Central Bank Sentiment and Policy Expectations*

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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 monthly statements affect the term structure of short-term interest rate expectations. We proceed in three steps. First, we measure sentiment using a computational linguistics approach. Second, we identify exogenous shocks to these quantitative measures using an augmented narrative approach following the information friction literature. Third, we estimate their impact on private agents' beliefs about future short-term interest rates using an event-study methodology and an ARCH model. We find that sentiment shocks increase private interest rate expectations at maturities around 1 and 2 years. We also find that this effect is non-linear and depends on the characteristics (size, sign and precision) of the sentiment signal conveyed to the public and on the state of the economy.

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

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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 largely 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 which are rather motivated by what he famously labeled "animal spirits". This paper aims to quantify these concepts of "animal spirits", "market sentiment" or "optimism" in central bank communication and to test their potential importance for economic decisions.

Quantifying this unobservable concept might potentially be crucial to understand how firms and households form their expectations and take their decisions. Angeletos and La'O (2013) have analysed how sentiment (or "waves of optimism and pessimism") orthogonal to fundamentals may drive business cycles through first-order and higher-order beliefs. More specifically, we explore empirically the theoretical prediction that waves of optimism or pessimism may have aggregate effects in the context of the Euro area and US monetary policy. We investigate whether the sentiment conveyed by European Central Bank (ECB) and Federal Open Market Committee (FOMC) policymakers in their statements, quantified using computational lexicographic algorithms, affect the term structure of private agents' short-term interest rate expectations.

Because long-term interest rates depend on the expected path of short-term interest rates plus a term premium, central bankers could influence these interest rates which are a key determinant of private sector decisions, by signalling future policy rate intentions. Central banks over the last decades have enhanced transparency of their actions and communication to the public in order to better signal future policy rate decisions and to shape private expectations (see e.g. Geraats, 2002; Woodford, 2005). The question of whether central bank communication has been successful to affect financial markets or to help predict interest rate decisions has already given rise to an abundant literature, surveyed by Blinder et al. (2008). This paper takes a different look at this question, and focuses on the sentiment conveyed by central bank communication rather than on its content about current or future policy and macroeconomic developments.

Our contribution to the literature is twofold. First, we quantify the sentiment conveyed by ECB and FOMC statements using computational lexicographic algorithms which constitutes, to our knowledge, an innovation in monetary economics. Many studies have coded indicators of the monetary policy stance conveyed by ECB or FOMC communications (see e.g. Ehrmann and Fratzscher, 2007) 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 to the public by monetary policymakers. The closest papers to ours are Lucca and Trebbi (2011) and Hansen, McMahon and Prat (2015). The former 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 communications, which sentiment is supposed to be orthogonal to. The latter 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. We aim to quantify whether there are such "waves of optimism and pessimism" conveyed to the public by monetary policymakers.

After quantifying this unobservable variable, 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. To do so, we first identify exogenous shocks to sentiments to get rid of any endogeneity bias and comply with the requirement that sentiment is orthogonal to fundamentals. We use the Romer and Romer (2004)'s approach that we augment by removing the private agents' information set and the contribution of past sentiment shocks following the information frictions literature. Second, we use a high-frequency identification approach to isolate the effects of sentiment shocks from other same-day events (the monetary decision, for instance) and other-day events so as to estimate the effect of sentiment on private interest rate expectations at maturities from 1 month to 10 years ahead. 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. Because the precision of the signal conveyed to the public would matter in a Bayesian updating model or because the sign, the size, the concomitant occurrence of a monetary policy shock or the position in the business cycle could also matter, we also look at the state-dependent 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 and from 1 to 3 years 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 sentiment measures, to the methodology used for the identification of sentiment shocks, to alternatives estimation methods such as TARCH, GARCH models or OLS, and to the parameter used for the event-study methodology: the window around policy statements and which days we look at in control group. 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 extremely 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 and that the timing and characteristics of the sentiment matters in that respect.

The rest of this paper is organized as follows. In Section 2 we present the framework and in Section 3 the automated lexicographic methodology. We discuss the financial and macro data in Section 4. Section 5 is focused on the identification of exogenous sentiment shocks. In Section 6 we investigate the responses of private interest rate expectations to sentiment shocks. 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" or "market sentiment" phenomenon. In standard macro models, these phenomena would be modelled as exogenous random shocks to preferences, endowments and technology, the stock of capital, or other fundamentals. However, shifts in market sentiment and aggregate demand often appear to obtain without innovations in people's preferences and abilities, or firms' know-how. The literature has explained observed macroeconomic fluctuations as the result of "animal spirits" in models with multiple equilibria or as departures from rationality as in Milani (2014) with a learning model.

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 extrinsic 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 are therefore called extrinsic. These shocks nevertheless 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.[1]

The joint distribution of the signals x_{it}, about the Total Factor Productivity (TFP) of i's trading partner, in the population of islands is allowed to depend on an exogenous random variable ξ_t 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 is extrinsic by imposing that variation in ξ_t does not cause variation in any island's belief about TFP of its own current and future trading partners, or of any other trading pair. 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.[2] 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 TFP, but ξ_t does not affect beliefs of either fundamentals. The main result is that, along the unique equilibrium, aggregate output and the average expectation can vary with the extrinsic shock ξ_t if and only if information is imperfect, and are increasing linear functions of ξ_t.

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 extrinsic shocks ξ_t provided by a specific agent: the central bank, using computational lexicographic models to quantify this

[1] 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.

[2] 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.

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' macro forecasts.

3. Quantifying Central Bank Sentiment

3.1 Central Bank Statements as a Source for Sentiment

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 two reasons. First, 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). Second, the schedule and timing of these meetings is 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.[3]

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.[4] 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 to capture central bank sentiment.

[3] However, because of OIS data availability (our dependent variable), our sample starts in August 2005.

[4] That would however be an interesting question and we leave that for future research.

3.2 Measuring Sentiment 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 Blei et al., 2003). One advantage of this method is to be fully automated and replicable, which remove the subjectivity of human-reading coded indices. We employ ECB and FOMC statements as a source of intangible information about the central bank's "waves of optimism and pessimism" and construct two measures from each ECB statement: one is the sentiment conveyed and the other its ambiguity.

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 more details).

To measure the sentiment of a document, we use "directional" word lists measuring words associated with positive and negative tone as proposed by three different dictionaries. First, we use the seminal positive and negative categories of the General Inquirer's Harvard IV-4 psychosocial dictionary to measure qualitative information.[5] These categories reflect Osgood et al. (1957)'s semantic differential findings regarding basic language universals. Nevertheless, the Harvard list has not been specifically designed for a financial context and Loughran and McDonald (2011) have developed another list of words that better reflect the tone in a financial context. For example Loughran and McDonald (2011) find that almost three-fourths of negative word counts in the Harvard dictionary are not negative in a financial context. Third, we use the dictionary proposed by Apel and Blix-Grimaldi (2012), which has been specifically developed to measure the tone of central bank communication.

These three dictionaries have different characteristics and are complementary. Our favourite dictionary -that we use as a benchmark- is the one of Apel and Blix-Grimaldi (2012) but we provide results for all three together to provide a comprehensive assessment of central bank sentiment. 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.

Once negative and positive words are identified with each dictionary, we construct our main variable of interest, a sentiment variable based on the balance between the numbers of positive and negative words that appear in statements, divided by the total number of words included into the document.

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

We therefore obtain three measures of sentiment using the three different dictionaries. The first is labelled Sentiment_AB based on the dictionary of Apel and Blix-Grimaldi (2012), the second is labelled Sentiment_LM, based on the dictionary of Loughran and McDonald

[5] The 182 General Inquirer categories were developed for social-science content-analysis research applications. The Harvard-IV-4 dictionary on the General Inquirer's Web site lists each word in the positive and negative categories: http://www.webuse.umd.edu:9090/tags/TAGNeg.html.

(2011), and the third is labelled Sentiment_Harv identified with the General Inquirer's Harvard dictionary. A positive value of these sentiment 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 sentiment variables are shown in Table 1 and Figure 1. The sentiment variables appear correlated to the business cycle over our sample.

Second, we define an ambiguity variable. We follow the dictionary approach of Loughran and McDonald (2011) to obtain words denoting uncertainty, with some emphasis on the general notion of imprecision, such as approximate, contingency, depend, fluctuate, indefinite, uncertain, and variability. This measure is dedicated to the investigation of whether statements are effective in delivering relevant information to the public. We use them as a measure of the overall precision of the signal conveyed to the public.

4. Financial and Macroeconomic Data

This section describes the financial and macroeconomic data used to identify exogenous shocks to our sentiment 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 different maturities, from 1-month to 10-year, of 3-month Eonia (resp. LIBOR) Overnight Indexed Swaps (OIS) for the euro area (resp. the US). OIS are instruments that allow financial institutions to swap the interest rates they are paying without having to refinance or change the terms of the loans they have taken from other financial institutions. Typically, when two financial institutions create an OIS, one of the institutions is swapping an interest rate and the other institution is swapping a fixed short-term interest rate at a given maturity. These OIS are therefore a good proxy of financial market participants' expectations about future short-term interest rates. 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 through communication, our analysis requires controlling for the effect of the monetary shock. 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 the current-month futures contract. 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:

$$S_t = \frac{D}{D-d}\left(f^0_{m,d} - f^0_{m,d-1}\right) \qquad (2)$$

S_t is the unexpected interest rate variation which constitutes a monetary shock, $f^0_{m,d}$ is the current-month futures rate and D is the number of days in the month and d the day of the decision. 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 our benchmark analysis.

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. 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 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 are realized each year in early February and early July until 2007Q3, and since then in February, April, July and November. These forecasts are published as two ranges encompassing each individual FOMC member's forecasts: the "full range" includes the highest and the lowest forecasts while the "central tendency" removes the three highest and three lowest forecasts. We use the midpoint of 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.

5. Identifying Exogenous Sentiment Shocks

After having quantified the sentiment conveyed by ECB statements, and because sentiment variables may surely be correlated to the business cycle and other macro or financial market variables, it is necessary to isolate exogenous and unpredictable shifts to sentiments, in order to be able to identify causal effects of policymakers' sentiment on private interest rate expectations.

The question of the most relevant identification strategies 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 credible 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. We thus require the estimated shocks (labelled RR_Sentiment_LM and RR_Sentiment_Harv) to be orthogonal to both central bank's and 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 structural shocks.

To do so, we estimate the following equation and extract the residuals of such a model that we consider as an exogenous sentiment shock:

$$\Xi_t = \beta_0 + \beta_1 \, \Xi_{t-j} + \beta_2 \, \Omega_t + \beta_3 \, \Psi_t + \beta_4 \, X_{t-1} + \beta_5 \, Z_t + \xi'_t \tag{3}$$

$$\xi'_t = \beta_6 + \beta_7 \, \xi'_{t-j} + \xi_t \tag{4}$$

where j is the number of days between each policy statement, so Ξ_{t-j} is the sentiment of the previous ECB or FOMC policy statement. We assume 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). The error term ξ_t reflects unexpected shocks to the sentiment variable. A consequence of this specification 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 arguing that the ECB sentiment is only based on past data realisations or that the ECB does not move markets in real-time are fragile assumptions. 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. Table 3 shows the estimated parameters of equations (3) and (4).

When extracting this exogenous component, the inclusion of both private and central bank forecasts in the regression model enables us to deal with three concerns. First, forecasts encompass rich information sets. Private agents and policymakers' information sets include a large number of variables. 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-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.

We assess the robustness of this methodology for extracting the sentiment shock in many ways. First, we compute shocks using two alternatives: a Taylor-type equation applied to sentiment and augmented with macro variables and a decomposition of policy tools (TT_Sentiment_LM and TT_Sentiment_Harv), and a VAR with financial market variables (VAR_Sentiment_LM and VAR_Sentiment_Harv). Second, we assess the autocorrelation and normality of these residuals. This calls for discarding VAR innovations as satisfactory shocks, since these shocks are auto-correlated and the kurtosis of their distribution is very low. Third, 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 macro and financial variables. The F-stats in the bottom end of Table 4 (panel A for the euro area and panel B for the US) show that the null hypothesis that our estimated series of exogenous shocks are unpredictable cannot be rejected. It suggests that the Romer-Romer-type and Taylor-type shock series are relevant to be used in our second-stage estimations to assess their effects on private inflation expectations, whereas the VAR innovations are not. Table 4 the properties and the correlation structure of shocks. Figure 2 plots the time series of the estimated sentiment shocks and Figure 3 their distribution.

6. The Effect of Sentiment Shocks on Policy Expectations

6.1. The event-study methodology

We use an event-study methodology to disentangle the effects of sentiment shocks from monetary policy surprises and news flows. This approach 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 policy announcements, or said differently that there is no other 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 reflect the effect of news about monetary policy. This is crucial for identification since it strips out endogenous variation in interest rate expectations associated with other shocks than monetary news. 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. Nakamura and Steinsson (2013) use a similar approach focusing on the increased volatility generated on announcement days.

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's and FOMC's 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. We decompose the informational content of these policy announcements in two components: the policy decision and the signals conveyed about the current and future state of the economy. However, the signals themselves contain information 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 ECB sentiment on 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 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 (3)-(4) are generated regressors that might cause biased standard errors, we compute standard errors robust to misspecification using the Huber-White-sandwich estimator.[6] The estimated equation is the following:

$$\Delta r_{t,h}^{E} = \beta_0 + \beta_1\, \xi_t + \beta_2\, S_t + \beta_3\, M_t + \varepsilon_t, \;\; \varepsilon_t \sim (0, \sigma_t^2) \tag{5}$$

$$\sigma_t^2 = \gamma_0 + \sum_{i=1}^{p} \gamma_i\, \varepsilon_{t-i}^2 \tag{6}$$

where $\Delta r_{t,h}^{E}$ is the change between t and t-1 in Euro area (resp. US) interest rate expectations for horizon h, ξ_t is the ECB (resp. FOMC) sentiment shock estimated through equations (3)-(4), 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). 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. Table 4 shows their correlation is 0.04 is the euro area and 0.18 in the US.

We are particularly interested in the β_1 coefficient which should be interpreted as the impact of ECB's sentiment on interest rate expectations taking into account both the monetary decisions on the key interest rates and, for robustness purposes, some other news that might have potentially occurred the same days. If we postulate the non-monetary shocks are zero, we can simply estimate the effects of sentiment with an OLS regression.

6.2. Linear evidence

We test the prediction -presented in section 2- that sentiment affects interest rate expectations by estimating equations (5)-(6) with an ARCH specification. Our benchmark analysis is performed with the sentiment measure generated with the dictionary of Apel and Blix Grimaldi (2012). The window considered spans from the day before the announcement close of business to the day of the announcement close of business. 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. The transmission lags of monetary policy are often estimated to be around 18 to 24 months for inflation, according to Bernanke and Blinder (1992), or Bernanke and Mihov (1998). Using Loughran and McDonald (2011)'s and Harvard's word lists, the β_1 coefficient remains positive and significant at least for the maturity of 1-year. These results show that positive shocks to sentiment (i.e. an optimism shock) increase private interest rate expectations. The information conveyed by the sentiment expressed in ECB and FOMC statements appears to be interpreted by private agents as relevant for horizons around and beyond those of the monetary transmission. 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

[6] 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.

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.

We then estimate different alternative specifications to assess the robustness of the benchmark result. We consider shocks identified through a Taylor-type equation applied to sentiment and augmented with macro variables and a shadow rate. We replace the denominator in equation (1) using the sum of positive and negative words instead of all words. We also consider shocks identified through a Taylor-type equation using Loughran and McDonald (2011)'s and Harvard's dictionaries. We test alternative estimation methods such TARCH, GARCH and OLS models. We estimate equation (5)-(6) 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. We also estimate with OLS the equation (5) on ECB and FOMC statement days only, which yield to a sample of 116 observations for the ECB and 82 for the FOMC. We also modify the window during 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. Finally, we include a lag of the dependent variable in equation (5). Tables 6-A and 6-B present estimates of β_1 for these alternative specifications. They confirm that the effect is positive and primarily at work around the 1-year maturity both in the euro area and in the United States.

6.3. State-dependent evidence

A further step is to investigate whether private agents process sentiment shocks differently conditional to the nature of the sentiment shock such as its sign (positive for optimism and negative for pessimism) or its size. The effect of sentiment can also depend on the clarity of the statements. In a Bayesian updating model, the weight given to the signal (the sentiment shock) should depend on the precision of the signal. We make use of a measure of ambiguity provided by Loughran and McDonald (2011)' dictionary that we assume capturing the precision of the sentiment conveyed in central bank statements. We could therefore 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.

Sentiment shocks could also be interpreted differently according to the state of the economy or with concomitant 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 positive monetary shocks (i.e. a contractionary shock) as the monetary shock 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 because it conveys specific information not shared with the monetary shock.

We augment equation (5) with an interaction term between sentiment shocks and the state variables we would like to focus on. Tables 7-A and 7-B show estimates for the different cases describe above. Looking at the effect conditional on the sign of the sentiment shock, it appears that in the United States, results are driven by pessimism (negative shocks) whereas in the euro area the effect of positive shocks is stronger than the effect of negative shocks. 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 year in the United States and this non-linear effect is weaker in the euro area and only present at the 1, 2 month and 1 year horizons. The effect of sentiment shocks is smaller when ambiguity is high rather than when ambiguity is low. The interaction term with the recession dummy is negative and significant in the United States for maturities of 1 and 2 year but is not significant in the euro area. The interaction term with inflation is positive and significant in the United States for maturities between 9 months and 3 year and is only significant in the euro area at 6 month and 2 year. 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 1 and 2 month in the euro area. These estimates suggest that the reaction of private agents to the sentiment conveyed by policymakers is extremely signal- and state-dependent.

7. Conclusion

This paper aims to quantify these concepts of "animal spirits", "market sentiment", or "optimism" and to test their potential importance in economic decisions. Using computational lexicographic methods, we quantify the sentiment conveyed by ECB statements. We are able to assess whether this policymakers' sentiment affects private interest rate expectations.

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 and from 1 to 3 years 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. 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 extremely 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 Sentiment variables

Euro Area | United States

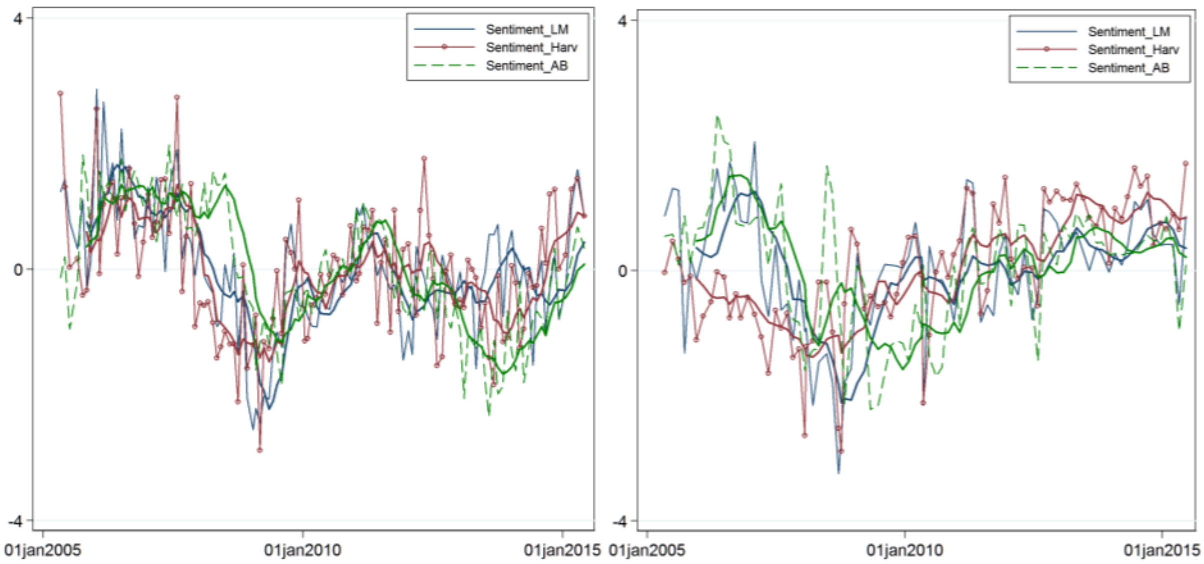

Figure 2 – Central Bank Sentiment shocks

Euro Area | United States

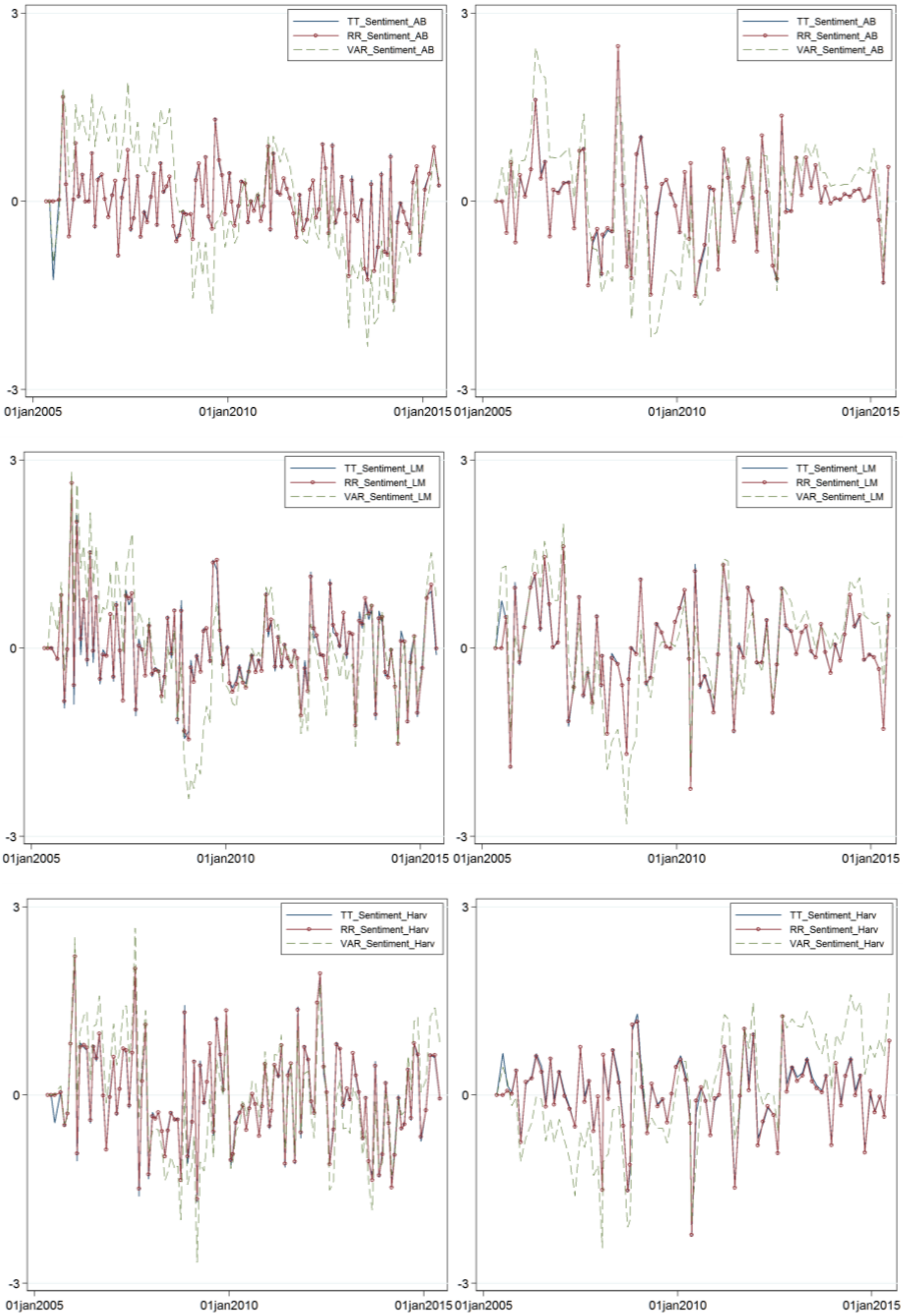

Figure 3 - Distribution of ECB's Sentiment shocks

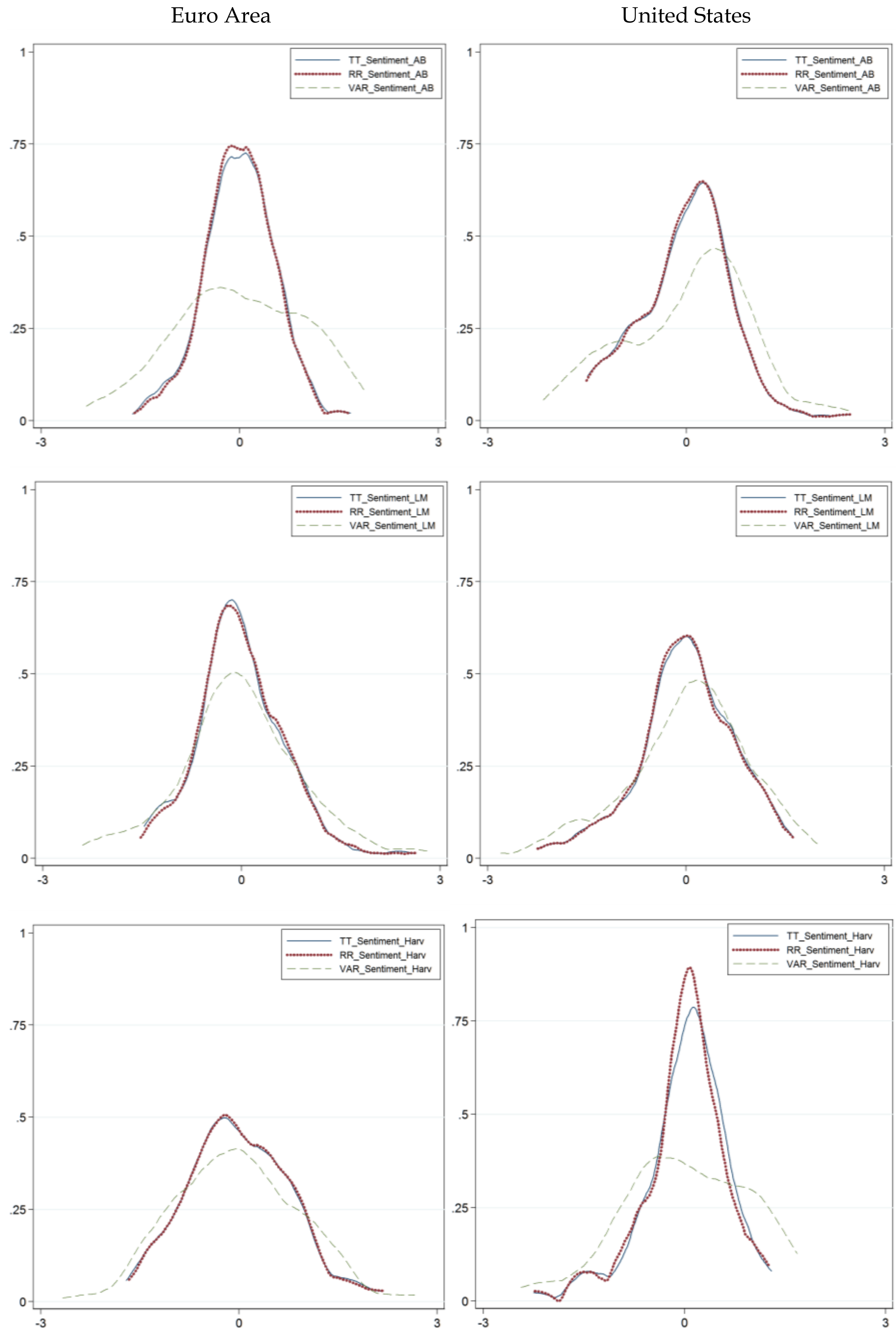

Table 1 - Descriptive Statistics: Sentiment variables

Euro Area					
Variable	Obs	Mean	Std. Dev.	Min	Max
All	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
Sentiment_AB	119	0.006	0.011	-0.020	0.028
Sentiment_LM	119	0.001	0.015	-0.038	0.045
Sentiment_Harv	119	0.123	0.020	0.064	0.180
Ambiguity	119	0.065	0.014	0.040	0.104
	Posit_AB	Negat_AB	Sent_AB	Sent_LM	Sent_Harv
Positive_AB	1				
Negative_AB	-0.43	1			
Sentiment_AB	0.85	-0.80	1		
Sentiment_LM	0.37	-0.46	0.51	1	
Sentiment_Harv	0.09	-0.43	0.34	0.64	1
United States					
Variable	Obs	Mean	Std. Dev.	Min	Max
All	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
Sentiment_AB	85	-0.001	0.011	-0.027	0.028
Sentiment_LM	85	0.002	0.016	-0.048	0.034
Sentiment_Harv	85	0.134	0.031	0.044	0.187
Ambiguity	85	0.060	0.016	0.010	0.103
	Posit_AB	Negat_AB	Sent_AB	Sent_LM	Sent_Harv
Positive_AB	1				
Negative_AB	0.13	1			
Sentiment_AB	0.48	-0.75	1		
Sentiment_LM	0.31	-0.25	0.45	1	
Sentiment_Harv	0.56	0.03	0.27	0.57	1

Table 2 - Descriptive Statistics: Benchmark model

Variable	Obs	Mean	Std. Dev.	Min	Max
Euro Area					
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

Table 3 - Shocks identification

Euro Area				United States			
	Equation (3)				Equation (3)		
	Sent_AB	Sent_LM	Sent_Harv		Sent_AB	Sent_LM	Sent_Harv
	(I)	(II)	(III)		(I)	(II)	(III)
l1.Sentiment	0.509***	0.426***	0.306***	l1.Sentiment	0.562***	0.477***	0.444***
	[0.02]	[0.02]	[0.02]		[0.02]	[0.02]	[0.02]
ecb_cpi_cy	-0.011	0.002	0.011	fomc_cpi_cy	0.017	0.021	0.010
	[0.01]	[0.01]	[0.01]		[0.01]	[0.01]	[0.01]
ecb_cpi_ny	0.013	0.048***	0.037**	fomc_cpi_ny	-0.010	-0.012	0.019
	[0.01]	[0.02]	[0.02]		[0.02]	[0.02]	[0.02]
ecb_gdp_cy	-0.001	-0.006	-0.001	fomc_gdp_cy	-0.002	-0.001	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	0.005	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	0.010	-0.007	0.005
	[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	0.029	-0.012
	[0.07]	[0.08]	[0.09]		[0.05]	[0.05]	[0.04]
cpi	0.000	-0.011	-0.017*	cpi	0.006	-0.003	-0.001
	[0.01]	[0.01]	[0.01]		[0.00]	[0.00]	[0.00]
l1.cpi	0.023*	-0.134***	-0.233***	l1.cpi	-0.013	-0.276***	-0.108***
	[0.01]	[0.02]	[0.02]		[0.02]	[0.02]	[0.02]
gdp	-0.009	-0.005	-0.029**	gdp	-0.01	-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	0.229***	0.225***	0.163***
	[0.01]	[0.02]	[0.02]		[0.02]	[0.02]	[0.01]
shadow	-0.010*	-0.005	-0.020***	shadow	-0.003	-0.003	-0.002
	[0.01]	[0.01]	[0.01]		[0.00]	[0.00]	[0.00]
l1.shadow	0.188***	0.036**	0.01	l1.shadow	0.023	0.02	-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	-0.005	0.003
	[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	0.008	0.008	0.005
	[0.01]	[0.01]	[0.01]		[0.01]	[0.01]	[0.01]
constant	0.104	-0.249*	-0.082	constant	0.047	-0.069	-0.029
	[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 (4)				Equation (4)		
	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)	0.049	-0.048	0.09
	[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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. 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	0.69	-1.47	2.63
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	-0.01	0.78	-1.71	2.16
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	0.55	-1.62	1.67
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					
	Sent_AB	TT_Sent_AB	RR_Sent_AB	VAR_Sent_AB	kutt_eonia
Sentiment_AB	1				
TT_Sentiment_AB	0.55	1			
RR_Sentiment_AB	0.55	0.98	1		
VAR_Sentiment_AB	0.99	0.56	0.57	1	
kutt_eonia	0.00	0.04	0.04	-0.01	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	1.27	0.48	0.31
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	3.64	2.58	0.00
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	1.19	0.35	0.37
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) coefficient		F-stat	p-value	Adjusted R^2
TT_Sentiment_AB	-0.05	TT_Sent_AB	1.19	0.28	0.03
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	-0.11	TT_Sent_LM	2.65	0.01	0.23
RR_Sentiment_LM	0.02	RR_Sent_LM	2.68	0.01	0.24
VAR_Sentiment_LM	0.64***	VAR_Sent_LM	8.93	0.00	0.59
TT_Sentiment_Harv	-0.05	TT_Sent_Harv	1.27	0.22	0.05
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 contemporaneous 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,

Table 4 – B. Properties of estimated FOMC sentiment shocks

Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
TT_Sentiment_AB	85	0.00	0.71	-1.49	2.45
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	0.01	0.75	-2.23	1.62
RR_Sentiment_LM	85	0.00	0.74	-2.24	1.62
VAR_Sentiment_LM	85	0.02	0.93	-2.80	1.98
TT_Sentiment_Harv	85	0.03	0.63	-2.25	1.30
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

	Sent_AB	TT_Sent_AB	RR_Sent_AB	VAR_Sent_AB	kutt_ffr
Sentiment_AB	1				
TT_Sentiment_AB	0.71	1			
RR_Sentiment_AB	0.69	1.00	1		
VAR_Sentiment_AB	1.00	0.72	0.69	1	
kutt_ffr	0.28	0.19	0.18	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	0.96	2.93	2.10	0.02
RR_Sentiment_AB	85	0.97	2.78	2.00	0.02
VAR_Sentiment_AB	85	0.97	2.58	1.85	0.03
TT_Sentiment_LM	85	0.98	1.58	0.90	0.19
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	0.95	4.04	2.73	0.00
RR_Sentiment_Harv	85	0.95	4.03	2.73	0.00
VAR_Sentiment_Harv	85	0.98	1.67	1.00	0.16

Autocorrelation test		**Predictability of exogenous shock series**			
	AR(1) coefficient		F-stat	p-value	Adjusted R^2
TT_Sentiment_AB	0.05	TT_Sent_AB	1.91	0.03	0.19
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	-0.05	TT_Sent_LM	1.64	0.07	0.14
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	0.09	TT_Sent_Harv	0.46	0.98	-0.16
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 contemporaneous 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,

Table 5 – A. Benchmark ECB model

	(1) oieur1m	(2) oieur3m	(3) oieur6m	(4) oieur9m	(5) oieur1y	(6) oieur2y	(7) oieur3y	(8) oieur5y	(9) oieur10
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 equation (5) 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) oieur1m	(2) oieur3m	(3) oieur6m	(4) oieur9m	(5) oieur1y	(6) oieur2y	(7) oieur3y	(8) oieur5y	(9) oieur10
AB dictionary									
	Mean equation								
RR_Sentiment_AB	0.005**	0.006**	0.001	0.002	0.030***	0.032***	0.025*	0.022	0.013
	[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***	0.005	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***	2.655***	2.376***	1.437***	0.601***	0.377***	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	0.006**	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	0.000	0.066	0.052***	0.071***	0.055***	0.065	0.032*	-0.040**	-0.046*
	[0.00]	[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 equation (5) 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) oieur10
Taylor-type shock identification with AB dictionary									
TT_Sentiment_AB	0.002	0.003*	0.004	0.008**	0.010***	0.016***	0.020***	0.021**	0.012
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]
RR shock identification with alternative computation of sentiment variables (using the AB dictionary)									
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]
Taylor-type shock identification with LM dictionary									
TT_Sentiment_LM	0.001	0.002	0.004	0.006**	0.007**	0.008	0.010*	0.005	0.000
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]
Taylor-type shock identification with Harvard dictionary									
TT_Sentiment_Harv	0.000	0.000	0.001	0.003	0.005**	0.002	0.004	0.004	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]
GARCH term									
RR_Sentiment_AB	0.001	0.002	0.003	0.007**	0.010***	0.011**	0.015**	0.018**	0.016**
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[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 (OLS estimation)									
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]
N	1030	1030	1030	1030	1030	1030	1030	1030	1030
Statement days only (OLS estimation)									
RR_Sentiment_AB	-0.003	0.005	0.007	0.010	0.013	0.016*	0.022**	0.021**	0.017**
	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
N	116	116	116	116	116	116	116	116	116
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]

Note: Robust standard errors in brackets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Each column corresponds to equation (5) for a different horizon. Controls and ARCH terms have been removed for space constraints and are available from the authors upon request.

Table 6 – B. Alternative FOMC specifications

	(1) oieur1m	(2) oieur3m	(3) oieur6m	(4) oieur9m	(5) oieur1y	(6) oieur2y	(7) oieur3y	(8) oieur5y	(9) oieur10
Taylor-type shock identification with AB dictionary									
TT_Sentiment_AB	0.005**	0.006**	0.001	0.002	0.030***	0.033***	0.025	0.021	0.011
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.02]	[0.02]
RR shock identification with alternative computation of sentiment variables (using the AB dictionary)									
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]
Taylor-type shock identification with LM dictionary									
TT_Sentiment_LM	-0.002	0.003	-0.001	-0.003	0.025***	0.01	0.003	0.004	0.001
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
Taylor-type shock identification with Harvard dictionary									
TT_Sentiment_Harv	0.009***	0.001	0.001	-0.001	0.030***	0.033***	0.034**	0.035	0.035
	[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**	0.005**	0.001	0.002	0.029***	0.033***	0.026	0.022	0.013
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.02]	[0.02]
GARCH term									
RR_Sentiment_AB	0.002	0.001	0.000	-0.001	0.000	0.002	0.001	0.001	0.006
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]
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]
Tuesday and Wednesday only (OLS estimation)									
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]
N	1034	1034	1034	1034	1034	1034	1034	1034	1034
Statement days only (OLS estimation)									
RR_Sentiment_AB	0.015	0.016	0.011	0.01	0.006	0.012	0.013	0.014	0.010
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
N	82	82	82	82	82	82	82	82	82
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]

Note: Robust standard errors in brackets. * p < 0.1, ** p < 0.05, *** p < 0.01. Each column corresponds to equation (5) for a different horizon. Controls and ARCH terms have been removed for space constraints and are available from the authors upon request.

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) oieur10
Sign (RR_Sentiment_AB)									
Positive ξ_t	0.000	0.007**	0.008*	0.013**	0.015**	0.024***	0.027**	0.026**	0.021*
	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
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]
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]
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]	[0.01]	[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 equation (5) 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. To facilitate the reading of the interacted effects, we compute the coefficient of one of the interacted variable while setting the value of the other variable at either a high value (mean + 1 S.D.) or a low value (mean - 1 S.D.). We focus on these values when interpreting the results rather than on 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)
	oieur1m	oieur3m	oieur6m	oieur9m	oieur1y	oieur2y	oieur3y	oieur5y	oieur10
Sign (RR_Sentiment_AB)									
Positive ξ_t	0.001	0.002	0.000	-0.001	-0.004	-0.009	-0.011	0.014	0.017
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.04]	[0.02]
Negative ξ_t	0.009	0.018	0.002	0.006	0.038***	0.042**	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	-0.003	-0.005	0.000	-0.007***	-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	0.006	0.008	0.001	0.000	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	-0.001	0.021***	0.017	0.012	0.016	0.013
	0.003	0.004	0.001	0.002	0.006	0.012	0.010	0.015	0.015
Small shocks	0.006*	0.009*	0.001	0.000	0.024***	0.021*	0.015	0.018	0.012
	0.003	0.005	0.001	0.003	0.007	0.012	0.011	0.015	0.016
Ambiguity									
Interaction	-0.017***	-0.011***	-0.012***	-0.007	-0.033***	-0.031***	-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***	0.017	0.015	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]
NBER recession dummy									
Interaction	-0.003	0.007**	-0.006	-0.007	-0.059***	-0.061***	-0.045	-0.043	-0.018
	[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***	0.039***	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	0.003	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***	0.039***	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	-0.003	-0.004	-0.024***	-0.022	-0.015	-0.015	-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	-0.002	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	0.004*	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	0.002	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	-0.014***	-0.007	-0.002	-0.002	-0.003
	[0.00]	[0.01]	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]
RR_Sentiment_AB	0.002	0.004***	0.001	0.002	-0.021***	0.023	0.022	0.019	0.009
	[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***	0.016	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 equation (5) 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. To facilitate the reading of the interacted effects, we compute the coefficient of one of the interacted variable while setting the value of the other variable at either a high value (mean + 1 S.D.) or a low value (mean - 1 S.D.). We focus on these values when interpreting the results rather than on 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 illustratives	
increas*	decreas*
accelerat*	decelerat*
fast*	slow*
strong*	weak*
high*	low*
gain*	loss*
expand*	contract*
Most frequent in ECB and FOMC 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
Sentiment_AB	Apel and Blix-Grimaldi (2012)	Authors' computations	For each ECB statement
Sentiment_LM	Loughran and McDonald (2011)	Authors' computations	For each ECB statement
Sentiment_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
Sentiment_AB	Apel and Blix-Grimaldi (2012)	Authors' computations	For each FOMC statement
Sentiment_LM	Loughran and McDonald (2011)	Authors' computations	For each FOMC statement
Sentiment_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 constant-inpolated to daily frequency so as to respect the information structure.