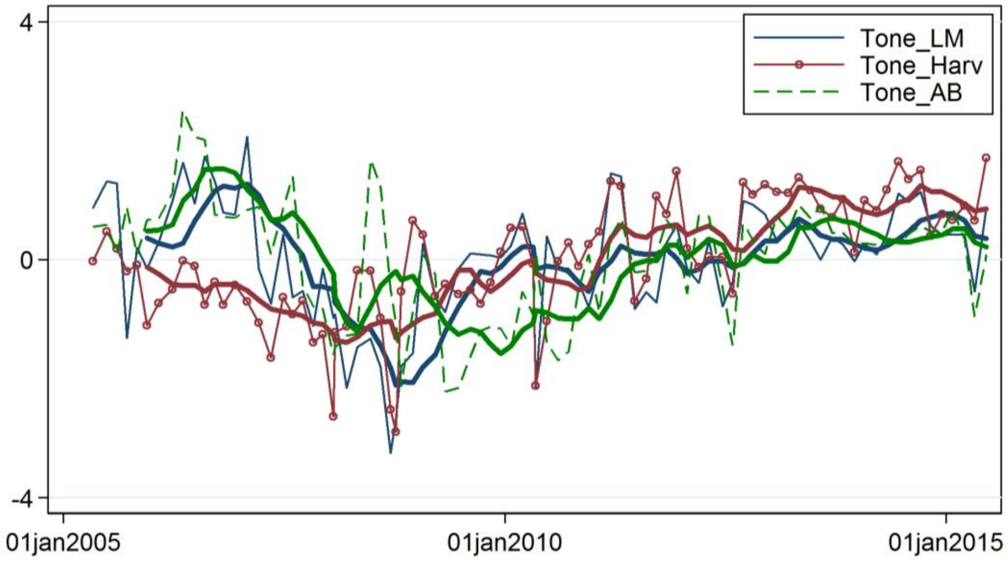
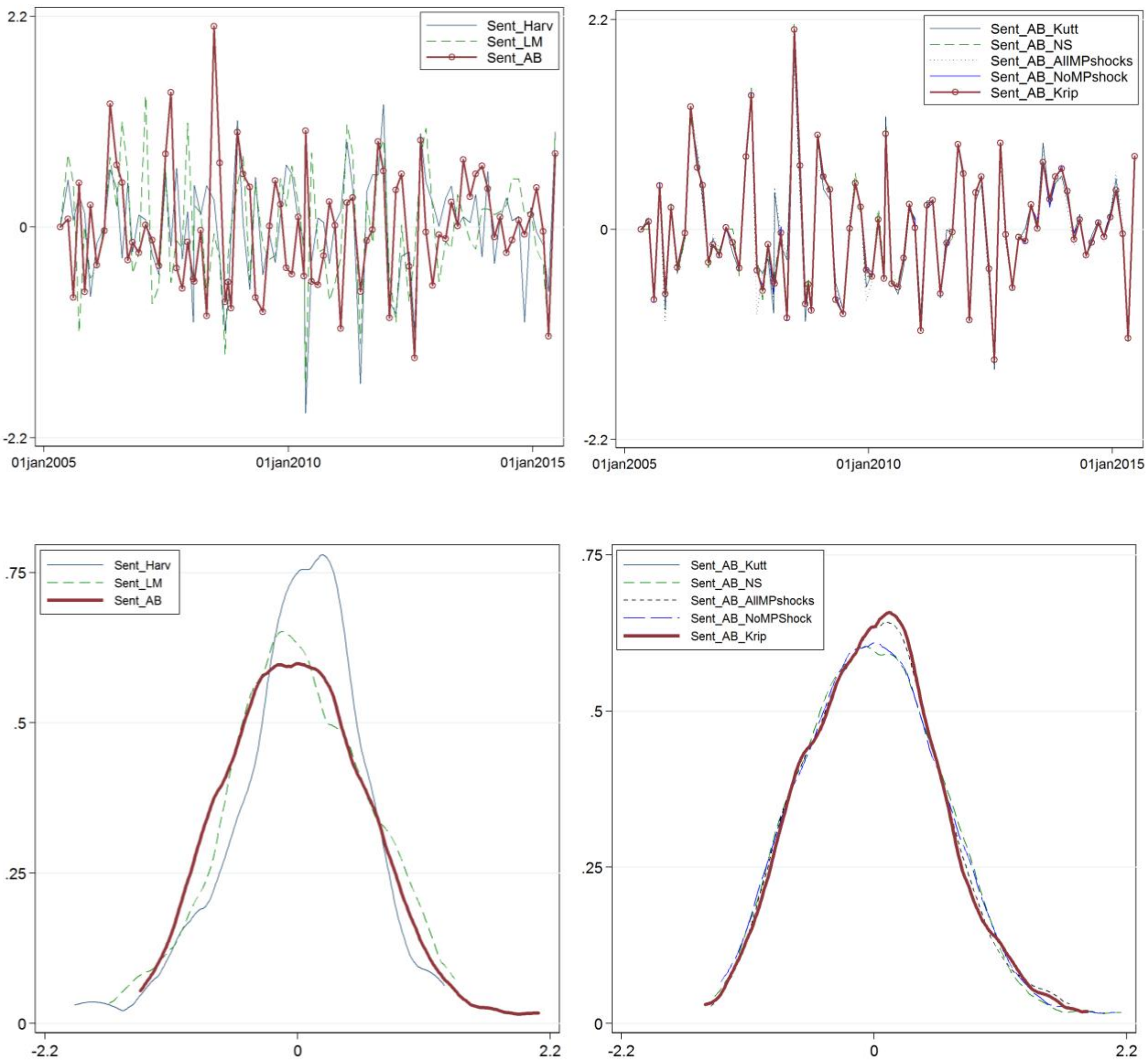
Figure 1. Central Bank Tone



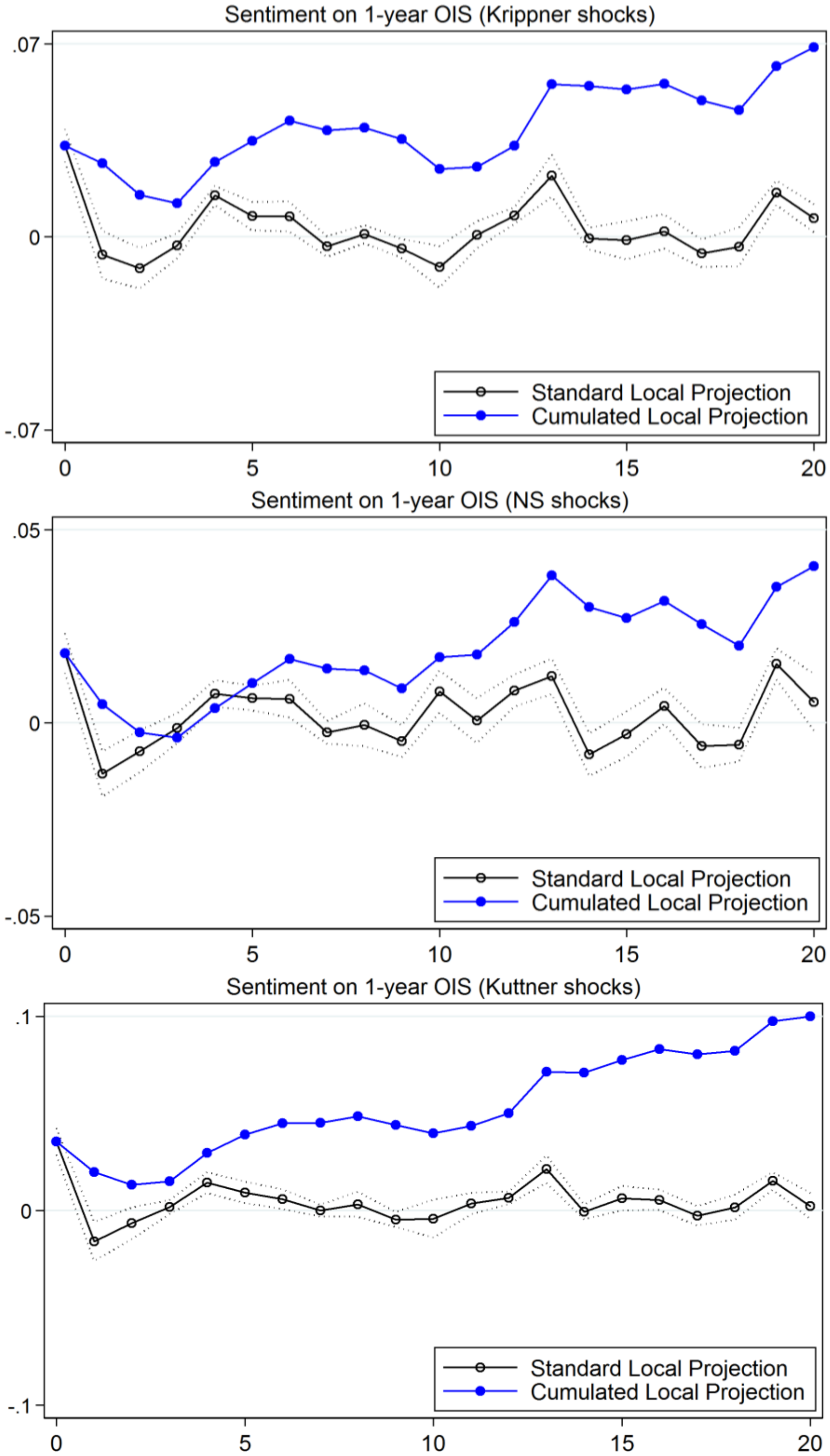
Note: The tone series have been computed from equation (1) and the three dictionaries Apel and Blix Grimaldi (2012) -AB-, Loughran and McDonald (2011) -LM-, and the General Inquirer's Harvard IV-4 psychosocial -Harv-, and they have been standardized to a normal distribution. The three bold lines are the respective moving average over the last 6 statements for the three tone measures.

Figure 2. Central Bank Sentiment shocks and their distribution



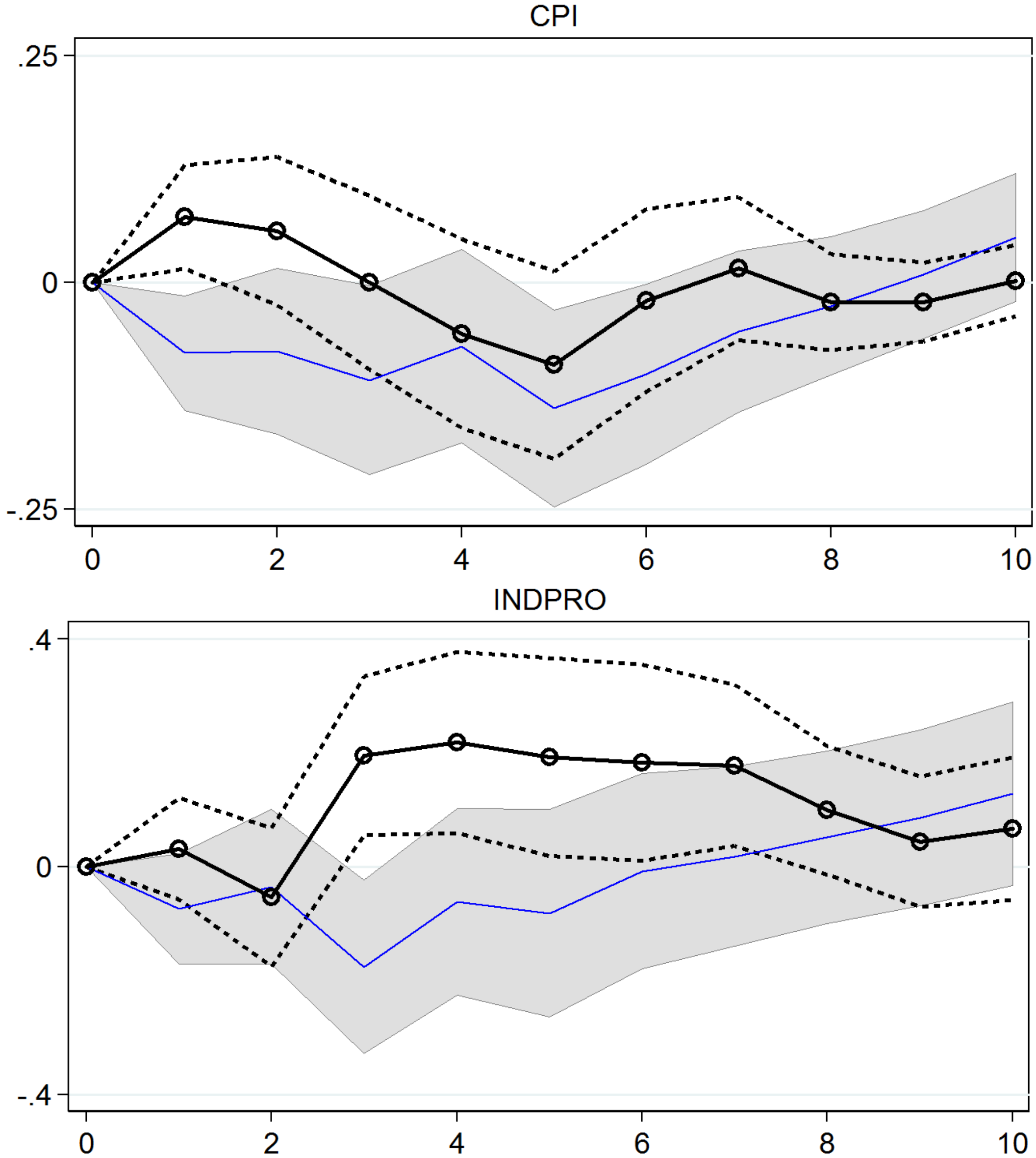
Note: The sentiment series have been computed from equations (6) and (7) using tone measures from the three dictionaries (AB, LM and Harvard) and using Krippner shocks, and from five different configurations for monetary shocks: the baseline case is with Krippner shocks –Krip–, and then Kuttner shocks –Kutt–, Nakamura and Steinson shocks –NS–, all these shocks together –AllMPshocks– and without any monetary shocks –NoMPShocks–.

Figure 3. Local Projection Estimates



Note: Impulse responses to a positive sentiment shock, over the following 20 business days, estimated with equations (8)-(9) using local projections as described in equation (10) with one standard error confidence intervals and the cumulated effect of horizon specific estimates. In the upper panel, Krippner shocks are used in equation (6) and (8), Nakamura and Steinsson shocks in the middle panel and Kuttner shocks in the bottom panel.

Figure 4. Impulse Response Functions



Note: Impulse responses to a positive sentiment shock (bold black circled line) and a positive monetary shock (thin blue line with a grey shaded area) over 10 periods, estimated with a VAR. The frequency corresponds to statement dates, so 8 observations a year. Point estimates are provided with 90 per cent confidence intervals.

Table 1. Central Bank Tone

	Obs	Mean	Std. Dev.	Min	Max
Descriptive statistics for FOMC statements					
All words	85	278	115	109	547
Positive_AB	85	3	2	0	7
Negative_AB	85	3	2	0	8
Positive_LM	85	10	6	1	24
Negative_LM	85	9	5	0	19
Positive_Harv	85	49	27	12	112
Negative_Harv	85	9	5	0	20
Descriptive statistics for FOMC tone					
Tone_AB	85	-0.001	0.011	-0.027	0.028
Tone_AB2	85	0.052	0.536	-1	1
Tone_LM	85	0.002	0.016	-0.048	0.034
Tone_Harv	85	0.134	0.031	0.044	0.187
Abs_Tone_AB2	85	0.433	0.318	0	1

Correlation table of FOMC tone	Tone_AB	Tone_AB2	Tone_LM	Tone_Harv	Abs_Tone_AB2
Tone_AB	1				
Tone_AB2	0.93	1			
Tone_LM	0.45	0.50	1		
Tone_Harv	0.27	0.26	0.57	1	
Abs_Tone_AB2	-0.06	0.09	0.02	-0.30	1

Note: The first panel shows some statistics about the number of words (all, positive and negative according to the three dictionaries) for the 85 FOMC statements considered. In the second panel, Tone_AB, Tone_LM and Tone_Harv are computed based on equation (1), while Tone_AB2 is based on equation (2). Abs_Tone_AB2 is the absolute value of Tone_AB2.

Table 2. Properties of estimated sentiment shocks

Correlation between sentiment shocks across dictionaries					
	Sent_AB	Sent_AB2	Sent_LM	Sent_Harv	Mean / SD
Sent_AB	1				0.00 / 0.62
Sent_AB2	0.87	1			0.00 / 0.61
Sent_LM	0.21	0.29	1		0.00 / 0.61
Sent_Harv	0.27	0.28	0.64	1	0.00 / 0.57

Correlation between sentiment shocks across identification strategies					
	Sent_AB_Kutt	Sent_AB_NS	Sent_AB_AllMP	Sent_AB_NoMP	Sent_AB_System
Sent_AB	0.97	0.99	0.95	0.99	0.99
	Sent_AB_AllDays	Sent_AB_VAR	Sent_AB_GB	Sent_AB_UnSkew	Sent_AB_WuXia
Sent_AB	0.87	0.60	0.74	0.89	0.99

Correlation between monetary and sentiment shocks					
	Sent_AB	Sent_AB_Kutt	Sent_AB_NS	Sent_AB_AllMP	Sent_AB_NoMP
Kuttner_shock	0.20	0.00	0.18	0.00	0.20
Krippner_shock	0.01	0.02	0.03	0.00	0.05
NS_FFR	0.00	-0.11	-0.01	0.00	0.01
NS_PolicyNews	0.04	-0.05	-0.01	0.00	0.06

Autocorrelation test		*Predictability of exogenous shock series*			
	AR(1) coef.		F-stat	p-value	Adjusted R^2
Sent_AB	-0.02	Sent_AB	0.82	0.67	-0.04
Sent_AB_Kutt	0.00	Sent_AB_Kutt	0.68	0.81	-0.07
Sent_AB_NS	-0.01	Sent_AB_NS	0.81	0.68	-0.04
Sent_AB_AllMP	-0.01	Sent_AB_AllMP	0.59	0.89	-0.09
Sent_AB_NoMP	-0.02	Sent_AB_NoMP	0.77	0.71	-0.05

Note: The vector of variables for predictability tests includes current and lagged (at the date of the previous statement) values of cpi, gdp, vix, ciss, r_euro50, oil, esi, eonia, shadow rate, opti_ab. Sent_AB is estimated with Tone_AB and Krippner shocks.

Table 3. Benchmark estimates

	(1) oiusd1m	(2) oiusd3m	(3) oiusd6m	(4) oiusd9m	(5) oiusd1y	(6) oiusd2y	(7) oiusd3y	(8) oiusd5y	(9) oiusd10y
AB dictionary & Krippner shocks in eq. (6) and (8)									
	Mean equation								
Sent_AB	0.022***	0.005	0.001	0.001	0.033***	0.039***	0.027	0.028	0.033
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.03]	[0.03]	[0.03]
Krippner_shock	0.419***	0.133*	0.099**	0.137***	0.338***	0.429***	0.423***	0.141	0.625**
	[0.09]	[0.08]	[0.04]	[0.05]	[0.10]	[0.11]	[0.14]	[0.50]	[0.29]
VIX	-0.001	-0.001	0.000	-0.001	0.003***	0.001	0.000	-0.001	-0.001
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
SP500	0.001**	0.000	-0.001	0.002***	0.005***	0.007***	0.011***	0.014***	0.017***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Oil	0.003***	0.001	0.003***	0.001**	0.000	-0.001	0.000	0.002	0.002
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
ISMBS	0.004***	0.000	0.001	0.001	0.010***	0.007***	0.004**	0.002	0.001
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Constant	-0.001*	0.000	0.000	0.000	-0.003***	-0.003***	-0.003**	-0.002*	-0.002
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
	Variance equation								
arch(1)	1.851***	3.122***	2.673***	2.362***	1.405***	0.690***	0.470***	0.320***	0.306***
	[0.41]	[0.69]	[0.63]	[0.43]	[0.23]	[0.15]	[0.11]	[0.08]	[0.07]
constant	0.000***	0.000***	0.000***	0.000***	0.000***	0.001***	0.002***	0.002***	0.002***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
N	2576	2576	2576	2576	2576	2576	2576	2576	2576
Using Kuttner shocks in eq. (6) and (8)									
Sent_AB_Kutt	0.004**	0.022**	0.001	0.000	0.036***	0.039***	0.030	0.031	0.017
	[0.00]	[0.01]	[0.00]	[0.00]	[0.01]	[0.01]	[0.02]	[0.02]	[0.02]
Kuttner_shock	0.062***	-0.01	0.052***	0.071***	0.02	0.04	0.02	-0.041	-0.055**
	[0.01]	[0.03]	[0.01]	[0.01]	[0.01]	[0.03]	[0.02]	[0.03]	[0.03]
Using NS shocks in eq. (6) and (8)									
Sent_AB_NS	0.004***	0.006***	0.001	0.002	0.018***	0.031**	0.024	0.015	0.003
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.02]	[0.02]	[0.01]
NS_FFR	0.236***	0.466***	0.122**	0.474***	0.344***	-0.119	-0.194	-0.647*	-0.846**
	[0.06]	[0.06]	[0.05]	[0.08]	[0.08]	[0.22]	[0.35]	[0.34]	[0.35]
NS_PolicyNews	0.212***	0.281***	0.267***	0.408***	-0.291	-0.383	-0.201	0.644	0.916**
	[0.06]	[0.09]	[0.06]	[0.09]	[0.19]	[0.37]	[0.57]	[0.41]	[0.45]
AB dictionary - Alternative measure of Tone based on eq. (2)									
Sent_AB2	0.020***	0.007	0.000	-0.003	0.037***	0.040**	0.008	0.015	0.021
	[0.00]	[0.01]	[0.00]	[0.00]	[0.01]	[0.02]	[0.02]	[0.02]	[0.04]
LM dictionary									
Sent_LM	0.001	0.002	-0.001	-0.002	0.030***	0.020	0.015	0.020	0.024
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.02]	[0.03]
Harvard dictionary									
Sent_Harv	0.001	-0.002	0.000	0.000	0.028***	0.028**	0.020	0.032	0.053**
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.02]	[0.02]	[0.02]

Note: Robust standard errors in brackets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Each column corresponds to a different ARCH estimation of the equations (8) and (9) for a different horizon. Controls and ARCH terms for the Kuttner, NS, LM and Harvard regressions (as well as Krippner shocks for the latter two) have been removed for space constraints and are available upon request. Sent_AB is estimated with Tone_AB and Krippner shocks.

Table 4. Alternative estimates: ECB

	(1) oieur1m	(2) oieur3m	(3) oieur6m	(4) oieur9m	(5) oieur1y	(6) oieur2y	(7) oieur3y	(8) oieur5y	(9) oieur10y
AB dictionary									
Sent_AB	0.000	0.002	0.003	0.007*	0.008**	0.012**	0.014*	0.014	0.01
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]
AB dictionary - Alternative measure of Tone based on eq. (2)									
Sent_AB2	0.001	0.003	0.004	0.008***	0.010***	0.016***	0.017**	0.021*	0.017*
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]
LM dictionary									
Sent_LM	0.000	0.002	0.006**	0.011***	0.013***	0.016***	0.018***	0.012*	0.005
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]
Harvard dictionary									
Sent_Harv	0.000	0.001	0.003	0.004*	0.007**	0.005	0.005	0.005	0.004
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]

Note: Robust standard errors in brackets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Each column corresponds to a different ARCH estimation of the equations (8) and (9) for a different horizon. Controls and ARCH terms for the LM and Harvard regressions have been removed for space constraints and are available upon request.

Table 5. Alternative estimates: Identification

	(1) oiusd1m	(2) oiusd3m	(3) oiusd6m	(4) oiusd9m	(5) oiusd1y	(6) oiusd2y	(7) oiusd3y	(8) oiusd5y	(9) oiusd10y
Using all monetary shocks together in eq. (6)									
Sent_AB_AllMP	0.018***	0.012*	0.001	0.002	0.036***	0.041**	0.016	0.023	0.029
	[0.00]	[0.01]	[0.00]	[0.00]	[0.01]	[0.02]	[0.04]	[0.03]	[0.03]
With no monetary shocks in eq. (6)									
Sent_AB_NoMP	0.022***	0.005	0.001	0.001	0.033***	0.038***	0.027	0.028	0.034
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.02]	[0.03]	[0.03]
Using Greenbook forecasts as instruments for FOMC forecasts in eq. (6)									
Sent_AB_GB	0.010***	0.015**	-0.002	-0.002	0.041***	0.048***	0.036	0.038	0.049*
	[0.00]	[0.01]	[0.00]	[0.00]	[0.01]	[0.01]	[0.03]	[0.03]	[0.03]
Including dispersion and skewness measures of FOMC forecasts in eq. (6)									
Sent_AB_UnSkew	0.021***	0.012**	0.000	0.001	0.035***	0.035**	0.000	0.014	-0.017
	[0.01]	[0.01]	[0.00]	[0.00]	[0.01]	[0.01]	[0.02]	[0.05]	[0.02]
Estimating eq. (6) as a system									
Sent_AB_System	0.022***	0.005	0.001	0.001	0.033***	0.039***	0.027	0.028	0.031
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.03]	[0.03]	[0.03]
Estimating eq. (6) on all 2576 observations									
Sent_AB_AllDays	0.019***	0.008	0.001	0.002	0.028***	0.034***	0.014	0.016	0.021
	[0.00]	[0.01]	[0.00]	[0.00]	[0.01]	[0.01]	[0.32]	[0.03]	[0.03]
VAR identification of Sentiment shocks									
Sent_AB_VAR	0.009***	0.003	0.001	0.002	0.021**	-0.002	-0.007	-0.002	-0.011
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.02]	[0.01]	[0.01]	[0.01]
Including Forward Guidance announcement dummies in eq. (8)									
Sent_AB	0.023***	0.006	0.002	0.001	0.032***	0.004	0.028	0.019	0.009
	[0.01]	[0.01]	[0.00]	[0.00]	[0.01]	[0.01]	[0.03]	[0.03]	[0.01]
Including the monthly change in Wu and Xia's shadow rate measure in eq. (6)									
Sent_AB_WuXia	0.022***	0.005	0.001	0.001	0.033***	0.038***	0.027	0.028	0.034
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.02]	[0.03]	[0.03]

Note: Robust standard errors in brackets. * p < 0.1, ** p < 0.05, *** p < 0.01. Each column corresponds to a different ARCH estimation of the equations (8) and (9) for a different horizon. Controls and ARCH terms have been removed for space constraints and are available from the authors upon request.

Table 6. Alternative estimates: Estimation

	(1) oiusd1m	(2) oiusd3m	(3) oiusd6m	(4) oiusd9m	(5) oiusd1y	(6) oiusd2y	(7) oiusd3y	(8) oiusd5y	(9) oiusd10y
Allowing coeffients of controls to vary on statement days									
Sent_AB	0.007***	0.007*	0.002	0.003	0.016**	0.014	-0.001	0.009	0.021
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
Including a lag of the dependent variable									
Sent_AB	0.028***	0.003	0.001	0.001	0.030***	0.037***	0.029	0.029	0.033
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.02]	[0.03]	[0.03]
No controls									
Sent_AB	-0.002	0.005	-0.001	0.002	0.038***	0.043***	0.039***	0.043*	0.031
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.02]	[0.02]	[0.03]
Pre-ELB & ZLB subsample[1]									
Sent_AB	0.011***	0.018***	0.009	-0.012	0.051***	0.048**	0.048**	0.043*	0.022
	[0.00]	[0.00]	[0.01]	[0.01]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]
TARCH term									
Sent_AB	-0.001	0.000	0.001	0.001	0.033***	0.038***	0.026	0.027	0.030
	[0.00]	[0.01]	[0.00]	[0.00]	[0.01]	[0.01]	[0.03]	[0.03]	[0.04]
ARCH(2)									
Sent_AB	0.019***	0.002	-0.002	0.002	0.026***	0.040***	0.033*	0.026	0.009
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.02]	[0.03]	[0.02]
ARCH(3)									
Sent_AB	0.002*	0.004*	0.001	0.002	0.022**	0.020	0.009	0.015	0.011
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.02]	[0.02]	[0.01]

Note: Robust standard errors in brackets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Each column corresponds to a different ARCH estimation of the equations (8) and (9) for a different horizon. Controls and ARCH terms have been removed for space constraints and are available from the authors upon request. [1] Sample of 870 observations ending December 15, 2008.

Table 7. State-dependent estimates

	(1) oiusd1y	(2) oiusd2y		(1) oiusd1y	(2) oiusd2y
Signal Precision			**VIX**		
Interaction	0.001	0.077***	Interaction	0.013**	0.022***
	[0.03]	[0.03]		[0.01]	[0.01]
Sent_AB	0.033*	-0.002	Sent_AB	0.026***	-0.001
	[0.02]	[0.01]		[0.01]	[0.01]
Abs_Tone_AB2	-0.001	-0.006	VIX	0.003**	0.001
	[0.01]	[0.01]		[0.00]	[0.00]
Sentiment coefficient when:			Sentiment coefficient when:		
High Precision	0.034***	0.055***	High VIX	0.039***	0.020*
	[0.01]	[0.01]		[0.01]	[0.01]
Low Precision	0.033**	0.007	Low VIX	0.013	-0.022
	[0.02]	[0.01]		[0.01]	[0.01]
CPI			**Output Gap**		
Interaction	0.011*	0.012*	Interaction	-0.016***	-0.017**
	[0.01]	[0.01]		[0.01]	[0.01]
Sent_AB	0.027***	0.032***	Sent_AB	0.012**	0.01
	[0.01]	[0.01]		[0.00]	[0.01]
CPI	-0.001*	0.000	Output Gap	-0.002***	-0.002
	[0.00]	[0.00]		[0.00]	[0.00]
Sentiment coefficient when:			Sentiment coefficient when:		
High Inflation	0.038***	0.044***	Expansion	-0.012	-0.015
	[0.01]	[0.01]		[0.01]	[0.01]
Low Inflation	0.017*	0.020	Recession	0.035***	0.034**
	[0.01]	[0.02]		[0.01]	[0.01]

Note: Robust standard errors in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Each column corresponds to a different ARCH estimation of the equations (8) and (9) for a different horizon, augmented with the relevant interaction term. Controls and ARCH terms have been removed for space constraints and are available from the authors upon request. We compute the coefficient of the sentiment variable while setting the state variable at either a high (mean + 1 S.D.) or a low value (mean - 1 S.D.) to interpret interacted effects with continuous variables. This makes the results easier to interpret than with the interaction term that gives information when the interacted variables are at their average values.

Table 8. Further effects of sentiment

ARCH estimation - Effect on inflation expectations					
	(1)	(2)	(3)	(4)	(5)
	swap_3y	swap_4y	swap_5y	swap_10y	beir_10y
Sent_AB	-0.01	0.011	0.001	-0.015**	-0.018**
	[0.02]	[0.02]	[0.02]	[0.01]	[0.01]
N	2576	2576	2576	2576	2576
Controls	Yes	Yes	Yes	Yes	Yes
Predicting next policy decisions					
	Baseline	Shadow	Shadow	Probit	Sent_AB2
	(1)	(2)	(3)	(4)	(5)
	fft	wu&xia	krippner	dumfft	fft
Sent_AB	0.060**	0.107**	0.086*	0.462*	0.056*
	[0.03]	[0.05]	[0.04]	[0.27]	[0.03]
N	81	81	81	81	81
R^2	0.99	0.99	0.99	0.27	0.99
	Tone_AB	SPF	Fut_fft	oiusd1m	oiusd1y
	(6)	(7)	(8)	(9)	(10)
	fft	fft	fft	fft	fft
Sent_AB	6.549***	0.075**	0.052*	0.053*	0.051*
	[1.72]	[0.03]	[0.03]	[0.03]	[0.03]
N	81	81	81	81	81
R^2	0.99	0.99	0.99	0.99	0.99
VAR Variance Decomposition					
	(1)	(2)		(3)	(4)
	IndPro	CPI		IndPro	CPI
Sent_AB	0.035	0.013	Krippner	0.010	0.037

Note: Standard errors in brackets. * p < 0.10, ** p < 0.05, *** p < 0.01. In the upper panel, each column corresponds to a different ARCH estimation of the equations (8) and (9) for a different horizon, augmented with the relevant interaction term. Controls and ARCH terms have been removed for space constraints and are available from the authors upon request. In the middle panel, all columns are estimated with OLS, except column (4) with a probit model and the dependent variable is a dummy variable taking the value 1 for rate increases, 0 for statu quo and -1 for rate decreases. In all columns, the dependent variable is considered in t+1 while all explanatory variables are considered in t. The lower panel shows the forecast error variance decomposition of the VAR model described in section 7.

APPENDIX
FOR ONLINE PUBLICATION

Table A. Dictionary word lists

Positive words	Negative words
Apel and Blix-Grimaldi (2012)	
25	26
Loughran and McDonald (2011)	
354	2349
General Inquirer's Harvard dictionary	
1915	2291
Most illustrative tokens	
increas*	decreas*
accelerat*	decelerat*
fast*	slow*
strong*	weak*
high*	low*
gain*	loss*
expand*	contract*
improv*	declin*
positiv*	negativ*
great*	question*
strength*	dampen*
strong*	concern*

Table B. Data description

Abbreviation	Description	Source	Frequency
oiusd1m	US 1 month OIS	Datastream	Daily
oiusd3m	US 3 month OIS	Datastream	Daily
oiusd6m	US 6 month OIS	Datastream	Daily
oiusd9m	US 9 month OIS	Datastream	Daily
oiusd1y	US 1 year OIS	Datastream	Daily
oiusd2y	US 2 year OIS	Datastream	Daily
oiusd3y	US 3 year OIS	Datastream	Daily
oiusd5y	US 5 year OIS	Datastream	Daily
oiusd10	US 10 year OIS	Datastream	Daily
Tone_AB	Apel and Blix-Grimaldi (2012)	Authors' computations	For each FOMC statement
Tone_LM	Loughran and McDonald (2011)	Authors' computations	For each FOMC statement
Tone_Harv	Harvard dictionary	Authors' computations	For each FOMC statement
FFR	Effective Federal Funds Rate	Datastream	Daily
FFT	Federal Funds Rate Target	Datastream	Daily
WuXia	Shadow rate	Wu-Xia (2016)	Monthly
Krippner	Shadow rate	Krippner (2015)	Daily
NS_FFR	Shock to the policy rate	Nakamura-Steinsson (2016)	For each FOMC statement
NS_PolicyNews	Shock to the monetary policy news	Nakamura-Steinsson (2016)	For each FOMC statement
CPI	CPI inflation rate (Year-over-Year %)	Bureau of Labor Statistics	Monthly
INDPRO	Industrial Production Index (YoY %)	Federal Reserve	Monthly
GDP	Real GDP growth (YoY %)	Bureau of Economic Analysis	Quarterly
VIX	Volatility Index of the CBOE	Datastream	Daily
ISMBS	ISM Report on Business Survey Index	Datastream	Monthly
Oil	WTI oil price growth (YoY %)	Datastream	Daily
SP500	Standard & Poor's 500 daily returns	Datastream	Daily
fomc_cpi_*	FOMC inflation projections for current and next calendar years	Federal Reserve	Quarterly
fomc_gdp_*	FOMC output projections for current and next calendar years	Federal Reserve	Quarterly
SPF_*	Survey of Professional Forecasters' inflation forecasts for 1Q, 4Q and 5Y	Federal Reserve	Quarterly

Note: Weekly, monthly and quarterly data are constant-interpolated to daily frequency so as to respect the information structure.

Table C. Descriptive Statistics: Benchmark model

	Obs	Mean	Std. Dev.	Min	Max
oiusd1m	2,576	1.45	2.02	0.07	5.37
oiusd3m	2,576	1.46	2.03	0.07	5.44
oiusd6m	2,576	1.47	2.04	0.07	5.56
oiusd9m	2,576	1.50	2.03	0.07	5.62
oiusd1y	2,576	1.84	1.98	0.25	5.76
oiusd2y	2,576	2.02	1.84	0.34	5.73
oiusd3y	2,576	2.27	1.73	0.42	5.72
oiusd5y	2,576	2.75	1.52	0.73	5.76
oiusd10y	2,576	3.48	1.22	1.54	5.85
Krippner_shock	82	-0.01	0.05	-0.24	0.13
Kuttner_shock	82	-0.09	0.40	-2.95	0.50
NS_FFR	82	0.00	0.04	-0.20	0.10
NS_PolicyNews	82	0.00	0.02	-0.13	0.05
VIX	2,576	21.46	8.16	11.72	59.77
SP500	2,576	0.00	0.01	-0.09	0.11
Oil	2,576	0.00	0.11	-0.55	0.33
ISMBS	2,576	53.37	4.12	37.6	61.3

Note: Kuttner monetary shocks are computed based on equation (3).

Table D. Sentiment shocks identification

Equation (6)		Equation (7)	
	Tone_AB		Resid. of (6)
l1.Tone	0.366***	AR(1)	-0.069
	[0.11]		[0.11]
fomc_pce_cy	0.613	constant	-0.001
	[0.41]		[0.07]
fomc_pce_ny	-0.311	N	84
	[0.72]	R^2	0.01
fomc_gdp_cy	0.007		
	[0.19]		
fomc_gdp_ny	0.158		
	[0.30]		
Krippner shock	0.881		
	[2.03]		
spf_cpi_0	-0.130		
	[0.08]		
spf_cpi_1	-0.009		
	[1.08]		
spf_cpi_10	-1.578		
	[1.41]		
cpi	0.056		
	[0.19]		
l1.cpi	0.256		
	[0.25]		
gdp	-0.984**		
	[0.49]		
l1.gdp	0.783*		
	[0.42]		
shadow	1.529		
	[1.08]		
l1.shadow	-1.61		
	[1.12]		
L.vix	-0.365*		
	[0.21]		
L.r_sp500	-0.015		
	[0.06]		
L.oil	0.16		
	[0.11]		
L.ismbs	0.111		
	[0.23]		
constant	3.074		
	[3.16]		
N	84		
R^2	0.61		

Note: Standard errors in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Parameters are estimated based on equations (6) and (7). L is the lag operator (i.e. the value the day before) and l1 is the value at the date of the previous statement.