What do press conferences tell us about central bankers sentiment (and why it matters)?

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Abstract

This study contributes to understanding the tone in press conferences held by the President of the European Central Bank (ECB) after a Governing Council meeting. We use a Large Language Model (LLM) for sentiment analysis, specifically focusing on the financial context using the finBERT model. We derive two types of sentiment indices, for the whole press conference, but also individually for its introductory statement as well as for its Q&A part. We find that the tone in the introductory part of the conferences is related to macro-events such as crises, the COVID-19 and the Ukraine war, while the Q&A portion is connected to both shocks and presidential periods. We also identify a strong link between sentiment and several macroeconomic variables. Variables related to inflation and industrial production have a significant, but differing impact on our polarity and subjectivity indexes. Our results contribute to the understanding of the tone in the ECB's communication and highlight the potential of large language models to unveil sentiment contained in central banks' narrative.

Keywords: Central bank communication, Sentiment Analysis, Large language models, Transformers.

JEL Codes: E40, E58, E71

1 Introduction

With its function of protecting the stability of the monetary system and controlling inflation, the decisions and announcements of the central bank always raise attention and serve as guideline actions for both experts and markets. Furthermore, the announcements of central banks in major countries have an influence not only within those countries but also spread widely to many other countries. For example, announcements by European central banks can lead to significant movements around the world. Among the various communication channels utilized by the European Central Bank (ECB), press conferences hold a significant place as they provide direct insight into the central bank's policy decisions, economic outlook, and strategic considerations.

Understanding the sentiment conveyed in these press conferences is essential for several reasons. First, sentiment analysis can reveal the underlying tone and emotional context of ECB communication, which can influence market behavior and public perception. Second, it provides a quantitative measure to analyze the ECB's communication strategy over time, identifying trends, shifts in policy emphasis, and responses to economic challenges. Third, by comparing sentiment across different time periods and economic contexts, researchers can assess the consistency and effectiveness of ECB messaging.

In this study, we contribute to the understanding of the ECB's press conference sentiment with several novel points. First, we apply the finBERT model, a large language model that allows us to analyze the sentiment in the financial context. Second, we investigate both the sentiment conveyed by the whole press conference as well as by its two distinct parts, the introductory statement and the Q&A parts. Third, we identify regimes in the different sentiment series, relating those regimes to monetary policy developments and different presidencies. Finally, we answer the question of whether the sentiment conveyed by the whole press conference, as well as by its two distinct sub-parts, can be explained by macroeconomic variables. Specifically, we find that the structure of the introductory sections of press conferences is aligned with shocks and crises, including the global financial crisis (GFC), Covid-19, and the Ukraine war. On the other hand, the tone of the Q&A parts is closely connected with the personality styles of the ECB's presidents. Interestingly, in addition to the change in the communication style of the presidents, we find a persistent decline in the fluctuation of sentiment indicators in the Q&A parts. This phenomenon could be explained by the adoption and adjustments made by presidents to stabilize the market.

The subsequent sections of this paper are structured as follows. Section 2 provides essential background discussions. Section 3 summarizes the methods applied and outlines the data structure in this study. The empirical results are presented in Section 4. We finally conclude in Section 5.

2 Literature review

The topic of central bank communication encompasses various directions and types of communication. Typically, the literature can be classified into two main branches: the first is about the construction of a sentiment indicator and the study of its determinants, while the second is about the impact of central bank communication on financial markets and its predictive power.

To quantify text in the economic literature, earlier studies, such as Rosa and Verga (2007); Ehrmann and Fratzscher (2007); Berger et al. (2011); Hayo and Neuenkirch (2013); Apergis and Pragidis (2019) have relied on hand-coding to assign a 'sentiment' to the statements made by central bankers. For instance, Berger et al. (2011) classify the overall monetary policy stance on a scale from -3 (strong inclination to lower rates) to +3 (strong inclination to increase rates) using four subcategories: overall policy intention, price stability, real economy, and monetary sector. Others rely on word counting to classify statements. Jansen and De Haan (2005) classify the ECB's statements into topical categories to investigate their impact on exchange rates and the strength of the currency. The major drawback of such hand coding is the introduction of subjectivity due to human interpretation. The development of lexicon models, along with dictionaries to classify texts has introduced more objectivity into the process. Traditional dictionary models may however not properly interpret financial content, this is why Loughran and McDonald (2011) developed an alternative word list, to better reflect the tone in financial texts. The Loughran-McDonald sentiment dictionary is also applied to central bank communications, such as in the studies of Schmeling and Wagner (2016); Anastasiou and Katsafados (2023). Schmeling and Wagner (2016) analyzed the transcripts of the ECB president's opening statements to determine the tone of the communication finding that the tone of the ECB's statements affects stock returns, volatility risk premia, policy rates, upward revisions of real GDP growth, recent higher stock market returns, and government bond yields. Anastasiou and Katsafados (2023) construct two textual sentiment variables from the monthly speeches of the ECB's president and employ them as direct measures of the depositors' perceived fear. Alternative word lists that aim for specific applications in financial economics such as for monetary policy appear in Correa et al. (2021); Luca Barbaglia and Manzan (2023); Shapiro et al. (2022). Bennani and Neuenkirch (2017) employ an automated search and word counting approach to create an indicator that measures the tone of the speeches delivered by members of the Governing Council and relate this variable to euro area and national macroeconomic forecasts. Picault and Renault (2017) develop their own field-specific dictionary to measure the stance of the ECB monetary policy (dovish, neutral, hawkish) and the state of the Eurozone economy (positive, neutral, negative) through the content of ECB press conferences. They find that quantifying ECB communication using their field-specific weighted lexicon helps to explain future ECB monetary decisions. Furthermore, markets are more (less) volatile on the day following a conference with a negative (positive) tone about the euro area economic outlook.

Later studies applied tools from computational linguistics to analyze central bank communication. To identify topics, the Latent Dirichlet Allocation (LDA) is a text generative model that enables the extraction of multiple themes that are not specified in advance, developed by Blei et al. (2003), and applied in several studies of central bank communication such as Hansen and McMahon (2016), Jegadeesh and Wu (2013) or Klejdysz and Lumsdaine (2023). The arrival and success of large language models have opened up new opportunities for advancing sentiment analysis, also in the financial context. Deep learning models, allow for a more nuanced analysis of central bank communication by considering the context of words and phrases. BERT type of models are applied to central bank narratives in Niţoi et al. (2023); Kanelis and Siklos (2024). Niţoi et al. (2023) use a pre-trained BERT model on a dataset of manually annotated sentences of monetary policy stance. They derive a central bank sentiment index which is then compared to other measures for capturing financial uncertainty. Their sentiment index is less noisy and has the ability to forecast the future path of policy stance. Also, compared to other lexicon-based sentiment indicators, the deep learning index has a higher predictive power in anticipating policy rates changes. Kanelis and Siklos (2024) are among the first to study the introductory statements of the ECB's press conferences with finBERT, which is the BERT model adapted to finance-related textual data. In our study, we follow this innovation by applying a finBERT model to the full speeches of the ECB's presidents during press conferences.

Generally, central bank communication plays a crucial role in steering the economic system and markets. Specifically, positive signals from central bank communication tend to lead markets in a positive direction, while uncertainty or inconsistency in communication often results in market volatility. Gorodnichenko et al. (2023) rely on a deep learning model to detect emotions embedded in press conferences after the Federal Open Market Committee meetings and examine the influence of these emotions on financial markets. They find that a positive tone in the voices of Federal Reserve chairs leads to significant increases in share prices. Other financial variables also appear to respond to sentiment expressed by the chairs. Relying on the fact that central banks often write press releases using the previous statement as a template, Ehrmann and Talmi (2020) study whether similarity in statements matters for financial markets. Financial market volatility is inferred from the responsiveness of 1-year government bond yields to press releases. The authors find that similar statements normally generate less market volatility, while substantial changes in statements lead to much higher volatility. Bennani (2020) explores the relationship between central bank communication and investor sentiment finding that an overconfident Fed chair is significantly associated with higher investor sentiment. Furthermore, investors are more sensitive to central bank communication during a recession and they adjust rapidly their sentiment following central bank communication. Apergis and Pragidis (2019) construct a sentiment index associated with the messages conveyed by the ECB and measure the effect of this index on both the mean and the volatility of certain major international stock markets. Results suggest a significant link between sentiment index and the mean and the volatility of returns, which is stronger during the crisis period. Klejdysz and Lumsdaine (2023) find that the content of the ECB press conference is informative for the stock market, and that market uncertainty increases when the ECB switches to a different communication regime.

While the literature on central bank communication covers various central banks around the world, this paper focuses specifically on the ECB press conferences. The ECB's press conferences provide significant additional information to financial markets beyond what is included in the monetary policy decisions. The value of this information is strongly connected to the nature of the decisions themselves (Ehrmann and Fratzscher, 2009), making press conferences one of the most influential communications of the ECB. Studies have also identified a link between the ECB's press conferences and various financial indices. This connection is stronger compared to other ECB communication tools, such as meeting accounts, Executive Board speeches (Kaminskas and Jurkšas, 2024), and inter-meeting speech communications (Kanelis and Siklos, 2024). In the study of Kanelis and Siklos (2024) the sentiment of the introductory statement is then explained by inter-meeting speeches of Board members, for which the authors differentiate between monetary policy and financial stability topics. Results suggest a significant positive relationship between the average sentiment of inter-meeting monetary policy-related speeches and the sentiment expressed in the introductory statements, but not in the financial stability topic.

Our study is closely related but is original from the following perspective. ECB press conferences have a specific structure comprising two parts, notably i) the introductory statements and ii) a questions and answers (Q&A) part. While most studies focus on the introductory statements (Rosa and Verga, 2007; Dybowski and Kempa, 2020; Kanelis and Siklos, 2024), some emphasize the role and complexity of the Q&A sections (Ehrmann and Fratzscher, 2009; Klejdysz and Lumsdaine, 2023). The novelty of our paper, is first, the usage of a finBERT model for the sentiment analysis of the full press conference as well as its two subparts. We then provide evidence that our sentiment indexes undergo clear regime switches and that they can be explained by macro-economic events and variables, similar to Bennani and Neuenkirch (2017) and Hayo and Zahner (2023). To the best of our knowledge, this paper is thereby the first one to relate the sentiment derived from a finBERT model applied to the ECB's press conferences with the state of the macro-economic variables which the ECB steers.

3 Data and Methodology

The sentiment time series in this study were obtained from the texts contained in ECB press conferences by applying the finBERT model on statements ranging from January 1999 until June 2024. The ECB organized press conferences at a monthly frequency starting from the 9th of June 1998. From 2015 onwards, the frequency of the meetings was changed to a six-week frequency. In total, we collect and analyze 280 press conferences of the ECB. The press conferences have a rich content and structure including: (1) the monetary policy decisions,

(2) an economic analysis, and (3) questions and answers.

In the second part of the analysis, we relate our sentiment series to macro-economic variables. These variables are obtained from the ECB's Statistical Data Warehouse (SDW), at a monthly frequency. We rely on the inflation rate, the change in industrial production, the unemployment rate, the one year-ahead forecast of the inflation rate, the deviation of the inflation rate from the 2% target, which we refer to as the inflation gap, and the deviation of the one year-ahead forecast from the 2% target.[1]

Our sentiment analysis method consists of five steps: (1) scraping of the official transcripts of the press conferences, (2) text pre-processing, (3) tone extraction and classification, (4) calculation of aggregate sentiment indicators, and (5) noise filtering. A detailed description of each step is provided below.

Scraping of the official transcripts of the press conferences. We retrieve the official transcript of each press conference posted on the website of the European Central Bank. On the official website of the ECB, there are six main types of communication including press conferences, press releases, monetary policy decisions, the ECB blog, speeches, and interviews. In this study, we collect and extract the texts associated to press conferences from January 1999 to June 2024.

Text pre-processing. In this study, each communication is a text including many paragraphs. We store these texts by publishing date in our database. We tokenize these texts into sentence units based on separation symbols such as ".", "!", "?". We use each sentence as the most granular unit for the entire study. By storing text at the sentence level, we decompose unstructured text into multiple structured parts, while keeping the meaning of texts in sentences.

Common Large Language Models (LLMs) based on the transformer architecture include BERT and GPT models. Even though both leverage the transformer architecture, they are designed with different purposes and function differently. BERT, short for Bidirectional Encoder Representations from Transformers, is designed to learn contextual representations of input sequences by considering both the left and right context. Thanks to its bidirectional approach, BERT excels at tasks that require a deep understanding of context such as Named Entity Recognition (NER) and Question & Answering (QA).

Tone extraction and classification. Sentiment analysis is a natural language processing (NLP) technique used to determine the emotional tone, attitude, or sentiment expressed in textual data. It involves analyzing written or spoken language to discern whether the text conveys a positive, negative, or neutral sentiment, as well as the intensity of that sentiment. In this study, we rely on the Large language model (LLM) with finBERT (Huang et al.,

[1]The forecasts are from the Survey of Professional Forecasters (SPF), which provides forecasts of inflation measured from the Harmonised Indices of Consumer Prices (HICP), for various horizons and by various professional forecasters. The average forecast point as well as the variance are available. We rely on the average forecast and on its standard deviation for a one-year ahead projection horizon.

2023) to derive sentiment indices.

There are three reasons for choosing finBERT. First, central bank communication typically contains information about economic prospects and the financial system and therefore are financially oriented. The general BERT model could lead to mis-classifications of the sentiment as it is trained in a general context. Indeed, Huang et al. (2023) indicate that finance vocabulary helps finBERT retain its performance (i.e., reduce its accuracy deterioration) when the training sample becomes smaller. Second, finBERT's performance outperforms both the Loughran-McDonald (LM) dictionary and other machine learning models (NB, SVM, RF, CNN, and LSTM) Third, finBERT could detect the negative sentiment more accurately than non-BERT models (Huang et al., 2023).

After the tokenization into sentences, each sentence is classified as positive, negative, or neutral. Note that with finBERT, the classification occurs into 'positive' and 'negative'. Dictionary-based models applied in studies on central bank communication often classify the statements into 'hawkish' or 'dovish'. Rather than focusing solely on isolated word frequencies, BERT models take entire sentences, are able to capture the intricate meanings and relationships of words and assign a sentiment of the type positive or negative. The positive/negative classification is thereby a bit larger and deviates from hawkish/dovish classification, which exclusively relates to inflation.[2] In the context of central bank communication, a positive label will occur when the speech refers to a positive economic outlook, a positive description of the state of the macroeconomy. The way of constructing the tone index is however the same as for polarity, in that the tone is defined as the number of 'hawkish' statements minus the number of 'dovish' statements (or words) over the total number of statements (or words) and in our case rather the number of 'positive' sentences minus the number of 'negative' sentences over the total number of sentences.

[Table 1 comes here]

[2]Our approach is thereby in line with Kanelis and Siklos (2024) or Correa et al. (2021)

Table 1: Sample of extracted sentiments.

Panel A – Introductory Statement

Tone	**Sentence**
Positive	"The euro area economy is continuing to recover and the labour market is improving further, helped by ample policy support." (03 Feb 2022)
Positive	"The euro area economy continues to recover strongly, although momentum has moderated to some extent." (28 October 2021)
Negative	"Persistently high and rising oil prices have had a visible direct impact on consumer prices this year, and inflation is likely to remain significantly above 2% in the coming months." (04 Nov 2004)
Negative	"Since our last Governing Council meeting in late January, the spread of the coronavirus (COVID-19) has been a major shock to the growth prospects of the global and euro area economies and has heightened market volatility." (12 March 2020)
Neutral	"Accordingly, we will continue to monitor very closely all developments over the period ahead." (05 February 2009)
Neutral	"As concerns the monetary policy stance of the ECB, it has to be focused on the euro area." (03 May 2012)

Panel B – Q&A Session

Tone	**Sentence**
Positive	"It is true to say - amazingly, I must say, basically, also for the US authorities - that the US economy seems to be continuing to grow at a pace which - we thought earlier - might be similar to that in Europe." (30 March 2000)
Positive	"Even more interestingly, the balance sheet repair for non-financial companies has actually improved markedly over the last few months." (19 January 2017)
Negative	"We continue to see evidence that there are short-term upward pressures on overall inflation, mainly on the account of energy and commodity prices." (03 February 2011)
Negative	"And the fact that headline inflation is higher than it should have been, had we not had this bad news, creates an additional element for which we have to be particularly alert as regards second-round effects." (08 November 2007)
Neutral	"As regards the future auctions, we will decide when the time comes." (02 July 2009)
Neutral	"It is too early to judge what the near future will bring." (30 March 2000)

Calculation of aggregate sentiment indicators. The number of occurences in each category are then used to calculate two distinct sentiment indicators, namely the polarity and the subjectivity of each text (i.e., of each press conference or of each of their sub-parts):

$$Polarity = \frac{N^+ - N^-}{N^+ + N^-} \tag{1}$$

$$Subjectivity = \frac{N^+ + N^-}{N} \tag{2}$$

where N is the total number of sentences in the text and N^+ (resp. N^-) is the number of positive (resp. negative) sentences in the text.

By construction, polarity ranges from -1 (indicating negative tones) to 1 (indicating positive tones). In contrast, subjectivity ranges from 0 (representing a neutral position) to 1 (representing a subjective position).

Most studies appear to use the polarity indicator to summarize the sentiment result e.g (Gorodnichenko et al., 2023; Hayo and Zahner, 2023; Mullings, 2023; Apergis and Pragidis, 2019; Hubert and Fabien, 2017; Picault et al., 2022). Correa et al. (2021) use a slightly different numerator, namely negative words - positive words. Gorodnichenko et al. (2023) use the polarity indicator to reflect dovish and hawkish tones. Bennani (2020) use a similar definition but in categories around the terms "confident" and "cautious". In this study, we extract the polarity indicator as well as a subjectivity indicator. We think this second indicator is warranted as it reflects a different type of information than the polarity indicator. While polarity reflects a positive sentiment, with higher polarity indicating more positivity, the subjectivity indicator reflects the strength of the sentiment, in the sense that the sentiment can be either neutral or instead subjective, in that it includes a lot of text with positive or negative tags (as opposed to a neutral tag). When this is the case, subjectivity will be higher.

Noise filtering. All our sentiment series, polarity and subjectivity, of the whole press conference, of the introductory statement and of the Q&A part are filtered with a Kalman filter. The Kalman filter estimates a process through feedback control. It predicts the process state at a specific time and then adjusts it based on incoming (noisy) measurements. This process involves two types of equations: the time update equation and the measurement update equation. Time update equations predict the next state and error estimates in advance (a priori) for the next time step, acting as predictor equations. Measurement update equations refine these predictions based on new measurements, functioning as corrector equations (Welch et al., 1995). Thus, the overall estimation method operates like a predictor-corrector algorithm used for numerical problem-solving.

The Kalman filter provides two outputs: filtering and smoothing. Filtering refers to the general process of extracting valuable information from a noisy signal. Smoothing, a specific type of filtering known as a "low-pass filter," passes low-frequency components while reducing high-frequency components. In some cases, filtering high-frequency data to predict future states by extracting relevant information from a noisy signal is the best use of the Kalman filter. Conversely, smoothing often relies more on past data, as averaging recent measurements can sometimes yield more accurate results than using only the latest measurement.

4 Results

4.1 Summary statistics

Table 2 presents the summary statistics of our sentiment series obtained with a finBERT for the three press-conference parts: (1) the full talk, (2) the introductory part, and (3) the Q&A part. Between January 1999 and June 2024, a total of 273 press conferences were held. However, ten of these press conferences contained content unrelated to the monetary policy context. Consequently, these ten conferences were excluded from the analysis (e.g. 13 December 2001, 03 Jan 2002, 08 May 2003, 17 September2003, 13 October 2003, 20 January 20051 and 2, 21 January 2005, 26 October 2014, 08 July 2021).

[Table 2 comes here]

The summary statistics presents two sentiment indicators: polarity and subjectivity. Polarity measures the strength of an opinion, while subjectivity reflects the extent to which a statement expresses opinions or feelings.

On average, the mean polarity of the three communication sections is positive, indicating that positive content generally outweighs negative content. Among the sections, the introductory part exhibits the highest mean polarity (0.40) compared to the overall press conferences (0.24). In contrast, the Q&A segment has the most negative mean polarity (-0.14). This pattern reflects the structural characteristics of ECB communications: the introductory section, being pre-prepared, tends to convey a consistently positive view of the central bank, while the Q&A segment is more dynamic and shaped by the questions posed, resulting in a more straightforward and less positive tone.

In terms of tone variability, the introductory section shows the highest deviation in polarity (0.22), followed by the overall press conferences (0.165) and the Q&A segment (0.16).

For subjectivity, the introductory section demonstrates an average subjectivity value approximately twice as high (0.71) as the overall press conference (0.32) and the Q&A segment (0.20). Additionally, subjectivity fluctuates less in the Q&A segment (standard deviation of 0.03) compared to the overall press conference (0.09) and the introductory section (0.09). These findings suggest that the subjectivity of the full communication is primarily driven by the introductory section, a conclusion that will be explored further in the subsequent analysis. We argue that introductory parts are often prepared in advance and utilize professional lexicon to maintain neutral statements, making it difficult to detect tone without context. Conversely, the Q&A parts depend on the situation and are challenging to prepare in advance, thus preserving the structure of natural language, which can be effectively captured by both models.

Table 2: Summary statistics

The table shows summary statistics of two sentiment indicators obtained with a FinBERT model after applying Kalman filter. The first indicator is polarity as defined by equation 3, the second indicator is subjectivity as defined by equation 3. Time series of the indicators are obtained from 263 full press conference speeches and introductory parts and Q&A parts from January 1999 to June 2024.

		Mean	**St. Dev.**	**Min**	**Pctl(25)**	**Median**	**Pctl(75)**	**Max**	**N**
Polarity	Full talk	0.24	0.17	−0.14	0.12	0.26	0.36	0.66	263
	Introductory	0.40	0.22	−0.13	0.25	0.41	0.54	0.90	263
	Q&A part	0.09	0.16	−0.32	0.00	0.11	0.20	0.44	263
Subjectivity	Full talk	0.32	0.03	0.25	0.30	0.32	0.33	0.39	263
	Introductory	0.71	0.09	0.41	0.67	0.73	0.78	0.85	263
	Q&A part	0.20	0.02	0.16	0.19	0.21	0.22	0.23	263

Kalman filter results

Figures 1 to 4 show the plots of the raw sentiment series, along with the filtered series. For all analyses that follow, filtered series are used.

Table A.1 outlines the models applied to each sentiment indicator, selected based on the optimal Akaike Information Criterion (AIC) values across three models: the Local Level Model (stochastic level, no trend), the Local Linear Trend Model with deterministic trend (stochastic level, deterministic trend), and the Local Linear Trend Model with a stochastic trend (stochastic level, stochastic trend). Specifically, the optimal model for the subjectivity indicator is the local stochastic level model without a trend, achieving an AIC of 785.94 and a noise-to-signal ratio of 72.23. The local linear stochastic model with a trend is the most suitable choice for the polarity indicator, yielding an AIC of 145.05 and a noise-to-signal ratio of 1.54.

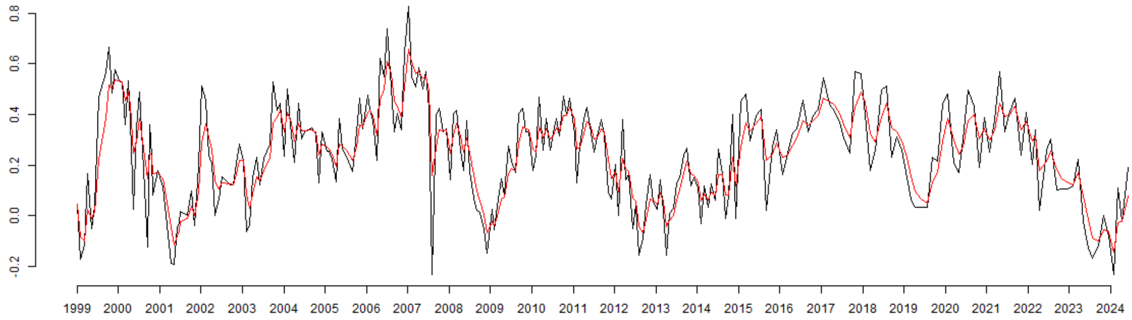
4.2 Sentiment regimes

In this section, we study the regimes of our sentiment series, by relating them to economic events and the periods of different presidencies. The tenures of the four presidents of the ECB are shown in Table 4.

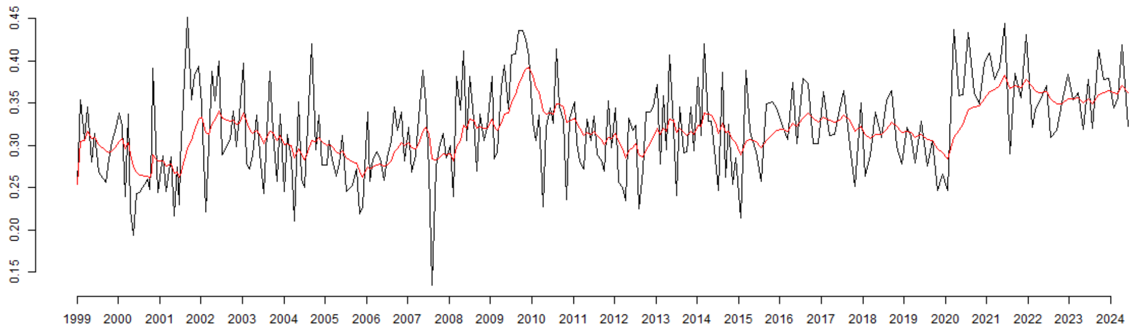
Table 3: Combination test

Notes: This table displays the regression of the subjectivity of the introductory part and Q&A part on the subjectivity of whole press conferences (Column 1), and the regression of the polarity of the introductory part and Q&A part on the polarity of whole press conferences (Column 2). $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

	Subjectivity		Polarity	
	(1)	(2)	(3)	(4)
subjectivity_bert_fil_0_main	0.129***	0.118***		
	(9.19)	(8.40)		
subjectivity_bert_fil_0_qa	1.094***	0.853***		
	(22.10)	(10.78)		
polarity_bert_fil_0_qa			0.590***	0.590***
			(39.52)	(39.45)
polarity_bert_fil_0_main			0.463***	0.467***
			(77.76)	(44.16)
Constant		0.058***		−0.002
		(3.84)		(-0.44)
Observations	263	263	263	263
Adjusted R^2	0.996	0.549	0.985	0.953
Panel 2 Test with β_0 of Q&A = 0 (row 1) and Q&A = 1 (row 2)				
$\beta\_0 = 0$, $\beta\_1 = 1$	4,608.62		3,279.2	
$\beta\_0 = 1$, $\beta\_1 = 0$	59,794.38		4,202.24	



(a) Polarity finBERT



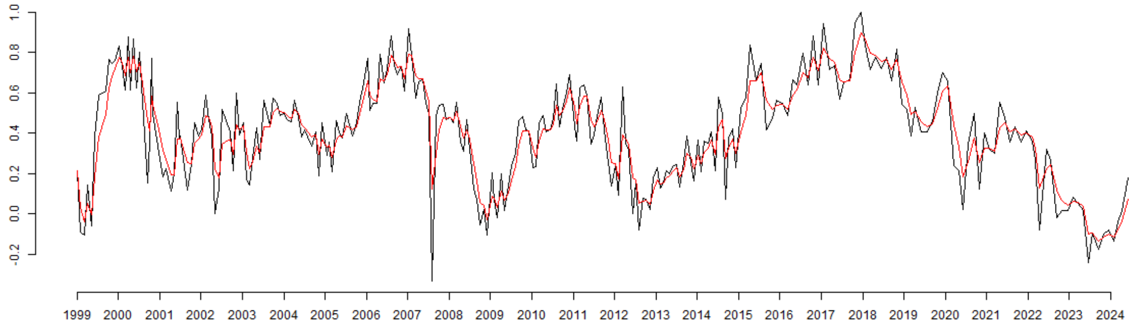
(b) Subjectivity finBERT

Figure 1: Comparison of the original and Kalman filtered sentiment series. Polarity and subjectivity indices are obtained using finBERT applied to the full press-conferences' text.The raw series are in black, the filtered series in red.

Table 4: Number of Presidents of ECB

No	**President**	**Start Date**	**End date**
Period 1	Wim Duisenberg	1 June 1998	31 October 2003
Period 2	Jean-Claude Trichet	1 November 2003	31 October 2011
Period 3	Mario Draghi	1 November 2011	31 October 2019
Period 4	Christine Lagarde	1 November 2019	Incumbent

[Place Table 5 here]



(a) Polarity finBERT

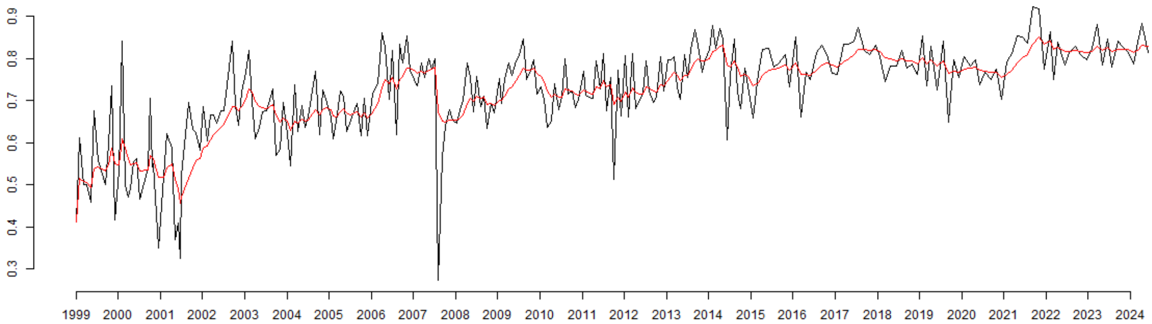
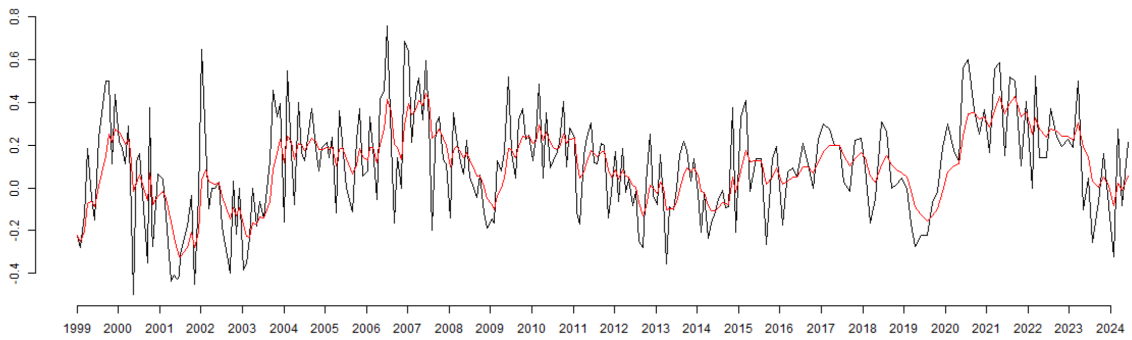


Figure 2: Subjectivity finBERT

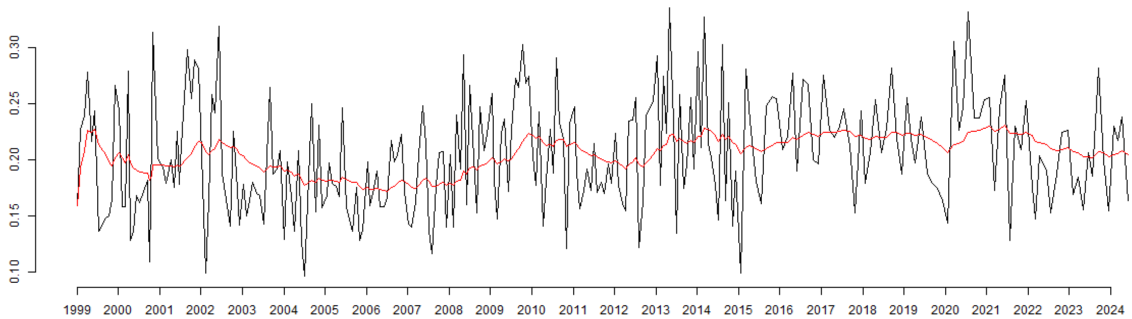
Figure 3: Comparison of the original and Kalman filtered sentiment series. Polarity and subjectivity indices are obtained using finBERT applied to the introductory part of the press-conference. The raw series are in black, the filtered series in red.

Table 5: Markov regime switching model for polarity, Jan 1999 to June 2024

Regimes	**Parameters**	**Whole conference**		**Introductory part**		**Q&A part**	
Regime 1	Coefficient	0.08***		0.26***		-0.04***	
		(7.75)		(17.11)		(−3.99)	
	Sigma	0.01		0.02		0.01	
Regime 2	Coefficient	0.35***		0.60***		0.21***	
		(34.63)		(40.00)		(19.26)	
	Sigma	0.01		0.02		0.01	
Transition Probability		Regime 1	Regime 2	Regime 1	Regime 2	Regime 1	Regime 2
Regime 1		0.94	0.04	0.04	0.94	0.95	0.04
Regime 2		0.06	0.96	0.96	0.05	0.05	0.96
Regime durations		17.60	25.41	25.90	19.11	20.10	24.34



(a) Polarity finBERT



(b) Subjectivity finBERT

Figure 4: Comparison of the original and Kalman filtered sentiment series. Polarity and subjectivity indices are obtained using finBERT applied to the Q&A part of the press-conference. The raw series are in black, the filtered series in red.

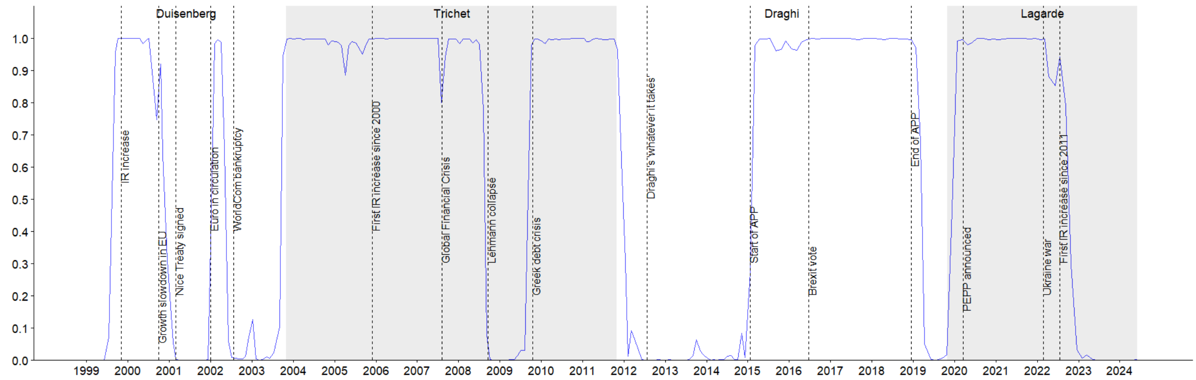
Table 6: Markov regime switching model for subjectivity, Jan 1999 to June 2024

Regimes	**Parameters**	**Whole conferences**		**Introductory part**		**Q&A part**	
Regime 1	Coefficient	0.31***		0.60***		0.22***	
		(275.62)		(131.35)		(240.00)	
	Sigma	0.00		0.00		0.00	
Regime 2	Coefficient	0.36***		0.76***		0.19***	
		(235.38)		(165.8)		(209.78)	
	Sigma	0.00		0.00		0.00	
Transition Probability		Regime 1	Regime 2	Regime 1	Regime 2	Regime 1	Regime 2
Regime 1		0.99	0.04	0.98	0.02	0.97	0.03
Regime 2		0.01	0.96	0.02	0.98	0.03	0.97
Regime durations		206.95	25.07	42.01	62.17	36.59	37.81

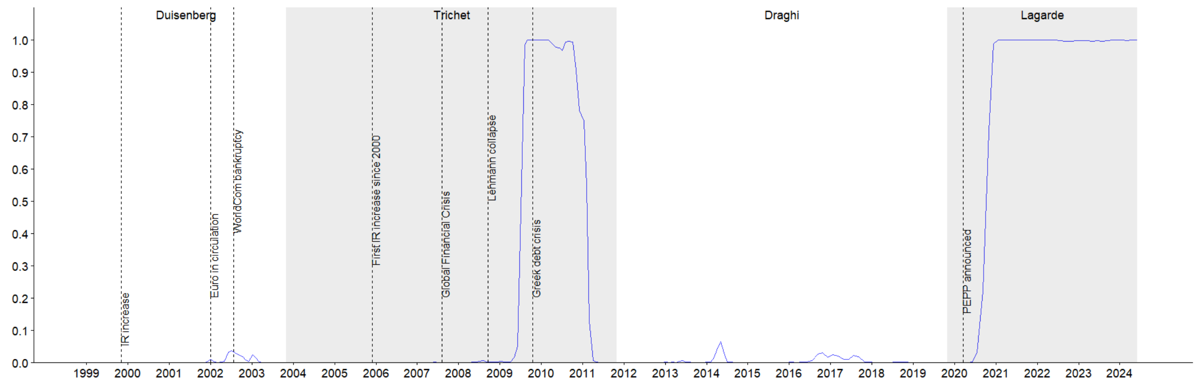
[Place Figure 5 here]

[Place Figure 6 here]

[Table 7 comes here]



(a) Polarity of whole press conferences



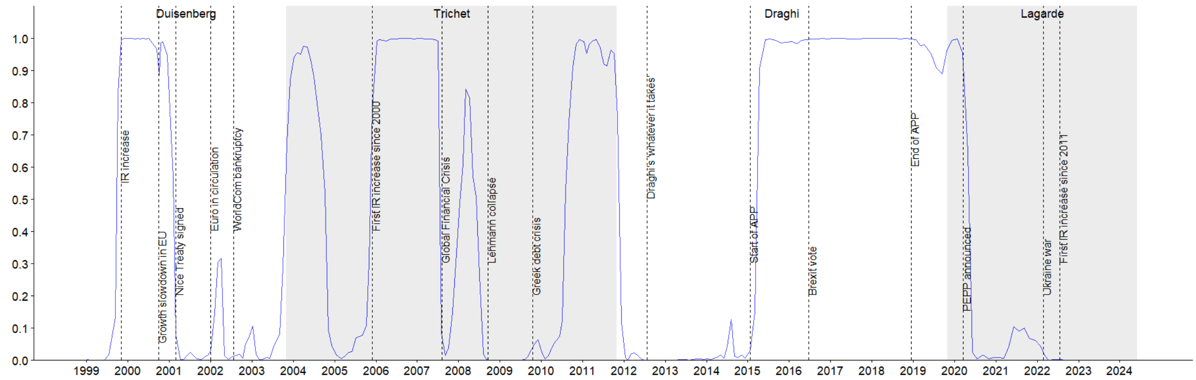
(b) Subjectivity of whole press conferences

Figure 5: A comprehensive view of full press conferences with Markov switching

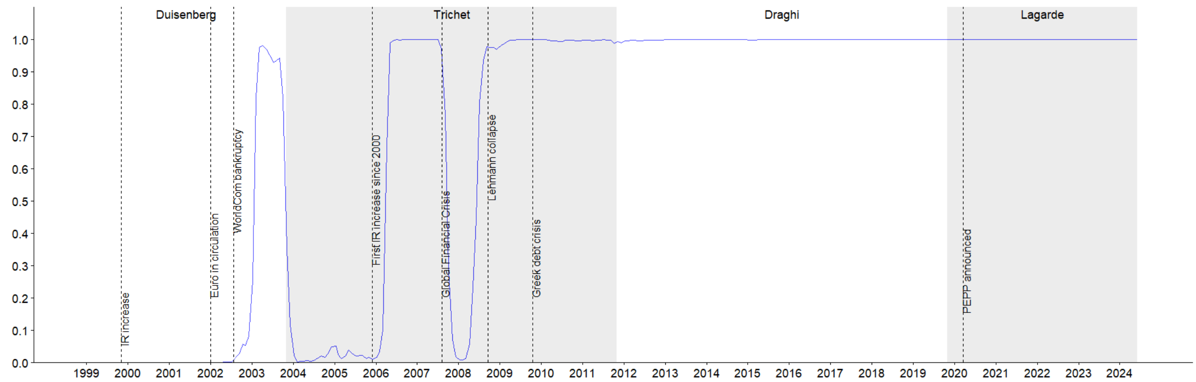
Table 7: Macro economic events

The table lists macroeconomic events associated with Markov switching analysis. The polarity columns indicate how each event impacted sentiment or tone in a given context. "In" represents an increase in the variable, "De" a decrease, and "No" no significant impact. The subjectivity columns capture whether responses were objective ("No") or subjective ("In" or "De").

Date	**Event**	**Short-Name**	**Polarity**			**Subjectivity**		
			Full	**Intro**	**Q&A**	**Full**	**Intro**	**Q&A**
4 Nov 1999	Interest rates increases	IR increases	In	In	In	No	No	De?
1 Oct 2000	Slowdown in growth in Europe	Growth slowdown in EU	De	No?De	No	No	No	No
26 Feb 2001	Signature of the Nice Treaty	Nice Treaty signed	No	De	No	No	No	No
1 Jan 2002	Euro comes in circulation	Euro in circulation	In	No?In	No	No	No	In
21 Jul 2002	WorldCom files for Chapter 11	WorldCom bankruptcy	No	No	No	No	In	No
1 Dec 2005	First interest rates increase since 2000	First IR increase since 2000	No	In	No	No	In	No
8 Aug 2007	Global financial crisis	Global Financial Crisis	No	De?In	No	No	De	No
15 Sep 2008	Collapse of Lehmann Brothers	Lehmann collapse	No? De	No	De	No	In	No
16 Oct 2009	Start of the Greek crisis	Greek debt crisis	In	No	No?In	In	No	In
26 Jul 2012	Draghi's 'whatever it takes' speech	Draghi's 'whatever it takes'	No	No	De	No	No	No
22 Jan 2015	Start of the APP	Start of APP	In	In	In	No	No	No
23 Jun 2016	UK votes the Brexit	Brexit vote	No	No	In	No	No	No
13 Dec 2018	End of APP net purchases	End of APP	De	No	De	No	No	No
18 Mar 2020	PEPP	PEPP announced	No?In	De	In	In	No	No
24 Feb 2022	Start of the war in Ukraine	Ukraine war	No?De	No	No	No	No	No
21 Jul 2022	First increase of interest rates	First IR increase since	De	No	No	No	No	No



(a) Polarity of introductory part



(b) Subjectivity finBERT

Figure 6: A comprehensive view of the introductory part with Markov switching

[Place Figure 7 here]

4.3 Sentiment and macroeconomic environment

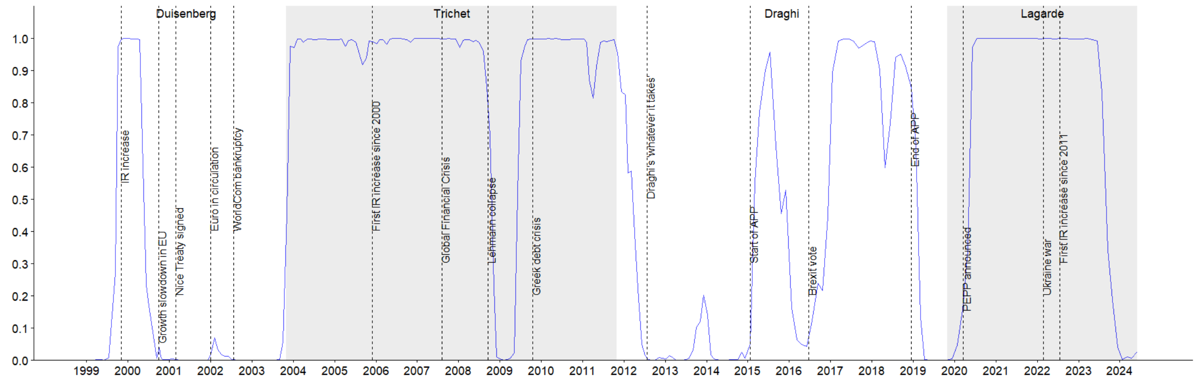
In this section we investigate the importance of various macro-variables in affecting the sentiment derived from press conferences. Our macro-variables relate to inflation and inflation forecasts, industrial production and unemployment. We use these variables as independent variables in the following regression model:

$$Sentiment_t = \alpha + \beta * X_t + \gamma * Z_t + \epsilon_t. \tag{3}$$

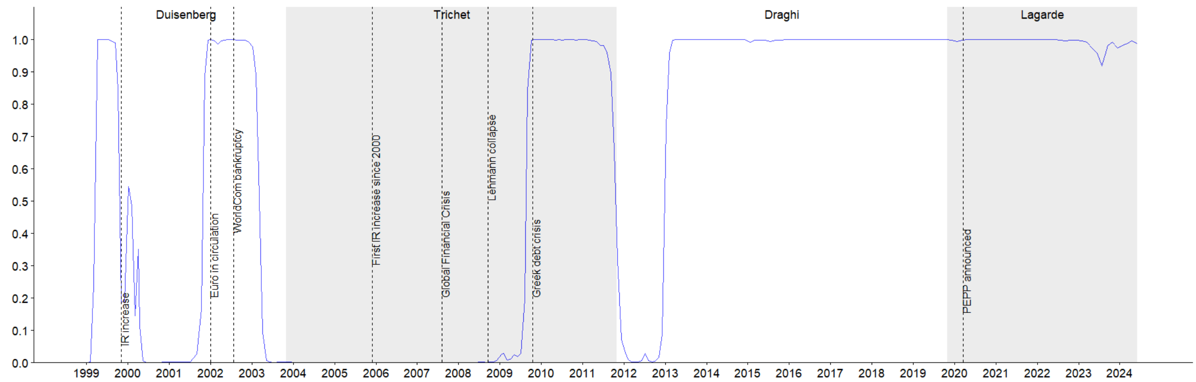
$Sentiment_t$ represents the polarity or subjectivity indicator of the press-conference's content, being derived either from the full talk, from the introductory part or from the Q&A part. X_t represents the macro-variable at time t, for which we alternatively take the inflation rate, the change in industrial production, the unemployment rate, the one year-ahead forecast of the inflation rate and the standard deviation of the inflation forecast. Z_t represents a set of control variables, namely the sentiment indicator in the month before ($Sent_{t-1}$) and a set of dummies representing the different presidencies($Duisenberg$, $Draghi$ and $Lagarde$), the baseline model being for President Trichet, for which no dummy is added.

Table 8: Regression results for the full talk. T-stats are presented under the coefficient and are obtained from robust standard errors.

	Model with inflation				Model with IP				Model with unemployment				1Y-ahead forecast				Forecast variability			
	M1	M2	M3	M4	M1	M2	M3	M4	M1	M2	M3	M4	M1	M2	M3	M4	M1	M2	M3	M4
Intercept	0.3409	0.0566	0.4347	0.0794	0.2458	0.0273	0.3189	0.0348	0.3416	0.0062	0.4639	0.0066	0.3140	0.0698	0.4256	0.0942	0.2697	0.0350	0.3339	0.0422
t-stat	19.67	4.39	20.08	4.53	21.81	3.12	17.99	2.67	5.33	0.21	5.51	0.16	7.99	3.58	9.28	3.82	21.55	3.65	18.33	3.16
Variable	-0.0436	-0.0103	-0.0553	-0.0141	0.0065	-0.0017	0.0069	-0.0017	-0.0100	0.0020	-0.0155	0.0033	-0.0360	-0.0235	-0.0575	-0.0310	-0.1131	-0.0286	-0.1140	-0.0350
t-stat	-6.45	-2.98	-7.73	-3.49	2.53	-1.41	2.81	-1.38	-1.45	0.65	-1.70	0.79	-1.63	-2.34	-2.42	-2.72	-2.96	-1.60	-2.57	-1.62
$Sentiment_{m-1}$		0.8598		0.8372		0.8976		0.8903		0.8941		0.8805		0.8856		0.8740		0.8812		0.8742
t-stat		29.10		26.41		31.00		28.99		32.63		30.10		31.35		29.36		30.67		28.96
Duisenberg			-0.1082	-0.0107			-0.1135	-0.0019			-0.1263	-0.0176			-0.1115	-0.0091			-0.1061	-0.0060
t-stat			-4.07	-0.75			-3.89	-0.13			-4.42	-1.29			-3.80	-0.63			-3.63	-0.41
Draghi			-0.1515	-0.0269			-0.1157	-0.0114			-0.0927	-0.0175			-0.1325	-0.0231			-0.1132	-0.0123
t-stat			-6.16	-1.98			-4.38	-0.86			-3.37	-1.35			-4.71	-1.66			-4.23	-0.92
Lagarde			-0.0210	0.0048			-0.1141	-0.0138			-0.1453	-0.0082			-0.0963	-0.0013			-0.0663	0.0027
t-stat			-0.64	0.28			-3.44	-0.84			-4.18	-0.49			-2.75	-0.08			-1.68	0.14
AdjR	13.5%	79.7%	25.0%	79.8%	2.0%	79.1%	10.3%	79.0%	0.4%	81.1%	11.5%	81.1%	0.6%	79.4%	9.5%	79.4%	2.9%	79.2%	9.7%	79.0%
Intercept	0.3114	0.0185	0.3159	0.0310	0.3186	0.0261	0.3134	0.0407	0.3424	0.0178	0.2816	0.0219	0.3104	0.0179	0.3262	0.0313	0.3115	0.0200	0.3114	0.0263
t-stat	111.31	2.93	101.25	4.13	203.41	3.84	149.80	5.11	32.25	2.43	22.84	2.79	51.90	2.79	54.76	3.88	171.84	3.06	129.90	3.51
Variable	0.0024	0.0000	-0.0020	-0.0005	-0.0026	-0.0004	-0.0024	-0.0005	-0.0028	-0.0004	0.0033	0.0003	0.0035	-0.0006	-0.0080	-0.0020	0.0326	0.0029	0.0055	0.0008
t-stat	2.21	0.11	-1.91	-1.33	-7.45	-2.78	-8.25	-3.48	-2.43	-1.06	2.50	0.53	1.05	-0.52	-2.60	-1.64	5.90	1.45	0.94	0.34
$Sentiment_{m-1}$		0.9424		0.9041		0.9197		0.8705		0.9552		0.9222		0.9474		0.9109		0.9365		0.9157
t-stat		46.89		38.39		43.20		34.44		49.15		40.16		47.78		38.05		44.79		38.33
Duisenberg			-0.0102	-0.0002			-0.0072	0.0000			-0.0096	-0.0007			-0.0109	-0.0003			-0.0100	0.0000
t-stat			-2.65	-0.12			-2.10	0.03			-2.28	-0.48			-2.86	-0.19			-2.61	-0.01
Draghi			0.0015	-0.0003			0.0029	0.0002			-0.0021	-0.0004			0.0000	-0.0006			0.0030	0.0001
t-stat			0.42	-0.20			0.94	0.16			-0.52	-0.25			0.00	-0.44			0.84	0.06
Lagarde			0.0441	0.0064			0.0400	0.0067			0.0470	0.0053			0.0451	0.0055			0.0394	0.0042
t-stat			9.33	3.09			10.19	3.47			9.22	2.48			9.90	2.70			7.58	1.91
AdjR	1.5%	89.6%	31.9%	89.9%	17.3%	89.9%	45.4%	90.3%	1.9%	90.8%	31.9%	91.0%	0.0%	89.9%	33.6%	90.1%	11.6%	90.0%	32.1%	90.0%



(a) Polarity of Q&A



(b) Subjectivity finBERT of Q&A

Figure 7: A comprehensive view of the Q&A part with Markov Switching

Regression results of the sentiment series obtained from the full press conference are shown in Table 8. It appears that on a stand alone basis the most recent inflation rate is best able to explain the polarity indicator with an R-squared reaching 13.5%. The coefficient on inflation is negative, suggesting that higher inflation decreases the polarity of the press conference. The addition of previous sentiment strongly increases the expla tory power of the model, showing that there is an important persistence in the sentiment. Dummies reflecting the presidencies are usually significant, although the impacts differ from one indicator to another. Dummies relating to Presidents Duisenberg and Draghi exhibit significant negative coefficients, suggesting less positivity in their speeches.

With an R-square of 17% the subjectivity indicator of the full press conference is best explained by the monthly change in industrial production when no control variable is added to the model. The coefficient on industrial production is significantly negative suggesting that a positive change in industrial production decreases the subjectivity of the press conference. Contrary to polarity, inflation appears to be less relevant for the subjectivity indicator. The subjectivity indicator is also explained by the most recent forecast deviation, as this variable taken alone explains 11.6% of the variance of the subjectivity indicator. As for polarity, there is evidence of important persistence in the subjectivity indicator. It also appears that President Lagarde, has a positive and significant impact on the subjectivity indicator, suggesting that press conference by President Lagarde tend to have more subjective content than under the Trichet presidency. Subjectivity of President Draghi's speeches is in line with the baseline model, while President Duisenberg's speeches have reduced subjectivity. The unemployment variable does not seem to have an influence on the polarity or subjectivity indicator, nor does the average inflation forecast.

Results for the sub-parts of the press conference, mely for the introductory part and the Q&A part appear in tables 9 and 10 and reflect the following tendencies. Polarity of the introductory part is best explained by inflation, the coefficient being statistically significant and negative. The R-squared reaches 28% which is much higher than for the full press-conference. It suggests the most recent inflation observation has a strong influence on the main speech of the press-conference, which is typically a statement written in advance for the President, where less subjective information of the President comes in. Our result strongly suggest the inflation variable as being very important for this statement. Although the R-squared is smaller, the standard deviation of inflation forecasts also significantly affects the polarity of the main speech. A higher standard deviation in the forecasts, reduces the polarity of the introductory part. Instead, the subjectivity of the introductory part does not seem to be affected by macro-variables. This result is expected as this first part of the press-conference is less influenced by subjective content, as opposed to the Q&A part where Presidents may express their thoughts with more personal tones. However there is now a strong and statistically significant impact of President dummies. Compared to a baseline model where the Trichet presidency would be considered with zero subjectivity, President Duisenberg has a lower subjectivity, while Presidents Draghi and Lagarde have a higher subjectivity. For sentiment indicators derived from the Q&A part, inflation tends to maintain its negative significant impact on polarity and contrary to the other part, also negatively impacts subjectivity. Most interestingly, the presidencies seem to have an important explanatory power, which is distinct from before. Presidents Duisenberg and Draghi, show less polarity (or positivity) in the Q&A part while President Lagarde shows more, compared to the baseline Trichet period. As for subjectivity, only Presidents Draghi and Lagarde appear to be more subjective than their predecessors.

5 Conclusion

The ECB is the heart of the European economic system, and its announcements and decisions can have a wide-ranging influence not only in Europe but also worldwide. The ECB's communications receive attention both in practice and in research. This study makes a significant contribution to financial communication and sentiment analysis by utilizing advanced models like finBERT to analyze the ECB's press conferences. It demonstrates the link between the sentiment derived from the ECB's press conferences and economic shocks. Our study also analyses the two sub-parts of the press-conference and shows how the different

Table 9: Regression results for the introductory part. T-stats are presented under the coefficient and are obtained from robust standard errors.

	Model with inflation				Model with IP				Model with unemployment				1Y-ahead forecast				Inflation gap			
	M1	M2	M3	M4	M1	M2	M3	M4	M1	M2	M3	M4	M1	M2	M3	M4	M1	M2	M3	M4
Intercept	0.560	0.075	0.574	0.077	0.390	0.023	0.428	0.031	0.348	-0.031	0.904	0.005	0.609	0.088	0.570	0.092	0.445	0.041	0.454	0.040
t-stat	28.67	4.66	22.16	4.24	28.95	2.16	20.74	2.20	4.11	-0.98	8.58	0.11	12.96	4.07	10.34	3.74	30.44	3.42	20.96	2.83
Variable	-0.077	-0.014	-0.068	-0.014	0.015	-0.002	0.015	-0.002	0.006	0.006	-0.052	0.003	-0.121	-0.033	-0.075	-0.032	-0.286	-0.046	-0.186	-0.040
t-stat	-10.08	-3.91	-7.94	-3.39	4.96	-1.35	5.13	-1.24	0.68	1.88	-4.51	0.66	-4.60	-3.28	-2.61	-2.90	-6.41	-2.52	-3.52	-1.91
$Sentiment_{m-1}$		0.885		0.882		0.945		0.929		0.931		0.918		0.921		0.916		0.917		0.914
t-stat		34.97		34.14		39.13		35.90		40.81		35.41		40.37		38.02		38.40		37.14
Duisenberg			-0.029	0.003			-0.043	0.007			-0.021	-0.004			-0.034	0.001			-0.027	0.004
t-stat			-0.92	0.20			-1.27	0.49			-0.59	-0.28			-0.95	0.08			-0.77	0.31
Draghi			-0.032	-0.004			0.012	0.004			0.088	0.000			-0.015	-0.007			0.010	0.004
t-stat			-1.08	-0.32			0.39	0.36			2.55	-0.01			-0.44	-0.51			0.31	0.35
Lagarde			-0.116	-0.013			-0.229	-0.027			-0.329	-0.023			-0.210	-0.013			-0.154	-0.007
t-stat			-2.95	-0.80			-5.91	-1.60			-7.57	-1.16			-5.00	-0.73			-3.27	-0.37
AdjR	27.8%	87.3%	29.4%	87.2%	8.3%	86.7%	20.3%	86.7%	-0.2%	87.0%	20.0%	86.9%	7.2%	87.4%	14.7%	87.3%	13.4%	87.1%	16.5%	87.0%
Intercept	0.702	0.028	0.706	0.071	0.718	0.030	0.709	0.073	0.724	0.018	0.737	0.048	0.693	0.029	0.697	0.071	0.703	0.029	0.707	0.070
t-stat	77.74	3.33	112.29	4.43	131.19	3.45	152.34	4.55	23.10	1.62	30.85	2.57	36.15	3.16	57.46	4.33	117.20	3.38	146.42	4.39
Variable	0.006	0.000	0.001	0.000	-0.003	0.000	-0.002	0.000	0.000	0.000	-0.003	0.000	0.012	0.000	0.006	0.000	0.077	0.003	0.009	0.001
t-stat	1.74	0.06	0.57	-0.21	-2.78	-0.88	-2.48	-1.12	-0.03	0.27	-1.25	0.37	1.14	-0.11	0.98	-0.11	4.18	0.71	0.79	0.12
$Sentiment_{m-1}$		0.963		0.902		0.961		0.898		0.975		0.929		0.963		0.902		0.961		0.901
t-stat		81.24		40.29		80.61		39.88		79.33		41.49		80.89		40.02		78.45		40.05
Duisenberg			-0.122	-0.009			-0.121	-0.009			-0.110	-0.006			-0.122	-0.009			-0.122	-0.009
t-stat			-15.87	-2.18			-15.73	-2.22			-13.56	-1.62			-15.68	-2.17			-15.81	-2.17
Draghi			0.066	0.007			0.065	0.007			0.070	0.004			0.067	0.007			0.065	0.007
t-stat			9.26	2.15			9.45	2.31			8.97	1.36			9.04	2.09			9.18	2.23
Lagarde			0.095	0.011			0.097	0.011			0.091	0.008			0.096	0.011			0.094	0.010
t-stat			10.02	2.61			11.11	2.74			9.26	2.10			10.34	2.63			8.98	2.34
AdjR	0.8%	96.2%	73.3%	96.4%	2.5%	96.2%	73.9%	96.4%	-0.4%	96.2%	69.9%	96.2%	0.1%	96.2%	73.3%	96.3%	6.0%	96.2%	73.2%	96.3%

Table 10: Regression results for the Q&A part. T-stats are presented under the coefficient and are obtained from robust standard errors.

	Model with inflation				Model with IP				Model with unemployment				1Y-ahead forecast				Inflation gap			
	M1	M2	M3	M4	M1	M2	M3	M4	M1	M2	M3	M4	M1	M2	M3	M4	M1	M2	M3	M4
Intercept	0.130	0.024	0.265	0.056	0.109	0.014	0.192	0.026	0.329	0.016	0.186	-0.007	0.037	0.033	0.236	0.070	0.100	0.013	0.195	0.028
t-stat	7.34	2.86	13.88	4.37	10.10	2.50	12.73	2.69	5.32	0.59	2.72	-0.19	0.99	2.06	6.06	3.43	8.39	2.22	12.61	2.82
Variable	-0.010	-0.005	-0.035	-0.012	0.001	-0.002	0.003	-0.002	-0.024	-0.001	0.001	0.004	0.044	-0.012	-0.023	-0.024	0.075	0.002	-0.017	-0.013
t-stat	-1.39	-1.80	-5.60	-3.45	0.30	-1.73	1.20	-1.48	-3.68	-0.29	0.11	1.09	2.11	-1.31	-1.16	-2.41	2.07	0.10	-0.44	-0.70
$Sentiment_{m-1}$		0.894		0.830		0.900		0.866		0.904		0.835		0.900		0.858		0.893		0.857
t-stat		33.82		26.19		33.95		27.50		34.31		26.29		33.23		27.56		33.10		27.26
Duisenberg			-0.194	-0.026			-0.195	-0.017			-0.248	-0.044			-0.194	-0.023			-0.192	-0.020
t-stat			-8.26	-1.89			-7.83	-1.18			-10.64	-3.11			-7.81	-1.63			-7.73	-1.45
Draghi			-0.185	-0.036			-0.162	-0.023			-0.163	-0.034			-0.166	-0.031			-0.158	-0.023
t-stat			-8.51	-2.86			-7.18	-1.83			-7.25	-2.70			-6.97	-2.41			-6.94	-1.80
Lagarde			0.083	0.029			0.023	0.007			0.024	0.016			0.035	0.017			0.033	0.014
t-stat			2.88	1.87			0.82	0.49			0.85	1.09			1.17	1.15			0.98	0.81
AdjR 0.4%	81.5%	35.2%	82.3%	-0.4%	81.5%	27.7%	81.6%	4.8%	83.4%	39.6%	84.1%	1.3%	81.4%	27.4%	81.8%	1.3%	81.2%	27.1%	81.4%	
Intercept	0.210	0.013	0.200	0.023	0.205	0.013	0.193	0.021	0.184	0.004	0.171	0.007	0.222	0.016	0.211	0.024	0.203	0.011	0.193	0.016
t-stat	133.77	3.68	132.69	4.95	215.08	3.69	165.66	4.82	30.70	1.35	27.35	2.06	68.59	4.03	71.78	4.88	184.93	3.17	151.18	3.95
Variable	-0.003	0.000	-0.004	-0.001	-0.001	0.000	-0.001	0.000	0.002	0.000	0.002	0.000	-0.010	-0.001	-0.011	-0.002	0.005	0.000	-0.003	0.000
t-stat	-4.37	-2.00	-7.46	-2.86	-4.65	-2.24	-6.02	-2.95	3.32	0.96	3.46	0.59	-5.67	-2.46	-6.96	-2.79	1.64	-0.12	-1.11	-0.20
$Sentiment_{m-1}$		0.940		0.888		0.939		0.893		0.975		0.956		0.935		0.892		0.948		0.915
t-stat		55.65		38.77		55.49		40.29		72.29		52.73		54.13		39.17		56.66		42.44
Duisenberg			0.009	0.002			0.011	0.002			0.008	0.000			0.008	0.001			0.010	0.001
t-stat			5.06	2.11			5.57	2.36			3.83	0.06			4.46	1.86			4.66	1.80
Draghi			0.021	0.002			0.023	0.003			0.020	0.001			0.019	0.002			0.023	0.002
t-stat			12.11	2.91			13.38	3.20			9.66	1.45			10.62	2.50			12.25	2.58
Lagarde			0.029	0.003			0.022	0.002			0.027	0.001			0.027	0.003			0.024	0.002
t-stat			12.68	2.98			10.18	2.18			10.41	1.01			11.89	2.55			8.75	1.41
AdjR	6.5%	92.8%	52.0%	93.0%	7.3%	92.8%	48.8%	93.0%	3.8%	95.6%	46.2%	95.6%	10.8%	92.8%	50.5%	93.0%	0.6%	92.6%	41.4%	92.7%

sentiment indicators are explained by some macro-variables.

The sentiment in the introductory part of the press conferences is closely linked to economic shocks and crises. There is a noticeable increase in negativity during events such as the Ukraine war and the global financial crisis. This connection can be attributed to the nature of the introductory parts, which serve two main purposes: (1) announcing monetary policies and economic analysis, and (2) providing forecasts. Thus, the introductory parts cannot ignore the macro shocks since the ECB need to declare their viewpoints and their reactions to crises in order to maintain market stability and avoid market crashes.

On the other hand, the tone in the Q&A parts of the press conferences reflects the personal style of the ECB's President, as these responses are given in reaction to questions. Our results demonstrate how the presidencies have impacted the sentiment indicators. Earlier Presidents tend to be associated with less polarity. The more telling result is about subjectivity though, for which we clearly show an increased subjectivity under Presidents Draghi and Lagarde.

Additionally, our research reveals the influence of the most recent inflation observation, as well as of the variability in inflation forecasts on sentiment indicators. The full press-conference, but especially the introductory part is meaningfully explained by inflation and forecast variability. It suggests that, before turning to the more subjective Q&A part where Presidents answer questions, this introductory part is shaped by the existing macro state and this is accurately captured by the large language model we use to reflect the communication's tone.

Our research thereby provides valuable insights into how central banks adapt their messaging to shape market perceptions and maintain stability. We also highlight the promising avenue of applying large language models to capturing nuances in tone and sentiment, and the potential to fine-tune the sentiment indicators as the models themselves keep improving. The ECB's communications being closely watched and monitored by the market, obtaining advanced sentiment indicators will certainly help our understanding and prediction of market reactions.

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A Appendix 1: Kalman Filter parameters

Table A.1: Kalman filter parameters

Sentiment Indicators	Kalman Model	Full conference AIC	Full conference VIC	Full conference Noise to Signal Ratio	Introductory part AIC	Introductory part VIC	Introductory part Noise to Signal Ratio	Q&A part AIC	Q&A part VIC	Q&A part Noise to Signal Ratio
Subjectivity	Local Level Model (stochastic level, no trend)	**-818.04**	**1.94**	**30.72**	**-592.23**	**0.68**	**18.39**	**-849.09**	**-0.36**	**197.33**
	Local Linear Trend Model (stochastic level, deterministic trend)	-805.04	1.99	27.15	-581.67	0.78	18.97	-834.21	-0.19	133.04
	Local Linear Trend Model (stochastic level, stochastic trend)	-805.03		27.18	-581.66		18.97	-834.20		131.85
Polarity	Local Level Model (stochastic level, no trend)	**-234.84**	**-0.19**	**2.47**	**-185.73**	**2.14**	**2.20**	**-58.48**	**2.62**	**8.58**
	Local Linear Trend Model (stochastic level, deterministic trend)	-225.86	-0.14	2.37	-177.02	2.20	2.11	-49.26	2.66	7.94
	Local Linear Trend Model (stochastic level, stochastic trend)	-225.86	-0.03	2.37	-177.01	2.30	2.11	-49.26	2.76	7.94