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Abstract
We explore empirically the theoretical prediction that waves of optimism or pessimism may have aggregate effects, in the context of monetary policy. We investigate whether the sentiment conveyed by ECB and FOMC policymakers in their statements affect the term structure of private short-term interest rate expectations. First, we quantify central bank tone using a computational linguistics approach. Second, we identify sentiment as exogenous shocks to these quantitative measures using an augmented narrative approach following the information friction literature. Third, we estimate the impact of sentiment on private agents' expectations about future short-term interest rates using a high-frequency methodology and an ARCH model. We find that sentiment shocks increase private interest rate expectations around maturities of one and two years. We also find that this effect is non-linear and depends on the state of the economy and on the characteristics (precision, sign and size) of the sentiment signal.

Keywords: Animal spirits, Optimism, Confidence, Central bank communication, Interest rate expectations, ECB, FOMC.

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 and beliefs about fundamentals, may have aggregate effects, in the context of the euro area and US monetary policy.[1] More specifically, we investigate whether the sentiment conveyed by European Central Bank (ECB) and Federal Open Market Committee (FOMC) policymakers in their statements, quantified using computational linguistic methods, affect the term structure of private agents' short-term interest rate expectations.

Because long-term interest rates – a key determinant of private 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 to affect financial markets or to help predict policy decisions has given rise to 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.

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 ECB and FOMC statements using computational linguistic methods and more precisely dictionary methods.[2] Their main advantages are

[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.

[2] This central bank sentiment could potentially stem from monetary policy committee members' subjective probabilities, non-nested information sets, risk aversion, cognitive bias, or even their press office. This question

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 an ambiguity measure of policy statements. Many studies have coded indicators of the monetary policy stance conveyed by ECB or FOMC 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 communications. However, while they use an automated lexicographic method, they focus on the policy stance content of central bank communication, which sentiment is supposed to be orthogonal to. 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 convey a given message matters.

Our second contribution to the literature is to investigate whether this policymakers' sentiment affects the term structure of private interest rate expectations, which are key to consumption and investment decisions. 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. However, our analysis aims to focus on the effects of sentiments, distinct from fundamentals and expectations of future fundamentals, as formalised in the above-mentioned literature. To do so, we identify exogenous shocks to central bank tone to avoid any endogeneity bias and to comply with the assumption of Angeletos and La'O (2013) that sentiments are orthogonal to fundamentals. We follow the identification strategy of Romer and Romer (2004) augmented first so that exogenous shocks are not only orthogonal to the central bank's information set but also to private agents' information set and second by removing the contribution of past sentiment shocks following insights from the information frictions literature.

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

however is beyond the scope of this paper, which objective is to investigate whether such sentiment does exist and its effect on policy 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.

of sentiment using the local projections method of Jorda (2005). Finally, because the precision of the signal conveyed to the public would matter in a Bayesian updating model or because the sign, the size, the position in the business cycle, the level of inflation or the concomitant occurrence of a monetary policy shock could also potentially matter, we assess the non-linear effects of sentiment shocks.

We find that positive shocks to sentiment increase private short-term interest rate expectations at horizons from 3 months to 10 years ahead in the euro area, and for horizons 1 and 3 months ahead and from 1 to 3 years ahead in the Unites States. The peak effect in terms of magnitude and significance is around the 1 and 2 years maturity both in the euro area and in the United States. This effect is robust to the dictionary used for the quantification of tone measures, to an alternative identification of sentiment shocks using residuals of a Taylor rule, to alternatives estimation methods such as TARCH or OLS models, and to the parameter used for the high-frequency methodology: the window around policy statements and which days we look at in a control group. We also show that this effect is persistent. Finally, we find 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 also depends on their sign and size, as well as on the level of inflation, the business cycle and monetary shocks. The reaction of private agents to the sentiment conveyed by policymakers is signal- and state-dependent.

These results give policymakers some insights on how private agents interpret and respond to the sentiment conveyed by central bank communication, that should be interpreted as optimism or pessimism signals beyond the policy decision and the central bank and private agents' macroeconomic information set. 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. Section 7 concludes.

2. Framework

This section sets out our theoretical framework using insights from the literature to derive predictions 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" phenomenon, 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. One should consider a positive sentiment shock 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 similar to a sunspot as it affects information sets without affecting the true aggregate fundamentals or any agent's beliefs about fundamentals (for the latter being fixed and common knowledge). This variable introduces aggregate variation in beliefs of equilibrium outcomes without any variation in beliefs of fundamentals and is referred to as a sentiment shock.[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 if and only if information is imperfect, and are increasing linear functions of ξ_t.

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 short-term interest rate r_t and the associated sentiment shocks ξ_t provided by a specific agent: the central bank, using computational lexicographic models to quantify this unobservable variable. In doing so, we need to respect two crucial assumptions described above: we need to take information frictions into account and sentiment shocks must be orthogonal to beliefs of fundamentals or "news shocks", so to private agents' and policymakers' macroeconomic forecasts.

3. Quantifying Central Bank Tone

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

To quantify the effect of central bank sentiment on interest rate anticipations, we first need to identify the main source through which central bank sentiment may happen 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

[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.

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 and enable to accurately identify their effects on our variables of interest.

ECB statements are published just before the monthly press conference explaining monetary policy decisions taken during the Governing Council meetings that happened earlier the same day, while FOMC statements are released at the end of the two-day FOMC meetings that are scheduled eight times a year. The ECB started to publish these statements in January 1999 with a monthly frequency and the FOMC in 1996 with a low frequency, increasing to eight times a year in 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 ECB and FOMC statements. Since August 2005, the ECB released 119 statements while the FOMC published 85 statements. On average, the ECB statements are usually three times longer (858 words) than the FOMC ones (278).[6]

Other types of communication could reveal central bank sentiment such as the minutes of the policy meetings like those of the FOMC or the Monetary Policy Committee (MPC) at the Bank of England. 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, speeches at conferences or during political events like the testimony to the US congress may also convey central bank sentiment. But their frequency, audience and context make it more difficult to capture consistently and to give them the same weight than statements following monetary policy decisions.[7] This choice means that we leave out Mario Draghi's "Whatever it takes" for instance. One could however argue that this speech pronounced in London the 26 July 2012 is an outlier. Given these considerations, we consider ECB and FOMC statements to capture central bank sentiment.

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

[6] 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. The FOMC has 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 and between the FOMC and the ECB 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] That would however be an interesting question and we leave that for future research.

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 from each ECB and FOMC statement: the first, our benchmark, is the tone conveyed; the second is the tone conveyed weighted by the clarity of the tone measure conveyed, and the third is the ambiguity of the overall statement published.

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, we use the seminal positive and negative categories of the General Inquirer's Harvard IV-4 psychosocial dictionary.[8] These categories reflect Osgood et al. (1957)'s semantic differential findings regarding basic and everyday language universals. Third, because the Harvard word list has not been specifically designed for a financial context, Loughran and McDonald (2011) have developed a list of words that better reflect the tone in a financial context. They suggest that almost three-fourths of negative words in the Harvard dictionary are not negative in a financial context.

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 of the Appendix shows the most illustrative and frequent positive and negative words identified in ECB and FOMC statements and gives the number of positive and negative words listed in each dictionary. 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 "i*ncreasing growth*" versus "*decreasing unemployment*", or that they could use a 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 message.

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.

$$\Xi_t = \frac{\mathrm{PositiveWords_t} - \mathrm{NegativeWords_t}}{\mathrm{TotalWords_t}} \qquad (1)$$

[8] 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/.

We therefore obtain three measures of tone, comprised 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.[9] 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 define an ambiguity variable at the level of the overall document. Loughran and McDonald (2011) provide a dictionary listing words denoting uncertainty, in addition to the one about tone, with some emphasis on the general notion of imprecision, such as "*approximate*", "*contingency*", "*depend*", "*fluctuate*", "*indefinite*", "*uncertain*" and "*variability*" for instance. This measure, computed as ratio of the number of uncertainty words over the total number of words in a document, is used to take into account the overall precision of the statement disclosed to the public.

4. Financial and Macroeconomic Data

This section describes the financial and macroeconomic data used to identify exogenous shocks to the tone variable Ξ_t conveyed by ECB and FOMC statements and to estimate the effects of sentiment shocks on the term structure of short-term interest rate expectations.

Our dependent variables are the different maturities, from 1-month to 10-year, of 3-month Eonia (resp. LIBOR) OIS for the euro area (resp. the US) as they are good proxies of expectations of future short-term interest rates. OIS are instruments that 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. 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 (for instance, from 6-month to 10-year in Christensen and Rudebusch, 2012). Our database has a daily frequency and spans from May 2005 to June 2015.

As explanatory variables, we use several macroeconomic and financial variables. Because monetary policy decisions are taken the same day as sentiment is conveyed to the public

[9] For comparison purposes over a similar scale (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.

through statements, our analysis requires controlling for the effect of the monetary shock.[10] We follow Kuttner (2001)'s methodology to identify monetary policy shocks in both the euro area and the US using changes in the price of futures contracts. 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 futures contracts on that day. This identification of monetary shocks relies on the financial market participants' interpretation of the monetary news disclosed that day, which encompasses central bank decisions, related to conventional or unconventional tools, and central bank information released at the same time. 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:

$$S_t = \frac{D}{D-d}\left(f_{m,d}^{0} - f_{m,d-1}^{0}\right) \quad (3)$$

S_t is the unexpected interest rate variation which constitutes a monetary shock, $f_{m,d}^{0}$ is the current-month futures rate and D is the number of days in the month and d the day of the decision. Our dataset also includes returns of the Eurostoxx 50 and Standard and Poor's 500 price indices, 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 financial stress (the CISS for the euro area and the VIX for the US). Finally, we control that changes in our dependent variable are not driven by changes in private sentiment by including the Economic Sentiment Indicator (ESI) of the European Commission for the euro area and the ISM Report on Business Survey index for the US. Table 2 presents the descriptive statistics of the data series used in this paper.[11]

For the identification of shocks, we also use the shadow rate calculated by Wu and Xia (2016) as an overall measure of monetary policy since our sample period encompasses periods when monetary policy makes use of both conventional and unconventional tools so as to take it into account with only one measure expressed in the interest rate space. The specification includes the year-over-year CPI inflation rate and real GDP growth rate.

We also use macroeconomic forecasts from central banks (ECB and FOMC projections) and private agents: ECB and US Surveys of Professional Forecasters (SPF). 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 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 realized 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

[10] 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).

[11] 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.

"central tendency" removes the three highest and three lowest forecasts. As standard in the literature, we use the midpoint of the full range.

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. 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.[12] Data sources are presented in Table B in the Appendix.

5. Identifying Exogenous Sentiment Shocks

After having quantified the tone conveyed by ECB and FOMC statements, we need to overcome 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 beliefs about the current and future state of the economy and sentiments. Thus, it is necessary to isolate exogenous sentiment shocks, orthogonal to fundamentals and expectations of future fundamentals, 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 theoretical assumption of Angeletos and La'O (2013).

5.1. Identification Strategy

The question 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 RR_Sentiment_xx, xx being either AB, LM or Harvard dictionaries) to be orthogonal to both central bank's and

[12] 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).

private agents' information sets and to macro and financial market information 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.

To do so, we estimate the following equations (4)-(5) at the daily frequency and extract the residuals ξ_t of such a model that we consider as an exogenous sentiment shock:

$$\Xi_t = \beta_0 + \beta_1\, \Xi_{t-j} + \beta_2\, \Omega_t + \beta_3\, \Psi_t + \beta_4\, X_{t-1} + \beta_5\, Z_t + \xi'_t \tag{4}$$

$$\xi'_t = \beta_6 + \beta_7\, \xi'_{t-j} + \xi_t \tag{5}$$

where j is the number of days between each policy statement, so Ξ_{t-j} is the tone of the previous ECB or FOMC policy statement. We assume in equation (4) that the sentiment variable ξ'_t must be orthogonal to the contemporaneous policymakers' information set Ω_t, to the private agents' one Ψ_t, to lagged 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, because ξ'_t is likely to be a combination of current and past sentiment shocks, we estimate equation (5) 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. The policymakers' information set Ω_t comprises ECB (resp. FOMC) inflation and output projections for current and next calendar years, Ψ_t includes the ECB (resp. US) SPF inflation forecasts for 1, 2 and 5 years ahead (resp. next quarter, next year and 10 years ahead), X_t contains the CISS (resp. the VIX), EuroStoxx50 daily returns (resp. Standard and Poor's 500), the oil price growth rate and the confidence index ESI (resp. the ISM survey), and Z_t comprises the level of the overall policy stance measured by the shadow rate of Wu and Xia (2016), the inflation rate and the monthly-interpolated real GDP growth rate.[13] Table 3 shows the estimated parameters of equations (4) and (5).

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 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.[14]

When extracting exogenous sentiment shock, 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, and forecasts present the advantages of encompassing rich information sets. Bernanke et al. (2005) show that a data-rich environment 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-

[13] Krippner (2013, 2014) proposes an alternative measure of the stance of monetary policy using factor models. His shadow rates have a correlation of 0.91 and 0.87 with the ones of Wu and Xia (2016) for the United States and euro area respectively. Our sentiment shocks with Krippner's measures have a correlation of 0.94 and 0.98 with our benchmark sentiment shocks for the United States and euro area respectively. Estimates of the effect of sentiment shocks on OIS are similar and available from the authors upon request.

[14] 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.

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.

5.2. Robustness tests

We assess the external validity of this identification strategy for extracting the sentiment shock in two ways. First, we compute sentiment shocks using two alternatives: *(i)* a Taylor rule-type equation applied to sentiment with a lag of the dependent variable, and contemporaneous inflation and output (TT_Sentiment_xx), and *(ii)* a VAR with financial market variables such as for the euro area: the VIX, the CISS (resp. the Saint-Louis Fed Financial Stress Index for the US), Eurostoxx 50 (resp. S&P500) returns, oil price variations, the Eonia (resp. the effective fed funds rate) and a tone measure ordered last in the vector of endogenous variables (VAR_Sentiment_xx). The first sentiment shock is the residual of the Taylor rule-type equation while the second sentiment shock is the Cholesky decomposition innovation. Figure 2 plots the time series and distribution of the estimated sentiment shocks using the AB dictionary (Figure A and B in the Appendix plots those using the LM and Harvard dictionaries). We then assess the autocorrelation and normality of these sentiment shocks. This calls for discarding VAR innovations as satisfactory shocks, since these shocks are auto-correlated and the kurtosis of their distribution is very low. Tables 4-A and 4-B (for the euro area and the US respectively) show normality and autocorrelation tests together with some descriptive statistics and the correlation of shocks. Second, if our estimated series of sentiment shocks are relevant, they should be unpredictable from movements in data. We assess the predictability of the estimated shock series with Granger-causality type tests using 22 macroeconomic and financial variables, including lagged sentiment. Tables 4-A and 4-B also show 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. It suggests that the Romer-Romer-type and Taylor rule-type shock series are relevant to be used in our second-stage estimations so as to assess their effects on private inflation expectations, whereas the VAR innovations are not.

We also assess the internal validity of our identification strategy for extracting the sentiment shock in two ways.[15] First, 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 (4) 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 (4) so as to ensure that our identification of sentiment shocks is not biased by endogeneity (see section 6.3). The fact that the correlation between ν_t and ξ_t is non-significant suggests that central bank projections are not influenced by the policymakers' sentiment. The correlation between our benchmark sentiment shock, RR_Sentiment_AB, and this alternative one, RR_Sentiment_AB_GB, is 0.68.

[15] The two tests are performed only for the FOMC for data availability reasons. The ECB does not publish both policymakers and staff forecasts, and the ECB forecasts are published as point forecasts so we cannot compute dispersion and skewness measures.

Second, 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 RR_Sentiment_AB_SK, is 0.99 and suggests that the estimated sentiment shock are not biased by the representation of the information set of policymakers.

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 ECB and 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.[16]

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 ECB and 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 make the sentiment variable orthogonal to fundamentals –as performed in section 5– so we can single out the causal effect of the central bank sentiment on revisions in private interest rate expectations.

There are two other issues that we need to overcome. First, as it is common with financial variables, the variance of our dependent variables changes over time. We therefore use an

[16] 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 (2013) use a similar approach focusing on the increased volatility generated by monetary news.

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 (4)-(5) are generated regressors that might cause biased standard errors; we compute standard errors robust to misspecification using the Huber-White-sandwich estimator.[17] The estimated equations are the following:

$$\Delta r^E_{t,m} = \beta_0 + \beta_1\, \xi_t + \beta_2\, S_t + \beta_3\, M_t + \varepsilon_t\,,\ \varepsilon_t \sim (0, \sigma^2_t) \qquad (6)$$

$$\sigma^2_t = \gamma_0 + \sum_{i=1}^{p} \gamma_i\, \varepsilon^2_{t-i} \qquad (7)$$

where $\Delta r^E_{t,h}$ is the change between t and $t\text{-}1$ in euro area (resp. US) interest rate expectations for horizon m, ξ_t is the ECB (resp. FOMC) sentiment shock estimated through equations (4)-(5), S_t is monetary surprises à la Kuttner (2001), and M_t is a vector of controls including the CISS (resp. the VIX), the Eurostoxx50 (resp. S&P 500) returns, oil price variations and the ESI index (resp. ISM). The number of lags p (4 for the euro area and 1 for the US) in the variance equation is determined by their significance. We also need to acknowledge that while sentiment shocks are orthogonal to macroeconomic and monetary policy developments by construction, they may not be to monetary shocks.[18] We are particularly interested in the β_1 coefficient which should be interpreted as the effect of central bank sentiment on revisions of interest rate expectations controlling for the monetary decision and some other financial developments captured by the M_t vector that might have potentially occurred the same days.

6.2. Benchmark estimates

We test the prediction -presented in section 2- that sentiment affects interest rate expectations by estimating equations (6)-(7) with an ARCH specification. Our benchmark analysis is performed with the sentiment measure generated with the dictionary of Apel and Blix Grimaldi (2012). We assess our hypothesis on interest rate expectations at horizons 1, 3, 6 and 9 months, and 1, 2, 3, 5 and 10 years. Our estimation sample starts in August 2005 so we have 2576 observations for each maturity. Tables 5-A and 5-B show the benchmark results. The β_1 coefficient is positive and significant for horizons from 3 months to 10 years ahead in the euro area, and for horizons 1 and 3 months and from 1 to 3 years in the Unites States. The peak effect in terms of magnitude and significance is at 1 to 3 years ahead in the euro area and at 1 and 2 years ahead in the United States. Using Loughran and McDonald (2011)'s and Harvard's word lists, the β_1 coefficient remains positive and significant for the maturity of 1-year at minimum. These results show that sentiment shocks increase private interest rate expectations. The information conveyed by the sentiment expressed in ECB and FOMC statements appears to be interpreted by private agents for similar horizons to the transmission lags of monetary policy, estimated to be around 18 months in Bernanke and Blinder (1992) or Bernanke and Mihov (1998). The β_2 coefficient associated with monetary surprises is also positive and significant but for horizons from 1 month to 3 years in the euro area and for horizons from 1 month to 9 months in the United States. It is worth stressing that in the euro area, shocks to sentiment account at maximum for 4% of the variance of interest rate expectations 3 and 5 years ahead on meeting days, while monetary shocks account at maximum for 31% of the variance of interest rate expectations but at shorter horizons, with this contribution decreasing with maturity. In the United States, shocks to sentiment account at maximum for 5% of the variance of interest rate expectations 2 and 3 years ahead, while monetary shocks only account at maximum for 7% of the variance of interest rates expectations 6 and 9 months ahead.

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[17] 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.

[18] Tables 4-A and 4-B show that their correlation is low: 0.04 is the euro area and 0.18 in the US.

6.3. Sensitivity analysis

We estimate various alternative specifications to assess the robustness of the benchmark result. First, we estimate the effects of the sentiment identified from an alternative tone measure weighted by the clarity (the sum of positive and negative words) of the tone conveyed -Ξ_t'- computed with equation (2). Second, because the Forward Guidance (FG) policy is using communication and statements as a tool to manage policy expectations, we estimate the effect of sentiment when controlling for the FG announcements (using dummies for the day FG has been introduced and then modified). Third, for the US only because of data constraints, we identify sentiment shocks by instrumenting FOMC forecasts with Greenbook forecasts or augment the policymakers' information set with dispersion and skewness measures of FOMC forecasts. Fourth, we consider shocks identified through a Taylor rule-type equation using Apel and Blix-Grimaldi (2012)'s, Loughran and McDonald (2011)'s and Harvard's dictionaries. Fifth, we test alternative estimation methods such as TARCH and OLS models. Threshold ARCH 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 then estimate equations (6)-(7) on Wednesday and Thursday for the ECB (respectively Tuesday and Wednesday for the FOMC) of the sample rather than all days. Assuming that P1 is our treatment sample and P2 our control sample, P1 includes ECB (resp. FOMC) announcements that happen the first Wednesday or Thursday of each month for the ECB (resp. Tuesday and Wednesday for the FOMC). P2 is another sample containing all other Wednesdays and Thursdays (resp. Tuesday and Wednesday for the FOMC) during our analysis period. P2 contains days different from P1 to the extent that none monetary or sentiment shocks occurred. However, because they are the same days in the week, they are comparable on several other dimensions such as worldwide publications of other economic news for example. The sample is reduced to 1030 observations for the ECB and 1034 for the FOMC. Seventh, although this goes against the very objective of high-frequency studies of isolating an event from others and should reduce the precision of the estimation, we modify the window over which we assess the response of changes in interest rate expectations: we consider the variation between *t* and *t-2*, and between *t+1* and *t-1*. Eighth, we then include a lag of the dependent variable in equation (6). Ninth, we estimate equation (6) without the M_t vector of controls to examine potential over-identification issues and further verify the orthogonality condition of our estimated shocks. Tenth, we estimate the effects of sentiment during normal times, so before the implementation of the FG policy or before the conventional tool of monetary policy has reached its Effective Lower Bound (ELB). Tables 6-A and 6-B present estimates of β_1 for these alternative specifications.[19] The robustness tests confirm the positive coefficient of sentiment shocks on interest rate expectations, primarily at work around the 1-year maturity both in the euro area and in the United States.

6.4. Dynamic estimates

This section investigates the dynamic effects of sentiment and assess how persistent is the effect evidenced in section 6.2. Our preferred approach is to use the local projections method of Jorda (2005). Impulse response functions obtained from VARs may be imposing excessive

[19] In order to control that the effect of sentiment is not a statistical artefact, we also estimate the effect of the absolute value of sentiment shocks, which should not yield the same outcomes as sentiment shocks make sense through their positive and negative values. The effect is not positive and significant, and so suggests than the effect of sentiment is not an artefact. Estimates are available from the authors upon request.

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.[20]

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:

$$y_{t+h} = \alpha_h + \beta_h \epsilon_t + \phi_h(L) X_t + \eta_{t+h} \tag{8}$$

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 (7) with OLS, we estimate the ARCH model of equations (6)-(7) so that the variable of interest is $\Delta r^E_{t,m}$ the daily change in euro area (resp. US) interest rate expectations for horizon h, the exogenous shock is the sentiment shock ξ_t, and the vector X_t encompasses the vectors S_t and M_t from equation (6) and $\eta_{t+h}$is estimated as in equation (7). Figure 3 plots the results from estimating the dynamic effects, over the following 15 business days, of sentiment shocks on 1- and 2-year OIS (the main maturities for which we find a significant effect) and shows that, except for 2-year OIS in the US for which the effect of sentiment shocks lessens, the effect in the euro area and for 1-year OIS in the US persists and even increases.

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. For instance, the effect of sentiment could depend on the ambiguity of 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 ambiguity described in section 3.2 to capture the precision of the message conveyed in central bank statements. We expect the effect of positive sentiment shocks to be stronger if the signal is more precise (i.e. if ambiguity is lower) and vice versa. The effect of sentiment could also depend on two features of the sentiment shock such as the sign (positive for optimism and negative for pessimism) or the size of sentiment shocks.

Sentiment shocks could also be interpreted differently according to the state of the economy or policy decisions. We test whether the effect of sentiment is different during a recession using a dummy that takes one in a recession according to the classification proposed by the CEPR and the NBER. We also estimate the effect of sentiment shocks conditional on the level of inflation. Finally, we could expect positive sentiment shocks to have less effect on interest rate expectations when interacted with a positive monetary shock (i.e. a contractionary shock) as the policy decision might already diffuse some optimism beyond the expected future state of the economy, whereas an equivalent positive sentiment shock would have more impact when associated with a negative monetary shock (i.e. an expansionary shock) because it conveys specific information not shared with the monetary shock.

We augment equation (6) with an interaction term between sentiment shocks and the state variables (that we also include in isolation in equation (6) if not already present) we would

[20] 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.

like to focus on. Tables 7-A and 7-B show estimates for the different cases described above. The non-linear effect of sentiment shocks conditional on the precision of the signal disclosed to the public (the ambiguity measure) is at work for maturities between 1 month and 2 years in the United States, and at the 1, 2 months and 1 year horizons in the euro area. As expected, the effect of sentiment shocks is stronger when ambiguity is low (so the signal is more precise) rather than when ambiguity is high. Looking at the effect of sentiment conditional on the sign of the sentiment shock, it appears that in the United States, results are driven by pessimism (negative shocks) whereas the interaction term in the euro area is not significant. The effect of negative sentiment shocks is significant whereas the effect of positive sentiment shocks is not, though they are not significantly different from each other. This suggests nevertheless a similar non-linearity than in the US. A much pronounced difference between the euro area and the US arises from the interaction with the size of sentiment shocks (estimated with their square values): big shocks have more impact than small shocks in the euro area, whereas small shocks have more impact than big shocks in the US. Following the insights of Bayesian belief updating, private agents get more information for their formation of beliefs about future policy from small shocks than big shocks in the US and this suggests that they are potentially less able to extract information about future policy from extreme values of sentiment conveyed by FOMC policymakers.

The interaction term with the recession dummy is negative and significant in the US for maturities of 1 and 2 years, but is never significant in the euro area. The FOMC sentiment has more effect during expansions than recessions, suggesting that private agents get more information for their beliefs about the expected future policy rate from sentiment when the economy is doing well. Said differently, their knowledge of the reaction function of policymakers during expansions may be less clear so they put more weight on additional signals. The interaction term with inflation is positive and significant in the US for maturities between 9 months and 3 year and is significant in the euro area at the 6 months and 2 years maturities. Both ECB and FOMC sentiment shocks have more effect when inflation is high. Again, this may suggest that when inflation is high private agents have a less clear knowledge of the reaction function of policymakers and so give more weight to sentiment to predict the future policy rate. Finally, the non-linear effect of sentiment shocks conditional on monetary shocks is significant and negative at maturities between 1 month and 1 year in the United States and at maturities of 1 and 2 months in the euro area. FOMC and ECB sentiment has a lower effect (even negative in the US) with positive monetary shocks than with negative monetary shocks. The effect of sentiment is reinforced by expansionary monetary shocks whereas sentiment seems less relevant when associated with contractionary shocks.[21] Overall, these estimates suggest that the reaction of private agents to the sentiment conveyed by policymakers is signal- and state-dependent.

7. Conclusion

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 ECB and FOMC statements. We are able to assess whether this policymakers' sentiment affects private interest rate expectations.

[21] We have also estimated the interaction of sentiment shocks with measures of private market sentiment proxied by the CISS or the VIX and found no non-linear effects. Estimates are available from the authors upon request.

We find that positive shocks to sentiment (i.e. optimism shocks) increase private interest rate expectations at horizons from 3 months to 10 years ahead in the euro area, and for horizons 1 and 3 months ahead and from 1 to 3 years ahead in the US. The peak effect in terms of magnitude and significance is around the 1 and 2 years maturity both in the euro area and in the US. We also find that the effect of sentiment shocks is smaller when the precision of the signal conveyed (i.e. the ambiguity of central bank statements) is low rather than when the precision is high. The effect of sentiment shocks also depends on their sign and size, as well as on the level of inflation, the business cycle and monetary shocks. The reaction of private agents to the sentiment conveyed by policymakers is signal- and state-dependent.

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 but that they do not convey the same information when they happen with tightening or easing policies. 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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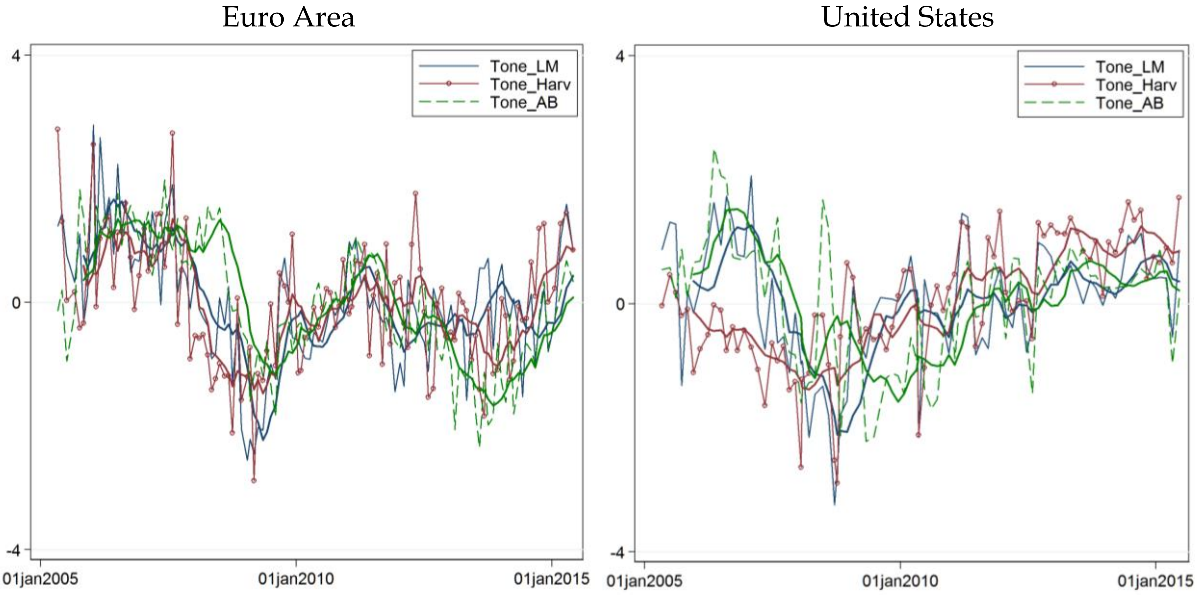
Figure 1. Central Bank Tone variables



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

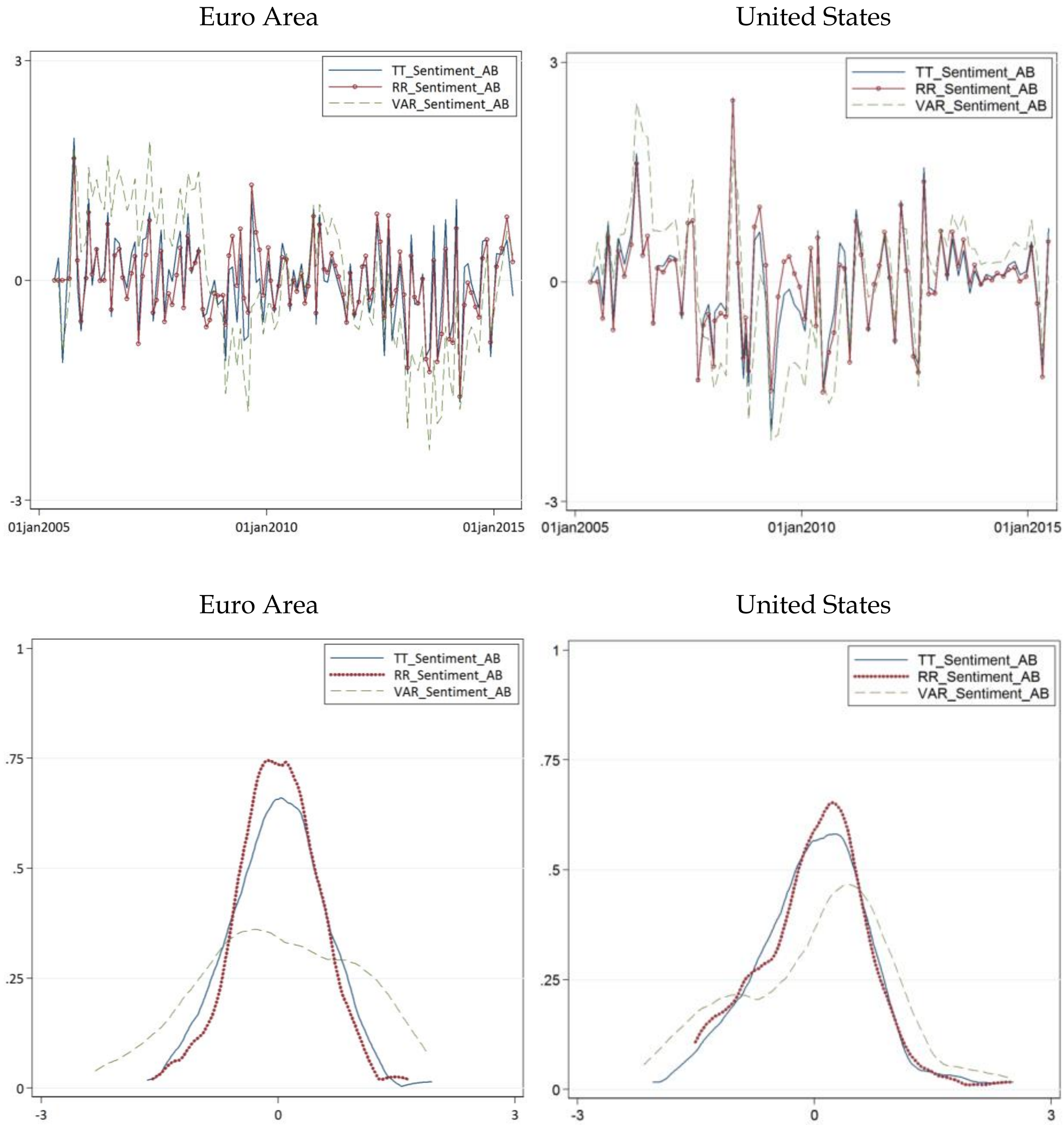
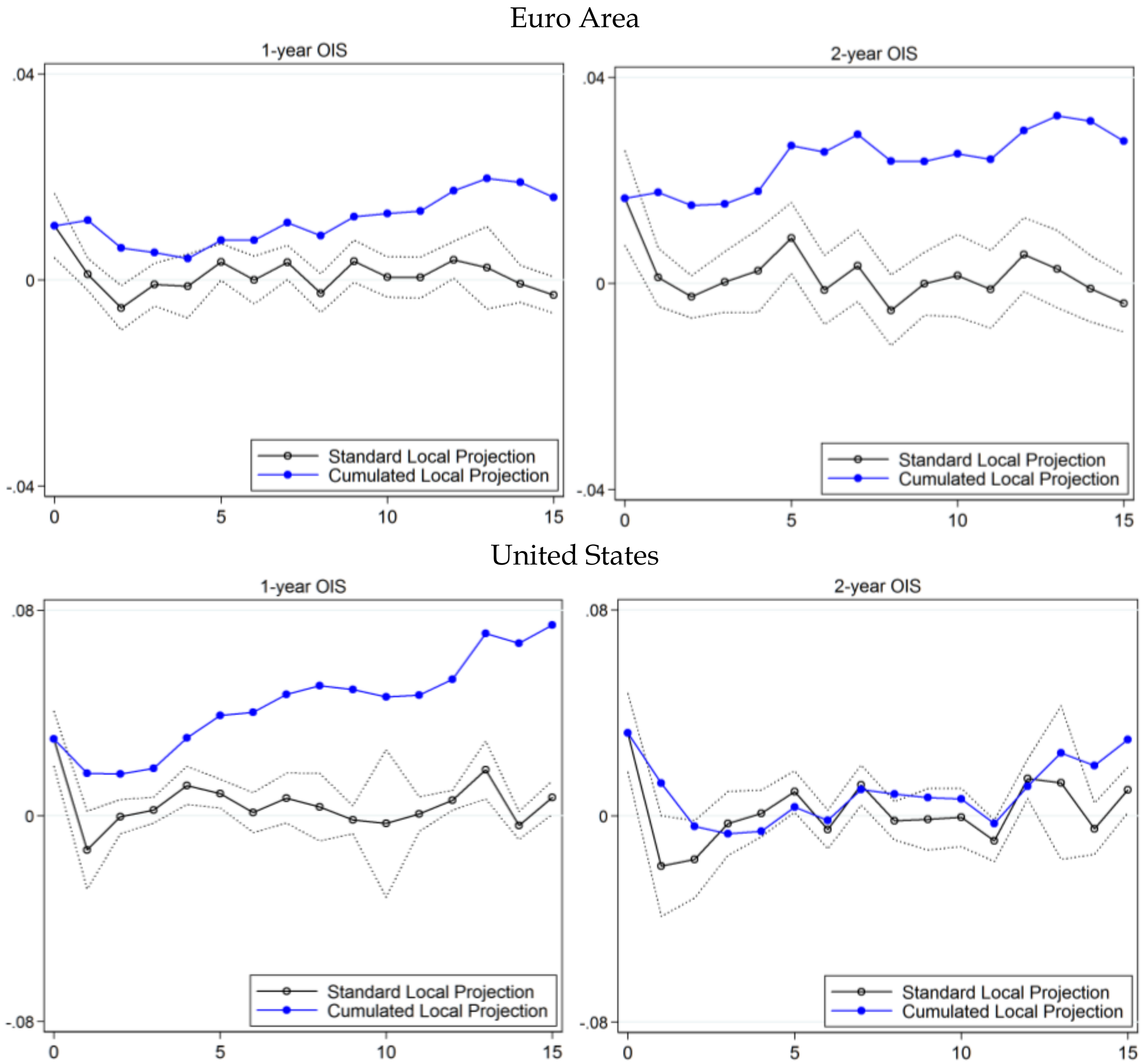


Figure 3. Local Projection Estimates



Note: Impulse responses to a positive sentiment shock, over the following 15 business days, estimated with equations (6)-(7) using local projections as described in equation (8) with 90 per cent confidence intervals and the cumulated effect of horizon specific estimates.

Table 1. Descriptive Statistics: Central Bank Tone variables

Euro Area					
Variable	Obs	Mean	Std. Dev.	Min	Max
All words	119	858	175	134	1319
Positive_AB	119	13	7	2	31
Negative_AB	119	7	4	0	21
Positive_LM	119	36	11	9	63
Negative_LM	119	37	13	5	74
Positive_Harv	119	167	36	37	278
Negative_Harv	119	62	17	13	103
Tone_AB	119	0.006	0.011	-0.020	0.028
Tone_AB2	119	0.239	0.441	-0.733	1
Tone_LM	119	0.001	0.015	-0.038	0.045
Tone_Harv	119	0.123	0.020	0.064	0.180
Ambiguity	119	0.065	0.014	0.040	0.104
	Tone_AB	Tone_AB2	Tone_LM	Tone_Harv	Ambiguity
Tone_AB	1				
Tone_AB2	0.97	1			
Tone_LM	0.51	0.54	1		
Tone_Harv	0.34	0.39	0.64	1	
Ambiguity	0.54	0.55	0.65	0.32	1
United States					
Variable	Obs	Mean	Std. Dev.	Min	Max
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
Tone_AB	85	-0.001	0.011	-0.027	0.028
Tone_AB2	84	0.053	0.539	-1	1
Tone_LM	85	0.002	0.016	-0.048	0.034
Tone_Harv	85	0.134	0.031	0.044	0.187
Ambiguity	85	0.060	0.016	0.010	0.103
	Tone_AB	Tone_AB2	Tone_LM	Tone_Harv	Ambiguity
Tone_AB	1				
Tone_AB2	0.93	1			
Tone_LM	0.47	0.52	1		
Tone_Harv	0.28	0.27	0.55	1	
Ambiguity	0.09	0.16	0.54	0.51	1

Note: Tone_AB, Tone_LM and Tone_Harv are computed based on equation (1), while Tone_AB2 is based on equation (2).

Table 2. Descriptive Statistics: Benchmark model

		Euro Area			
Variable	Obs	Mean	Std. Dev.	Min	Max
oieur1m	2576	1.40	1.53	-0.13	4.31
oieur3m	2576	1.42	1.55	-0.13	4.35
oieur6m	2576	1.45	1.57	-0.13	4.45
oieur9m	2576	1.49	1.59	-0.14	4.57
oieur1y	2576	1.52	1.60	-0.14	4.67
oieur2y	2576	1.66	1.57	-0.16	4.82
oieur3y	2576	1.81	1.52	-0.14	4.86
oieur5y	2576	2.13	1.43	-0.07	4.81
oieur10y	2576	2.70	1.23	0.19	4.86
kutt_eonia	2576	0.00	0.01	-0.22	0.17
ciss	2576	0.26	0.20	0.02	0.84
r_euro50	2576	0.00	0.01	-0.08	0.10
oil	2576	0.00	0.11	-0.55	0.33
esi	2576	98.52	9.96	69.3	113.1
		United States			
Variable	Obs	Mean	Std. Dev.	Min	Max
oiusd1m	2652	1.50	2.01	0.07	5.37
oiusd3m	2652	1.51	2.03	0.07	5.44
oiusd6m	2652	1.54	2.04	0.07	5.56
oiusd9m	2652	1.56	2.04	0.07	5.62
oiusd1y	2652	1.90	1.99	0.25	5.76
oiusd2y	2652	2.08	1.85	0.34	5.73
oiusd3y	2652	2.32	1.73	0.42	5.72
oiusd5y	2652	2.80	1.52	0.73	5.76
oiusd10y	2652	3.51	1.22	1.54	5.85
kutt_ffr	2652	0.00	0.07	-2.95	0.50
vix	2652	21.27	8.12	11.72	59.77
r_sp500	2651	0.00	0.01	-0.09	0.11
oil	2627	0.00	0.11	-0.55	0.33
ismbs	2652	53.51	4.15	37.6	61.3

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

Table 3. Sentiment shocks identification

Euro Area				United States			
	Equation (4)				Equation (4)		
	Tone_AB	Tone_LM	Tone_Harv		Tone_AB	Tone_LM	Tone_Harv
	(I)	(II)	(III)		(I)	(II)	(III)
l1.Tone	0.509***	0.426***	0.306***	l1.Tone	0.562***	0.476***	0.444***
	[0.02]	[0.02]	[0.02]		[0.02]	[0.02]	[0.02]
ecb_cpi_cy	-0.011	0.002	0.011	fomc_pce_cy	0.022*	0.024*	0.004
	[0.01]	[0.01]	[0.01]		[0.01]	[0.01]	[0.01]
ecb_cpi_ny	0.013	0.048***	0.037**	fomc_pce_ny	-0.016	-0.024	0.006
	[0.01]	[0.02]	[0.02]		[0.02]	[0.02]	[0.02]
ecb_gdp_cy	-0.001	-0.006	-0.001	fomc_gdp_cy	0.001	0.002	0.002
	[0.00]	[0.00]	[0.00]		[0.01]	[0.01]	[0.00]
ecb_gdp_ny	0.002	0.011	0.021*	fomc_gdp_ny	0.006	0.004	0.000
	[0.01]	[0.01]	[0.01]		[0.01]	[0.01]	[0.01]
spf_1	0.029	0.010	0.011	spf_cpi_0	-0.004	-0.003	-0.002
	[0.03]	[0.04]	[0.05]		[0.00]	[0.00]	[0.00]
spf_2	0.023	-0.034	0.017	spf_cpi_1	0.011	-0.003	0.018
	[0.05]	[0.07]	[0.08]		[0.03]	[0.03]	[0.03]
spf_5	-0.101	0.103	-0.039	spf_cpi_10	-0.035	0.034	-0.004
	[0.07]	[0.08]	[0.09]		[0.04]	[0.05]	[0.04]
cpi	0.000	-0.011	-0.017*	cpi	0.005	-0.003	0.000
	[0.01]	[0.01]	[0.01]		[0.00]	[0.00]	[0.00]
l1.cpi	0.023*	-0.134***	-0.233***	l1.cpi	-0.013	-0.277***	-0.108***
	[0.01]	[0.02]	[0.02]		[0.02]	[0.02]	[0.02]
gdp	-0.009	-0.005	-0.029**	gdp	-0.012	-0.004	-0.006
	[0.01]	[0.01]	[0.01]		[0.01]	[0.01]	[0.01]
l1.gdp	0.226***	0.351***	0.368***	l1.gdp	0.230***	0.225***	0.163***
	[0.01]	[0.02]	[0.02]		[0.02]	[0.02]	[0.01]
shadow	-0.010*	-0.005	-0.020***	shadow	-0.004	-0.004	-0.003
	[0.01]	[0.01]	[0.01]		[0.00]	[0.00]	[0.00]
l1.shadow	0.188***	0.036**	0.01	l1.shadow	0.023	0.021	-0.353***
	[0.02]	[0.02]	[0.02]		[0.02]	[0.02]	[0.02]
L.ciss	0.006	-0.010*	0.005	L.vix	-0.006	-0.006	0.001
	[0.00]	[0.01]	[0.01]		[0.01]	[0.01]	[0.01]
L.r_euro50	-0.002	-0.003	-0.005*	L.r_sp500	-0.001	0.001	0.008***
	[0.00]	[0.00]	[0.00]		[0.00]	[0.00]	[0.00]
L.oil	0.000	0.006*	0.001	L.oil	0.003	0.002	0.002
	[0.00]	[0.00]	[0.00]		[0.00]	[0.00]	[0.00]
L.esi	0.011	0.000	0.026**	L.ismbs	0.005	0.005	0.004
	[0.01]	[0.01]	[0.01]		[0.01]	[0.01]	[0.01]
constant	0.104	-0.249*	-0.082	constant	0.037	-0.080	-0.044
	[0.11]	[0.13]	[0.15]		[0.09]	[0.10]	[0.08]
N	2626	2626	2626	N	2626	2626	2626
R^2	0.70	0.51	0.34	R^2	0.49	0.43	0.61
	Equation (5)				Equation (5)		
	Resid. of (I)	Resid. of (II)	Resid. of (III)		Resid. of (I)	Resid. of (II)	Resid. of (III)
	(IV)	(V)	(VI)		(IV)	(V)	(VI)
AR(1)	-0.054	-0.115	-0.055	AR(1)	0.048	-0.048	0.090
	[0.09]	[0.09]	[0.09]		[0.11]	[0.11]	[0.11]
constant	0.009	-0.007	-0.008	constant	-0.003	0.005	0.019
	[0.05]	[0.06]	[0.07]		[0.08]	[0.08]	[0.07]
N	116	116	116	N	83	83	83
R^2	0.003	0.013	0.003	R^2	0.002	0.002	0.008

Note: Standard errors in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Paremeters are estimated based on equations (4) and (5). L is the lag operator (i.e. the value the day before) and l1 is the value at the date of the previous statement.

Table 4–A. Properties of estimated ECB sentiment shocks

Descriptive statistics					
Variable	Obs	Mean	Std. Dev.	Min	Max
TT_Sentiment_AB	119	-0.01	0.74	-1.81	2.78
RR_Sentiment_AB	119	0.00	0.68	-1.52	2.63
VAR_Sentiment_AB	119	-0.02	0.94	-2.40	2.81
TT_Sentiment_LM	119	-0.02	0.83	-2.50	2.15
RR_Sentiment_LM	119	0.00	0.77	-1.66	2.21
VAR_Sentiment_LM	119	-0.03	0.93	-2.67	2.66
TT_Sentiment_Harv	119	0.00	0.59	-1.66	1.95
RR_Sentiment_Harv	119	0.00	0.53	-1.59	1.67
VAR_Sentiment_Harv	119	0.00	0.97	-2.32	1.90
Correlation					
	TT_Sent_AB	RR_Sent_AB	VAR_Sent_AB	kutt_eonia	Tone_AB
TT_Sentiment_AB	1				
RR_Sentiment_AB	0.89	1			
VAR_Sentiment_AB	0.60	0.57	1		
kutt_eonia	0.06	0.04	-0.01	1	
Tone_AB	0.59	0.55	0.99	0.00	1
	RR_Sent_AB	RR_Sent_LM	RR_Sent_Harv	kutt_eonia	esi
RR_Sentiment_AB	1				
RR_Sentiment_LM	0.22	1			
RR_Sentiment_Harv	0.02	0.46	1		
kutt_eonia	0.04	0.17	-0.03	1	
esi	0.06	0.14	0.07	0.14	1
Shapiro-Francia normality test					
Variable	Obs	W'	V'	z	Prob>z
TT_Sentiment_AB	119	0.99	0.98	-0.05	0.52
RR_Sentiment_AB	119	0.99	1.26	0.46	0.32
VAR_Sentiment_AB	119	0.99	1.37	0.63	0.26
TT_Sentiment_LM	119	0.97	3.43	2.46	0.01
RR_Sentiment_LM	119	0.97	3.30	2.39	0.01
VAR_Sentiment_LM	119	0.98	1.64	0.98	0.16
TT_Sentiment_Harv	119	0.99	1.17	0.31	0.38
RR_Sentiment_Harv	119	0.99	1.42	0.70	0.24
VAR_Sentiment_Harv	119	0.99	1.14	0.26	0.40

Autocorrelation test		**Predictability of exogenous shock series**			
	AR(1) coef.		F-stat	p-value	Adjusted R^2
TT_Sentiment_AB	-0.20**	TT_Sent_AB	2.30	0.00	0.19
RR_Sentiment_AB	-0.01	RR_Sent_AB	1.13	0.33	0.02
VAR_Sentiment_AB	0.80***	VAR_Sent_AB	14.29	0.00	0.71
TT_Sentiment_LM	-0.23**	TT_Sent_LM	3.56	0.00	0.32
RR_Sentiment_LM	0.02	RR_Sent_LM	2.68	0.00	0.24
VAR_Sentiment_LM	0.64***	VAR_Sent_LM	8.93	0.00	0.59
TT_Sentiment_Harv	-0.10	TT_Sent_Harv	2.06	0.01	0.16
RR_Sentiment_Harv	0.00	RR_Sent_Harv	1.24	0.24	0.04
VAR_Sentiment_Harv	0.49***	VAR_Sent_Harv	4.06	0.00	0.36

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, copti_ab, copti_lm, copti_harv.

Table 4–B. Properties of estimated FOMC sentiment shocks

Descriptive statistics					
Variable	Obs	Mean	Std. Dev.	Min	Max
TT_Sentiment_AB	85	-0.01	0.74	-2.05	2.52
RR_Sentiment_AB	85	0.00	0.71	-1.51	2.47
VAR_Sentiment_AB	85	0.01	0.97	-2.16	2.45
TT_Sentiment_LM	85	0.00	0.79	-2.22	1.69
RR_Sentiment_LM	85	0.00	0.74	-2.25	1.62
VAR_Sentiment_LM	85	0.02	0.93	-2.80	1.98
TT_Sentiment_Harv	85	0.01	0.70	-2.07	1.71
RR_Sentiment_Harv	85	0.00	0.62	-2.23	1.26
VAR_Sentiment_Harv	85	0.02	0.93	-2.44	1.68
Correlation					
	TT_Sent_AB	RR_Sent_AB	VAR_Sent_AB	kutt_ffr	Tone_AB
TT_Sentiment_AB	1				
RR_Sentiment_AB	0.97	1			
VAR_Sentiment_AB	0.74	0.70	1		
kutt_ffr	0.17	0.18	0.28	1	
Tone_AB	0.74	0.69	0.99	0.28	1
	RR_Sent_AB	RR_Sent_LM	RR_Sent_Harv	kutt_ffr	ismbs
RR_Sentiment_AB	1				
RR_Sentiment_LM	0.27	1			
RR_Sentiment_Harv	0.26	0.58	1		
kutt_ffr	0.18	0.02	-0.18	1	
ismbs	0.09	0.14	0.00	0.33	1
Shapiro-Francia normality test					
Variable	Obs	W'	V'	z	Prob>z
TT_Sentiment_AB	85	0.97	2.18	1.53	0.06
RR_Sentiment_AB	85	0.96	2.80	2.01	0.02
VAR_Sentiment_AB	85	0.97	2.58	1.85	0.03
TT_Sentiment_LM	85	0.97	2.65	1.90	0.03
RR_Sentiment_LM	85	0.98	1.65	0.98	0.16
VAR_Sentiment_LM	85	0.98	1.90	1.26	0.10
TT_Sentiment_Harv	85	0.97	2.58	1.85	0.03
RR_Sentiment_Harv	85	0.95	4.06	2.74	0.00
VAR_Sentiment_Harv	85	0.98	1.67	1.00	0.16

Autocorrelation test		**Predictability of exogenous shock series**			
	AR(1) coef.		F-stat	p-value	Adjusted R^2
TT_Sentiment_AB	0.02	TT_Sent_AB	2.28	0.01	0.25
RR_Sentiment_AB	0.01	RR_Sent_AB	1.96	0.02	0.20
VAR_Sentiment_AB	0.66***	VAR_Sent_AB	6.33	0.00	0.58
TT_Sentiment_LM	-0.09	TT_Sent_LM	2.06	0.02	0.21
RR_Sentiment_LM	-0.01	RR_Sent_LM	1.62	0.07	0.14
VAR_Sentiment_LM	0.57***	VAR_Sent_LM	4.36	0.00	0.46
TT_Sentiment_Harv	0.03	TT_Sent_Harv	1.27	0.23	0.06
RR_Sentiment_Harv	0.01	RR_Sent_Harv	0.47	0.97	-0.16
VAR_Sentiment_Harv	0.73***	VAR_Sent_Harv	5.47	0.00	0.53

Note: The vector of variables for predictability tests includes current and lagged (at the date of the previous statement) values of cpi, gdp, vix, stlfsi, r_sp500, oil, ismbs, ffr, shadow rate, copti_ab, copti_lm, copti_harv.

Table 5–A. Benchmark ECB model

	(1) oieur1m	(2) oieur3m	(3) oieur6m	(4) oieur9m	(5) oieur1y	(6) oieur2y	(7) oieur3y	(8) oieur5y	(9) oieur10y
AB dictionary									
	Mean equation								
RR_Sentiment_AB	0.002	0.003*	0.004*	0.008**	0.011***	0.017***	0.021***	0.021**	0.012*
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]
kutt_eonia	0.094**	0.268**	0.382***	0.401***	0.399***	0.341*	0.237*	0.162	-0.01
	[0.04]	[0.14]	[0.12]	[0.11]	[0.13]	[0.18]	[0.12]	[0.10]	[0.10]
ciss	0.000	0.000	0.000	0.000	0.000	0.000	-0.002	-0.002	-0.001
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
r_euro50	0.000	0.000	0.002***	0.003***	0.005***	0.008***	0.012***	0.015***	0.016***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
oil	0.000	0.002**	0.002*	0.002*	0.002*	0.001	0.001	0.001*	0.002*
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
esi	0.000	0.002***	0.003***	0.002**	0.003***	0.003**	0.001	0.001	0.001
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
constant	0.000	0.001**	0.002**	0.002	0.001	0.000	-0.001	-0.001*	-0.002**
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
	Variance equation								
arch(1)	0.514***	0.537***	0.455***	0.465***	0.304***	0.285***	0.221***	0.144***	0.132***
	[0.11]	[0.16]	[0.14]	[0.10]	[0.06]	[0.08]	[0.05]	[0.03]	[0.03]
arch(2)	0.337***	0.168**	0.111*	0.197***	0.167***	0.155***	0.032	0.159***	0.102***
	[0.07]	[0.08]	[0.07]	[0.07]	[0.05]	[0.05]	[0.03]	[0.04]	[0.03]
arch(3)	0.383***	0.202**	0.356*	0.300*	0.255**	0.227***	0.119***	0.030	0.038*
	[0.10]	[0.10]	[0.21]	[0.15]	[0.12]	[0.07]	[0.04]	[0.02]	[0.02]
arch(4)	0.451***	0.311***	0.283**	0.234***	0.417***	0.293***	0.264**	0.090***	0.125***
	[0.12]	[0.09]	[0.12]	[0.08]	[0.11]	[0.08]	[0.12]	[0.03]	[0.04]
constant	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.001***	0.001***	0.001***
	[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
R^2 and Partial R^2 - Variance decomposition on statement days									
R^2	0.28	0.41	0.41	0.34	0.31	0.30	0.28	0.24	0.24
RR_Sentiment_AB	0.00	0.01	0.01	0.02	0.02	0.02	0.04	0.04	0.03
kutt_eonia	0.18	0.31	0.30	0.22	0.18	0.15	0.08	0.05	0.01
LM dictionary									
RR_Sentiment_LM	0.001	0.002	0.004	0.006**	0.007**	0.007	0.010*	0.006	0.001
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]
kutt_eonia	0.091**	0.265*	0.373***	0.386***	0.379***	0.299	0.211*	0.161	-0.006
	[0.04]	[0.14]	[0.12]	[0.11]	[0.12]	[0.22]	[0.13]	[0.11]	[0.11]
Harvard dictionary									
RR_Sentiment_Harv	0.000	0.000	0.001	0.003	0.005**	0.002	0.003	0.004	0.003
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]
kutt_eonia	0.092**	0.266*	0.379***	0.396***	0.401***	0.328*	0.233*	0.172	-0.004
	[0.04]	[0.14]	[0.11]	[0.11]	[0.14]	[0.20]	[0.12]	[0.11]	[0.10]

Note: Robust standard errors in brackets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Each column corresponds to equations (6) and (7) for a different horizon. R^2 and partial R^2 are computed from OLS estimates. Controls and ARCH terms for the LM and Harvard regressions have been removed for space constraints and are available upon request.

Table 5–B. Benchmark FOMC model

	(1) oiusd1m	(2) oiusd3m	(3) oiusd6m	(4) oiusd9m	(5) oiusd1y	(6) oiusd2y	(7) oiusd3y	(8) oiusd5y	(9) oiusd10y
AB dictionary									
	Mean equation								
RR_Sentiment_AB	0.005**	0.006**	0.001	0.002	0.030***	0.032***	0.025*	0.022	0.012
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.02]	[0.02]
kutt_ffr	0.061***	0.062***	0.052***	0.069***	0.006	0.020	0.015	-0.051**	-0.060**
	[0.01]	[0.02]	[0.01]	[0.01]	[0.01]	[0.02]	[0.02]	[0.03]	[0.03]
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]
r_sp500	0.000	0.000	-0.001	0.002***	0.005***	0.007***	0.011***	0.014***	0.016***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
oil	0.001***	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	0.003***	0.000	0.001	0.001	0.011***	0.007**	0.005*	0.003	0.002
	[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	-0.004***	-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)	2.478***	3.178***	2.654***	2.375***	1.438***	0.601***	0.376***	0.295***	0.267***
	[0.57]	[0.69]	[0.63]	[0.42]	[0.24]	[0.16]	[0.08]	[0.06]	[0.06]
constant	0.000***	0.000***	0.000***	0.000***	0.000***	0.001***	0.002***	0.002***	0.003***
	[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
R^2 and Partial R^2 - Variance decomposition on statement days									
R^2	0.19	0.28	0.28	0.26	0.11	0.22	0.18	0.12	0.09
RR_Sentiment_AB	0.03	0.04	0.02	0.02	0.01	0.05	0.05	0.04	0.02
kutt_ffr	0.02	0.06	0.07	0.07	0.00	0.04	0.05	0.05	0.05
LM dictionary									
RR_Sentiment_LM	-0.002	0.003	-0.001	-0.003	0.025***	0.013	0.004	0.005	0.001
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
kutt_ffr	0.026***	0.065*	0.052***	0.072***	0.026	0.028	0.020	-0.046*	-0.057**
	[0.00]	[0.03]	[0.01]	[0.01]	[0.02]	[0.03]	[0.02]	[0.02]	[0.03]
Harvard dictionary									
RR_Sentiment_Harv	0.009***	0.001	0.001	-0.001	0.031***	0.034***	0.033**	0.034*	0.033
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.02]	[0.02]	[0.03]
kutt_ffr	0.023***	0.066	0.052***	0.071***	0.055***	0.065	0.032*	-0.040**	-0.046*
	[0.01]	[0.04]	[0.01]	[0.01]	[0.02]	[0.06]	[0.02]	[0.02]	[0.03]

Note: Robust standard errors in brackets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Each column corresponds to equations (6) and (7) for a different horizon. R^2 and partial R^2 are computed from OLS estimates. Controls and ARCH terms for the LM and Harvard regressions have been removed for space constraints and are available upon request.

Table 6–A. Alternative ECB specifications

	(1) oieur1m	(2) oieur3m	(3) oieur6m	(4) oieur9m	(5) oieur1y	(6) oieur2y	(7) oieur3y	(8) oieur5y	(9) oieur10y
Alternative computation of Tone based on equation (2)									
RR_Sentiment_AB2	0.002	0.002	0.003	0.008***	0.009***	0.014***	0.017**	0.019**	0.013
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]
Including Forward Guidance announcement dummies									
RR_Sentiment_AB	0.000	0.003*	0.004	0.008**	0.010**	0.016***	0.020***	0.019**	0.013
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]
Taylor rule-type shock identification with AB dictionary									
TT_Sentiment_AB	0.002	0.004**	0.005*	0.008***	0.011***	0.014***	0.015**	0.015**	0.009
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]
Taylor rule-type shock identification with LM dictionary									
TT_Sentiment_LM	0.002*	0.003	0.005	0.006**	0.007**	0.008	0.008	0.003	-0.002
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]
Taylor rule-type shock identification with Harvard dictionary									
TT_Sentiment_Harv	0.001	0.001	0.002	0.003	0.006**	0.003	0.004	0.003	0.003
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]
TARCH term									
RR_Sentiment_AB	0.002	0.003*	0.005*	0.008**	0.011***	0.017***	0.021***	0.021**	0.013*
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]
ARCH(1)									
RR_Sentiment_AB	-0.001	0.005	0.003	0.012	0.015**	0.020**	0.023***	0.024***	0.017**
	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
OLS estimation									
RR_Sentiment_AB	-0.002	0.005	0.008	0.012	0.014*	0.018*	0.022**	0.021**	0.017**
	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
Wednesday and Thursday only[1]									
RR_Sentiment_AB	-0.002	0.005	0.008	0.011	0.014*	0.018*	0.021**	0.021**	0.017**
	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
Δr^E between t+1 and t-1									
RR_Sentiment_AB	0.000	0.002	0.001	0.004*	0.007**	0.010**	0.016***	0.010	0.005
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]
Δr^E between t and t-2									
RR_Sentiment_AB	0.002**	0.005**	0.006**	0.006**	0.008**	0.011*	0.011	0.011	0.011
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]
Including a lag of the dependent variable									
RR_Sentiment_AB	0.002	0.003*	0.004	0.008**	0.011***	0.017***	0.021***	0.021**	0.012*
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]
No controls									
RR_Sentiment_AB	0.001	0.005	0.007*	0.012**	0.014**	0.019***	0.022***	0.023**	0.016**
	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
Pre-ELB subsample[2]									
RR_Sentiment_AB	-0.007*	0.005	0.008	0.012*	0.013	0.018	0.019	0.018*	0.011
	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
Pre-FG subsample[3]									
RR_Sentiment_AB	-0.002	0.005*	0.007	0.009*	0.010	0.021**	0.024**	0.024**	0.020**
	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[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 equations (6) and (7) for a different horizon. Controls and ARCH terms have been removed for space constraints and are available from the authors upon request. [1]OLS estimation with 1030 observations. [2]Sample of 972 observations ending May 6, 2009. [3]Sample of 2057 observations ending July 3, 2013.

Table 6–B. Alternative FOMC specifications

	(1) oiusd1m	(2) oiusd3m	(3) oiusd6m	(4) oiusd9m	(5) oiusd1y	(6) oiusd2y	(7) oiusd3y	(8) oiusd5y	(9) oiusd10y
Alternative computation of Tone based on equation (2)									
RR_Sentiment_AB2	0.004	0.009	-0.001	-0.002	0.034***	0.039***	0.027	0.018	0.005
	[0.00]	[0.01]	[0.00]	[0.00]	[0.01]	[0.01]	[0.02]	[0.02]	[0.01]
Including Forward Guidance announcement dummies									
RR_Sentiment_AB	0.005**	0.007*	0.001	0.002	0.032***	0.033***	0.028**	0.017	0.006
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.02]	[0.01]
Identification using Greenbook forecasts as instruments for FOMC forecasts									
RR_Sent_AB_GB	0.005**	0.009*	0.001	0.000	0.043***	0.049***	0.042*	0.044	0.032
	[0.00]	[0.01]	[0.00]	[0.00]	[0.01]	[0.02]	[0.02]	[0.03]	[0.03]
Identification including dispersion and skewness measures for FOMC forecasts									
RR_Sent_AB_SK	0.005**	0.006**	0.001	0.002	0.030***	0.032***	0.025*	0.021	0.012
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.02]	[0.02]
Taylor rule-type shock identification with AB dictionary									
TT_Sentiment_AB	0.005**	0.007**	0.001	0.003	0.029***	0.034***	0.029**	0.029	0.018
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.02]	[0.01]
Taylor rule-type shock identification with LM dictionary									
TT_Sentiment_LM	-0.001	0.002	-0.001	-0.002	0.021***	0.01	0.005	0.007	0.001
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.02]	[0.01]	[0.02]	[0.02]
Taylor rule-type shock identification with Harvard dictionary									
TT_Sentiment_Harv	0.000	0.002	0.001	0.001	0.027***	0.033***	0.029	0.029	0.030
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.02]	[0.02]	[0.03]
TARCH term									
RR_Sentiment_AB	0.004**	0.006	0.001	0.002	0.029***	0.033***	0.025	0.022	0.013
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.02]	[0.02]
ARCH(2)									
RR_Sentiment_AB	0.001*	0.003***	0.001	0.000	0.018***	0.026**	0.025	0.016	0.004
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.03]	[0.02]	[0.01]
OLS estimation									
RR_Sentiment_AB	0.015	0.016	0.012	0.01	0.007	0.014*	0.013	0.013	0.008
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
Wednesday and Thursday only[1]									
RR_Sentiment_AB	0.015	0.017	0.012	0.011	0.01	0.015*	0.014	0.012	0.006
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
Δr^E between t+1 and t-1									
RR_Sentiment_AB	0.000	-0.001	-0.007	0.000	-0.002	-0.001	-0.001	-0.005	0.005
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.02]	[0.02]	[0.02]	[0.02]
Δr^E between t and t-2									
RR_Sentiment_AB	0.016***	0.001	-0.002	-0.006	0.013**	-0.003	-0.011	-0.002	-0.008
	[0.00]	[0.00]	[0.01]	[0.00]	[0.01]	[0.01]	[0.01]	[0.02]	[0.02]
Including a lag of the dependent variable									
RR_Sentiment_AB	0.004**	0.005***	0.002	0.002	0.025***	0.031***	0.027**	0.022	0.013
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.02]	[0.02]
No controls									
RR_Sentiment_AB	-0.001	0.006**	0.001	0.003	0.037***	0.030***	0.029**	0.031	0.025
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.02]	[0.02]
Pre-FG & ELB subsample[2]									
RR_Sentiment_AB	0.011	0.007	0.018	0.010	0.062***	0.044**	0.042**	0.038*	0.019
	[0.01]	[0.01]	[0.02]	[0.02]	[0.02]	[0.02]	[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 equations (6) and (7) for a different horizon. Controls and ARCH terms have been removed for space constraints and are available from the authors upon request. [1]OLS estimation with 1034 observations. [2]Sample of 870 observations ending December 15, 2008.

Table 7–A. State-dependent effects of ECB Sentiment shocks

	(1) oieur1m	(2) oieur3m	(3) oieur6m	(4) oieur9m	(5) oieur1y	(6) oieur2y	(7) oieur3y	(8) oieur5y	(9) oieur10y
Ambiguity									
Interaction	-0.006***	-0.005*	-0.003	-0.006	-0.008*	-0.010	-0.010	-0.008	-0.009
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]
RR_Sentiment_AB	0.003	0.004*	0.005*	0.008***	0.011***	0.017***	0.022***	0.022***	0.013*
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]
Ambiguity	0.001	0.002	0.002	0.002	0.003	0.002	-0.002	-0.002	-0.003
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
RR_Sentiment_AB coefficient when:									
High Ambiguity	0.001	0.003*	0.004	0.007**	0.009**	0.015***	0.020***	0.021**	0.011
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]
Low Ambiguity	0.004**	0.005**	0.005*	0.010***	0.012***	0.019***	0.024***	0.024**	0.015*
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]
Sign									
Interaction	-0.007**	0.003	0.001	0.005	0.002	0.011	0.017	0.002	0.004
	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]	[0.02]	[0.02]	[0.02]
RR_Sentiment_AB	0.003	0.001	0.001	0.004	0.007**	0.010*	0.015*	0.016	0.003
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]
Sign	0.003***	0.002	0.005	0.003	0.005	0.002	-0.004	0.006	0.010
	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
RR_Sentiment_AB coefficient when:									
Positive ξ_t	-0.004**	0.003	0.002	0.009	0.009	0.021	0.032*	0.018	0.007
	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]	[0.02]	[0.02]	[0.02]
Negative ξ_t	0.003	0.001	0.001	0.004	0.007**	0.010*	0.015*	0.016	0.003
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]
Size (RR_Sentiment_AB squared)									
Interaction	-0.002*	0.002*	0.003**	0.004*	0.004	0.006**	0.005	0.004	0.007
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]
RR_Sentiment_AB	0.002	0.004*	0.005**	0.009***	0.011***	0.017***	0.021***	0.021**	0.012*
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]
RR_Sentiment_AB coefficient when:									
Big shocks	0.002	0.004**	0.005**	0.009***	0.011***	0.017***	0.021***	0.021**	0.013*
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]
Small shocks	0.002	0.003*	0.004*	0.008***	0.011***	0.016***	0.020***	0.020**	0.011
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]
CEPR recession dummy									
Interaction	0.002	0.001	-0.003	-0.004	-0.007	0.008	0.007	-0.008	-0.006
	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]	[0.02]	[0.02]	[0.02]
RR_Sentiment_AB	0.001	0.003	0.005	0.009**	0.012***	0.015**	0.020**	0.022**	0.014*
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]
CEPR	0.000	0.000	0.001	0.001	0.000	0.002	0.000	0.001	0.002
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
CPI									
Interaction	-0.002	0.000	0.006**	0.005	0.005	0.013**	0.010	0.010	0.010
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]
RR_Sentiment_AB	0.002	0.003*	0.006**	0.010***	0.013***	0.021***	0.023***	0.024**	0.015*
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]
CPI	0.000	0.002	0.002***	0.002**	0.002**	0.002**	0.000	0.000	0.001
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
RR_Sentiment_AB coefficient when:									
High inflation	0.000	0.004	0.012***	0.015**	0.018**	0.034***	0.033**	0.033**	0.025*
	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.02]	[0.02]	[0.01]
Low inflation	0.003	0.003	0.000	0.005	0.007**	0.009**	0.014*	0.014*	0.005
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]
Monetary shocks									
Interaction	-0.004**	-0.006**	-0.003	-0.005	-0.003	-0.001	0.000	-0.001	0.000
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]
RR_Sentiment_AB	0.000	0.003	0.005	0.009**	0.011***	0.016***	0.021***	0.020***	0.012*
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]
kutt_eonia	0.002***	0.005**	0.005***	0.006***	0.005***	0.004*	0.003*	0.002	0.000
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
RR_Sentiment_AB coefficient when:									
Δ+ kutt_eonia	-0.004	-0.003	0.001	0.005	0.008**	0.015**	0.021***	0.019**	0.012
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]
Δ- kutt_eonia	0.005***	0.010*	0.008	0.014*	0.014**	0.018*	0.021**	0.022**	0.013
	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]

Note: Robust standard errors in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Each column corresponds to equations (6) and (7) 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 7–B. State-dependent effects of FOMC Sentiment shocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	oiusd1m	oiusd3m	oiusd6m	oiusd9m	oiusd1y	oiusd2y	oiusd3y	oiusd5y	oiusd10y
Ambiguity									
Interaction	-0.018***	-0.011***	-0.012***	-0.007	-0.033***	-0.032***	-0.024	-0.025	-0.022
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.02]	[0.02]
RR_Sentiment_AB	0.010***	0.008***	0.006***	0.003	0.011***	0.018***	0.016	0.014	0.005
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]
Ambiguity	-0.001	0.003	-0.003**	0.000	0.006	0.013	0.009	0.002	-0.004
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]
RR_Sentiment_AB coefficient when:									
High Ambiguity	0.007***	0.006***	0.004***	0.002	0.006	0.012**	0.012	0.010	0.001
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]
Low Ambiguity	0.013***	0.010***	0.008***	0.004	0.017***	0.023***	0.021**	0.019	0.009
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]
Sign									
Interaction	-0.009	-0.015	0.001	-0.005	-0.045***	-0.055**	-0.047	0.007	0.022
	[0.01]	[0.01]	[0.00]	[0.00]	[0.01]	[0.02]	[0.03]	[0.05]	[0.04]
RR_Sentiment_AB	0.009	0.018	0.002	0.006	0.038***	0.041**	0.032	0.025	0.008
	[0.01]	[0.01]	[0.00]	[0.00]	[0.01]	[0.02]	[0.02]	[0.02]	[0.02]
Sign	0.001	0.000	-0.002	-0.001	0.004	0.006	0.005	-0.012	-0.013
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.02]	[0.04]	[0.03]
RR_Sentiment_AB coefficient when:									
Positive ξ_t	0.000	0.002	0.003	0.000	-0.006	-0.013	-0.015	0.032	0.030
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.02]	[0.05]	[0.03]
Negative ξ_t	0.009	0.018	0.002	0.006*	0.038***	0.041**	0.032*	0.025	0.008
	[0.01]	[0.01]	[0.00]	[0.00]	[0.01]	[0.02]	[0.02]	[0.02]	[0.02]
Size (RR_Sentiment_AB squared)									
Interaction	-0.002	-0.005	0.000	-0.002	-0.014***	-0.014***	-0.013**	-0.007	0.002
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]
RR_Sentiment_AB	0.005	0.008	0.001	0.002	0.022***	0.019	0.013	0.017	0.012
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.02]	[0.02]
RR_Sentiment_AB coefficient when:									
Big shocks	0.005*	0.007*	0.001	0.002	0.021***	0.017	0.012	0.016	0.013
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.02]	[0.02]
Small shocks	0.006*	0.009*	0.001	0.003	0.024***	0.021*	0.015	0.018	0.012
	[0.00]	[0.01]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.02]	[0.02]
NBER recession dummy									
Interaction	-0.003	0.007**	-0.006	-0.007	-0.059***	-0.061***	-0.045	-0.043	-0.019
	[0.01]	[0.00]	[0.01]	[0.01]	[0.01]	[0.02]	[0.03]	[0.06]	[0.06]
RR_Sentiment_AB	0.005	0.002	0.002	0.003	0.034***	0.038***	0.030**	0.027	0.015
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.02]	[0.02]
NBER	0.003***	0.011***	0.011***	0.002	0.006**	0.002	0.002	0.001	0.001
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
RR_Sentiment_AB coefficient when:									
Expansion	0.005*	0.002*	0.002	0.003	0.034***	0.038***	0.030**	0.027	0.015
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.02]	[0.02]
Recession	0.002	0.009	-0.004	-0.004	-0.024***	-0.022	-0.015	-0.016	-0.004
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.03]	[0.06]	[0.05]
CPI									
Interaction	0.004	0.004	-0.001	0.003**	0.019***	0.019**	0.019**	0.015	0.006
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]	[0.02]
RR_Sentiment_AB	0.004	0.006	0.005**	0.002	0.017***	0.024**	0.016	0.017	0.011
	[0.00]	[0.01]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.02]	[0.02]
CPI	-0.001**	0.001	-0.003***	0.000	-0.001	0.000	0.000	0.000	-0.001
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
RR_Sentiment_AB coefficient when:									
High inflation	0.008*	0.011	0.004	0.005*	0.036***	0.043***	0.035**	0.032**	0.017
	[0.00]	[0.01]	[0.00]	[0.00]	[0.01]	[0.02]	[0.01]	[0.02]	[0.02]
Low inflation	0.000	0.002	0.007**	-0.001	-0.002	0.005	-0.003	0.001	0.005
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.03]	[0.03]
Monetary shocks									
Interaction	-0.007***	-0.014***	-0.006***	-0.005	-0.015***	-0.007	-0.002	-0.002	-0.003
	[0.00]	[0.01]	[0.00]	[0.01]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]
RR_Sentiment_AB	0.002	0.004***	0.001	0.002	-0.021***	0.022	0.022	0.019	0.008
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.02]	[0.02]	[0.01]
kutt_ffr	-0.001**	-0.001	0.000	0.003	-0.005**	-0.003	0.000	-0.005	-0.006
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
RR_Sentiment_AB coefficient when:									
Δ+ kutt_ffr	-0.004**	-0.010**	-0.004***	-0.003	-0.035***	0.015	0.020	0.017	0.006
	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.02]	[0.02]	[0.02]	[0.02]
Δ- kutt_ffr	0.009***	0.019***	0.008***	0.007	-0.006	0.030***	0.024*	0.021	0.011
	[0.00]	[0.01]	[0.00]	[0.01]	[0.00]	[0.01]	[0.01]	[0.02]	[0.01]

Note: Robust standard errors in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Each column corresponds to equations (6) and (7) 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.

APPENDIX

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*
Most frequent in statements	
improve	crucial
improvement	decline
positive	imbalances
progress	negative
greater	questions
stability	challenges
strengthen	dampened
strengthening	concerns
strong	volatility
stronger	weak

Table B. Data description

Abbreviation	Description	Source	Frequency
Euro Area			
oieur1m	Euro 1 month OIS	Datastream	Daily
oieur3m	Euro 3 month OIS	Datastream	Daily
oieur6m	Euro 6 month OIS	Datastream	Daily
oieur9m	Euro 9 month OIS	Datastream	Daily
oieur1y	Euro 1 year OIS	Datastream	Daily
oieur2y	Euro 2 year OIS	Datastream	Daily
oieur3y	Euro 3 year OIS	Datastream	Daily
oieur5y	Euro 5 year OIS	Datastream	Daily
oieur10	Euro 10 year OIS	Datastream	Daily
Tone_AB	Apel and Blix-Grimaldi (2012)	Authors' computations	For each ECB statement
Tone_LM	Loughran and McDonald (2011)	Authors' computations	For each ECB statement
Tone_Harv	Harvard dictionary	Authors' computations	For each ECB statement
ambiguity	Loughran and McDonald (2011)	Authors' computations	For each ECB statement
eonia	Eonia	Datastream	Daily
shadow	Shadow rate	Wu and Xia (2016)	Monthly
cpi	CPI inflation rate (year-over-year %)	Eurostat	Monthly
gdp	Real GDP growth (year-over-year %)	Eurostat	Quarterly
ciss	Composite Indicator of Systemic Stress	ECB	Weekly
esi	Economics Sentiment Indicator	European Commission	Monthly
oil	WTI oil price growth (year-over-year %)	Datastream	Daily
r_euro50	Eurostoxx 50 price index	Datastream	Daily
ecb_cpi_*	ECB/Eurosystem staff inflation projections for current and next calendar years	ECB	Quarterly
ecb_gdp_*	ECB/Eurosystem staff output projections for current and next calendar years	ECB	Quarterly
SPF_*	Survey of Professional Forecasters' inflation forecasts for 1, 2 and 5 years	ECB	Quarterly
United States			
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
Ambiguity	Loughran and McDonald (2011)	Authors' computations	For each FOMC statement
ffr	Effective Federal Funds Rate	Datastream	Daily
shadow	Shadow rate	Wu and Xia (2016)	Monthly
cpi	CPI inflation rate (year-over-year %)	Bureau of Labor Statistics	Monthly
gdp	Real GDP growth (year-over-year %)	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 (year-over-year %)	Datastream	Daily
r_sp500	Standard & Poor's 500 price index	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 Q+1, Q+4 and 5 years	Federal Reserve	Quarterly

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

Figure A. Central Bank Sentiment shocks using LM and Harvard dictionaries

Euro Area United States

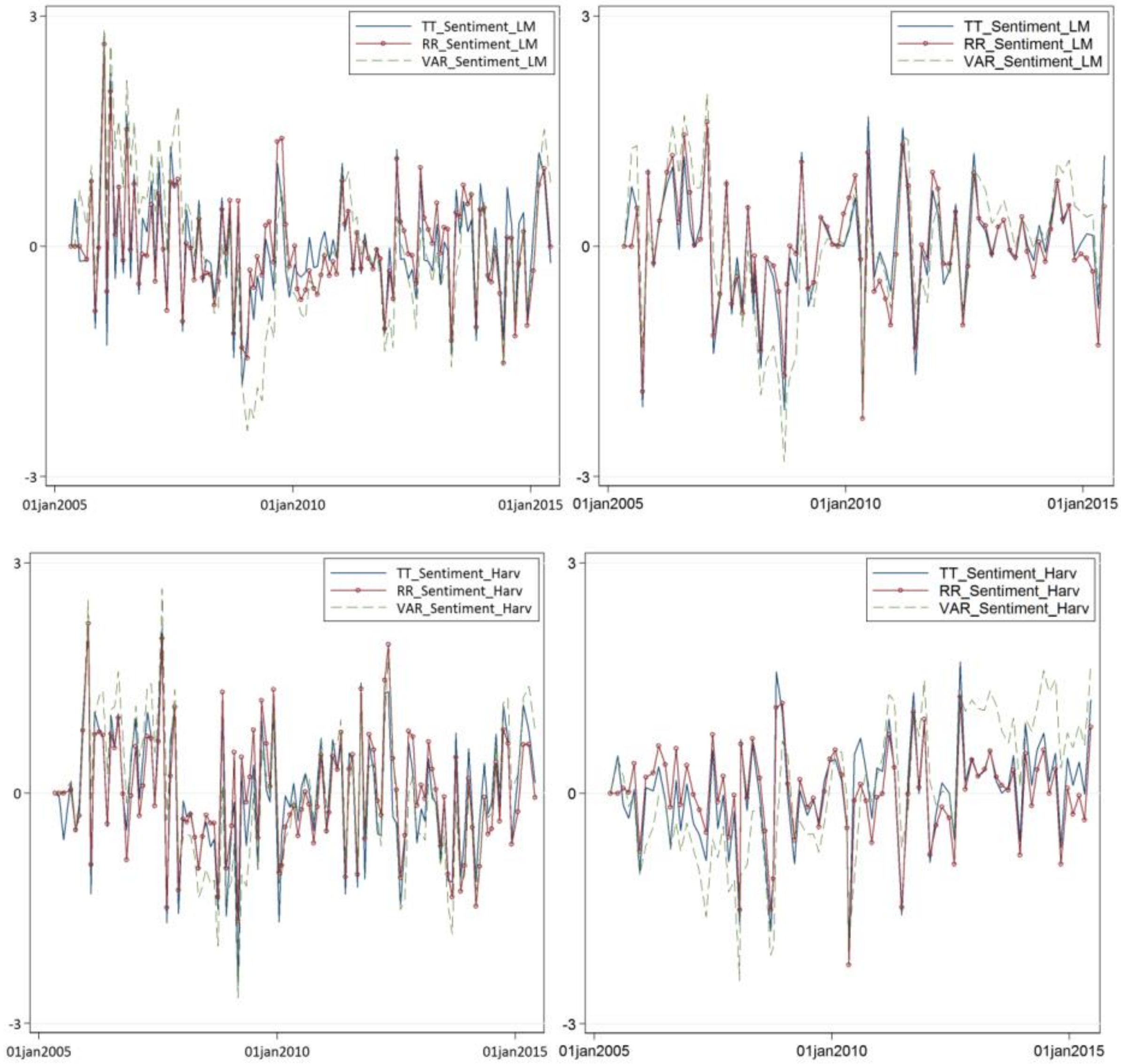


Figure B. Distribution of Central Bank Sentiment shocks using LM and Harvard dictionaries

Euro Area United States