Asset Prices Reactions following European Central Bank Narratives

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Abstract

Central banking has experienced significant changes over time, shifting from discretionary policy-making to a more transparent approach. Central banks communication became an essential tool to relay their policies and leading to an increased interest toward the quantification of their content. In this paper, we investigate the impact of European Central Bank communication wording on financial markets. We use Natural Language Processing and Machine Learning to categorize both Introductory Statements and their relative Questions and Answers (Q&A) of European Central Bank Press Conferences into topics aligned with monetary policy stances and economic perspectives. The paper encompasses a dataset comprising 173 transcripts, spanning from 2004 to 2020, and consists of over than 10,000 hand-labelled sentences. The study incorporates high-frequency financial data with several asset prices across different maturities and examines whether financial markets are being driven by the tones of European Central Bank topical contents. Our results highlights the importance of the Questions & Answers to explain financial markets short term dynamics.

Keywords: Natural Language Processing, Machine Learning, European Central Bank Communication, Financial Markets, Modeling.

JEL classification: XXX.

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1 Introduction

Central banks play a climactic role in influencing financial markets, shaping economic prospects and influencing financial decisions. Among these institutions, the European Central Banck (ECB) implements the Euro Area's monetary policy and therefore influences European economic growth. It carefully conveys transparency, clarity and credibility to various stakeholders, including policy makers, financial markets, media and general public, to effectively and efficiently manage its monetary policy, sustain its economic strength and foster markets confidence, by providing a better forecast of financial asset dynamics in order to reduce volatility and uncertainty. Central banks send clear and consistent signals and messages, and studying their contents allows market participants to align their expectations and investment choices with monetary policies present and future path. Researchers have delved into central banks communication analysis by applying various methodologies to dissect the used language, the chosen words, and to gauge the sentiments. Such methodologies enable to decipher how central banks communicate, understand and interpret their words and subsequently predict its effect on financial markets end the economy.

Lexical and computational techniques have opened avenues for analyzing and quantifying the vast amounts of data emanating from the ECB communication contents, in order to capture sentiment tones that may greatly influence the markets rather than only considering economic fundamentals (Gardner et al., 2022). Several studies have shown that macroeconomic data may be supplemented by such indicators (Heinemann and Ullrich, 2007; Rosa and Verga, 2007; Hayo and Neuenkirch, 2010).

Manual annotation (Jansen and De Haan, 2005; Rosa and Verga, 2008) vocabularies and custom dictionaries (Loughran and McDonald, 2011) are primary approaches capturing meanings in single dimensions (e.g., Hawkish / Dovish and Positive / Negative). Nevertheless, manual classification may be extremely laborious and time consuming. It may highly lead to potential inaccuracies and costs. Furthermore, sentiment analysis with predefined word-lists is often considered subjective with limited dimensions and may lead to inefficiency for several reasons: (i) dictionaries are built based on researchers' own interpretation of the correct meanings of words, (ii) the linguistic vocabularies may escape various nuances and interactions between terms when they are applied to an augmented text, where the communication style and words change over time, (iii) the performance of a dictionary depends on its suitability for classifying a given textual corpus. Using a non-designed field-specific thesaurus may lead to significant misclassification, thereby inadequately capturing the tone conveyed in the text.

Researchers have increasingly adopted machine learning (ML) and deep learning (DL) modeling as a way to automatically handle text analytics. The main key benefit of such methods is their ability to learn words and sentences weights and thereby comprehend the sentiment of an entire expression. Nonetheless, it is worth noting that such modeling techniques demand sizable labeled data sets, that generally are expensive and need significant time to be constructed.

Our work expands two streams of the existing literature. First, we contribute methodologically to the quantification of central banks communications with text analytic tools. We use Natural Language Processing (NLP) and Machine Learning (ML) techniques to construct sentiment indexes designed for central banking reporting and we investigate the following questions:

- To what extent does our proposed tones influence asset prices behavior?
- How does our central banking sentiment indicators perform comparing to other lexical and computational sentiment tones?

We focus on press conferences as one of the most pivotal ECB communication channels. In such conferences, the ECB President delivers crucial updates on interest rates and economic forecasts to the media and to the broader audience on the same day as the decision announcement of the Governing Council. During the introductory statements (IS) of these conferences, the President reads texts prepared by monetary experts which provide insights and more comprehensive explanations on the rationale behind the decision that concerns the economic conditions and the future direction of monetary policy. A follow up Q&A with journalists is also conducted to address any ambiguities and provide clarifications. Such interaction serves as a valuable opportunity of incremental information elaboration. Through Q&A sessions, journalists can seek out further details and insights, leading to better understanding.

To establish the sentiment tones, we scrutinize 173 ECB press conferences transcripts, that contain more than 10,000 manually classified and labelled IS sentences into Monetary Policy (MP) and Economic Perspectives (EP) concerns. ECB opening statements are followed by Questions and Answers (Q&A) sessions, we use NLP to process and transform the statements into numerical vectors suitable to drive ML models and algorithms in order to cluster the Q&A contents. We compare various supervised ML classifiers performances on IS that are fitted and tested on random phrases.

The main objective of testing different classifiers is to identify which one performs better because each model has a specific functioning and a complex structure. We look at which classifier optimizes performances, ensures robustness and then we want to guarantee that the most suitable classifier is used as the data evolves.

Additionally, we contribute to the existing literature by presenting the manually annotated ECB press conferences corpus where the categories correspond to monetary policy stances, namely, *accommodative, neutral* and *restrictive*, and to economic perspectives inclinations, namely, *positive, neutral* and *negative*. The set will be freely and publicly accessible online, in the aim to enhance the use of our sentiment indexes and promote further research on measuring the central banks tonality.

Second, we study the European financial markets reactions following the perception of both opening statements and Q&A speeches treating the two topics. We also compare our sentiment indicators to those obtained using the Loughran and McDonald (2011) dictionary that covers positive and negative words from 10,000 financial reports and FinBERT which is a language model introduced by Araci (2019) and based on pre-training of the Google's Bidirectional Encoder Representations from Transformers (BERT) on a vast corpus of over 3,300,000 million words with more than 110 million parameters.

The objective of our study is to answer to the main research question which concerns whether Q&A contents provide supplementary information that influences financial markets, and hence they contribute to valuable insights to the academic and financial communities.

The rest of the paper is organized as follows. Section 2 provides a comprehensive literature review. Section 3 details the methodological steps involved in processing and transforming ECB press conferences contents using NLP techniques and sentiments construction using ML modeling. Section 4 examines empirically the markets reactions where we assess the impact of ECB narratives on European financial markets. Section 5 consolidates the findings and Section 6 concludes the paper.

2 Related literature

Central banks employ a panoply of channels to effectively and transparently transmit their messages. These channels include speeches (Neuhierl and Weber, 2019; Hansen et al., 2019), minutes (Apel and Grimaldi, 2014; Hansen et al., 2018), press releases (Altavilla et al., 2019; González and Tadle, 2020), press conferences (Picault and Renault, 2017; Parle, 2022; Baranowski et al., 2023), and even announcements on social media like journals (Bianchi et al., 2023) and tweets (Binder, 2021). Each channel serves openly and clearly to disseminate important information of central bank's policy decisions to various stakeholders.

Several studies have demonstrated the significant impact of central banking narratives on several financial aspects. For example, such information influences interest rates (Hansen and McMahon, 2016; Schmeling and Wagner, 2019), exchange rates (Jansen and de Haan, 2007; Conrad and Lamla, 2010; Rosa, 2012) and equities (Picault and Renault, 2017; Schmeling and Wagner, 2019; Cieslak and Schrimpf, 2019).

While research primarily concentrated qualitatively on central banking analysis, the use of quantitative tools ensuring monetary policy assessment appeared to be limited. Researchers heavily depended on information provided by economists during meetings. Blinder et al. (2008) highlighted that the data obtained from interviews could be unreliable and may introduces inaccuracies and noises in the analysis. However, there has been a significant shift in such data manipulation towards quantitative methods. Central banks major signals can be extracted and numerically transformed by using either manual, lexical or automated approaches. The hand-coding method involves reading and grouping utterances into predefined categorical content that are transformed into an ordinal scale. Rosa and Verga (2007) manually ranked ECB statements on a scale of -2 (very dovish) to 2 (very hawkish), and found that these measures complement macroeconomic data in predicting changes in ECB interest rates. Ehrmann and Fratzscher (2007) captured monetary policy and economic perspective sentiments from the Federal reserve (Fed), Bank of England (BoE) and ECB statements. For the first topic, the narratives are grouped into tightening (+1), neutral (0) and easing (-1), and for the second topic, the contents are rated as strong (+1), neutral (0) and weak (-1). These inclinations were used as indicators to measure how much agreement or disagreement there was among committee members regarding decision making processes and the overall effectiveness on the three central banks.

To overcome hand-classifying and coding schemes, researchers relied on sentiment analysis with dictionaries, lexicons or n-grams as an alternative approach to categorize sentences into distinct topics (Loughran and McDonald, 2011; Apel and Grimaldi, 2014; Bennani and Neuenkirch, 2017; Correa et al., 2021; Gardner et al., 2022). The most used dictionary ensuring financial and economic corpus classification is attributed to Loughran and McDonald (2011). The authors built this glossary by analyzing 10,000 news articles and used it to explain stock returns volatility. The dictionary gained substantial popularity and found extensive application in central bank analysis and quantification (Hansen and McMahon, 2016; Shapiro and Wilson, 2019; Armelius et al., 2020). Further dictionaries were also introduced to measure central banks tones. Correa et al. (2021) introduced a collection of words related to central banks narratives and was used to derive sentiments from financial stability documents.

To improve and procure accurate sentiment analysis, authors proposed lexicons that focus on full sentences. For example, Picault and Renault (2017) examined European stock markets responses to ECB press conferences opening statements by developing a domain-specific lexicon that is well-customized to ensure ECB phrases classification. Their study reveals a noticeable augmentation (reduction) in market volatility when the tone of the statements is about monetary policy that leans towards hawkishness (dovishness), and the economic prospects that shows pessimism (optimism).

Another perspective considered the augmentation of existing dictionaries or the combination of different ones to obtain greater outcomes (Apel et al., 2022) used Federal Open Market Committee (FOMC) transcripts and minutes to extend the Apel and Grimaldi (2014) dictionary to determine the hawkishness level exhibited by the decision making committee. Some other researches considered a hybrid lexical and unsupervised Machine Learning (ML) combination. For example, Hansen and McMahon (2016) involved Apel and Grimaldi (2014) dictionary and topic modelling to quantify FOMC statements.

Another way to handle automatically and efficiently text data is to rely on supervised ML and DL (Deep Learning) classifiers with labeled data. NLP feature transformation techniques play a crucial role to numerically convert the qualitative informational contents. For example, the Bag of Words (BOW) approach considers the textual corpus as a set of unique words with respective frequencies. The Term-Frequency Inverse Document Frequency (TF-IDF) technique calculates the importance of each term in a document relative to its occurrence across the entire corpus. Word Embedding (Word2Vec) algorithm generates dense linguistic embeddings that capture semantic relationships between words. Employing such tools ensures numerical representations that are integrated into several ML and DL models (Decision Trees, Random Forest, Neural Networks, etc.). Such modeling heavily rely on the availability of labelled texts.

In supervised learning setting, the text features are associated with labelled target or categories which allow the models, during the training phase, to learn the truth and to effectively identify text characteristics with their corresponding labels. In this context, Baumgärtner and Zahner (2021) considered 23,000 speeches of 130 central banks to forecast monetary policy surprises, financial uncertainty and gender bias. Their method considers word and document embeddings to transform the speeches into sparse vectors and to ensure their classification with pre-trained neural networks.

ECB communications, particularly through press conferences, has become paramount for researchers. Its messages conveyed during these events have subtle effects on financial markets. Words and tones characteristics may significantly shape markets perceptions and expectations regarding the policy directions. Information of such contents may be transmitted in form of topics or conveyed through tones.

Our aim is to evaluate ECB press conferences informativeness which helps markets participants to make more accurate predictions regarding future paths of monetary policy and economic perspectives. We investigate whether asset prices respond to the information conveyed during these conferences, by deriving IS and Q&A tones, that serve as explanatory features in linear regressions to study the relationship between ECB communication and financial markets behaviour.

Note that Q&A classification and quantification was firstly underlined by Baranowski et al. (2023) that considered an extended version of the Bennani and Neuenkirch (2017) dictionary. In our case, we bring a first answer to such task based on an automated approach.

3 Methodology

In this section, a quantitative analysis of Q&A contents is performed (section 3.1) based on a unique labelled data set (section 3.2). Section 3.3 shows empirically the impact of the ECB communication on intraday different classes of financial assets and indices and finally (section 3.4) gives the baseline models.

It is to note that the statements initially cover the 2004-2020 period (173 conferences). Since financial assets for years 2004 and 2005 are unavailable, the regression analysis covers the 2006-2020 period (152 conferences). However, we consider using the entire period (2004-2020) for ML modelling in order to enhance the learning process with a greater terms diversity during the conferences.

Our computational investigation was conducted using Python (Anaconda distribution) under the Windows environment. The different steps described in the following sections were executed using different Python packages.

3.1 Q&A Content Quantification

In this work, we examine the European financial markets behavior after the perception of ECB communication.

It is known that the ECB employs a specific communication approach to convey information and elucidate its monetary policy decisions. This process begins with a press release at 1:45 PM - Central European Time (CET) on the day of the Governing Council monetary policy meeting. The press release presents the policy decision without any clarification. Successively, at 2:30 PM CET, a press conference is held by the President and the Vice-President of the ECB and it is considered utterly informative for market participants as it sheds light on the potential future stances of the monetary policy and the economy.

During ECB press conferences, the ECB President takes the lead in transmitting a detailed narration of the decision that was produced by the Governing Council. The hearing starts with an opening statement about ECB's evaluation of economic and monetary policy curves, and takes approximately 15 minutes. After that, a Q&A session of 45 minutes with journalists takes place. The session is also an outlet for the attending journalists to freely ask questions to both ECB President and Vice-President.

Q&A quantification is still an understudied area. Research have primarily concentrated on introductory statements which are commonly associated to economic sentiments, while neglecting the inclusion of monetary policy. For example, Parle (2022) studied the stock indices dynamics following the perception of economic information of ECB press conferences. The author constructed indexes of hawkishness/dovishness with LM dictionary and the Dynamic Subject Algorithm of Blei and Lafferty (2006) and found a positive and significant relationship between his tone measures and the stock market indexes.

Our approach to quantify introductory statements and Q&A textual contents relies on leveraging artificial intelligence tools, particularly NLP, to convert the text characteristics into measurable attributes and Machine Learning to perform sentiment analysis.

More precisely, we first classify and label introductory statements into two categories: monetary policy (MP) and economic perspectives (EP) inclinations. The data set is then randomly divided into training and testing samples to ensure a diversified range of sentences from different periods. The main focus is on text features, thus the chronological order of the information is omitted in the analysis during the random sampling. We run various classifiers using the numerically transformed train text and its corresponding labels.

To address the issue of over-fitting, we perform a pipeline containing grid searches to find simultaneously optimal feature size and optimal classifiers parameters values. Once optimal models are selected, they are fitted on the testing set to predict the labels and their corresponding probabilities. To assess the model's quality, we use metrics such as the accuracy to evaluate the classifiers' performance. After determining the best model, we run it on the data to ensure Q&A classification.

3.2 Data set

Our dataset is extracted from the official ECB website and contains 173 introductory statements transcripts and their corresponding Q&A, the period under consideration is 2004-2020. Our analysis considers IS tagging to ensure the Q&A tones used to study financial market reactions.

Table 1 displays an extract from the Introductory Statements (IS) set. The first column presents ECB president speech in form of separated sentences and the second column corresponds to the labeled sentiments referring to Monetary Policy (MP) or Economic Perspectives (EP). Note that the classified sentences are associated with a date and the different sentiment classes correspond to:

- Accommodative, Neutral and Restrictive if the sentence concerns the Monetary Policy (MP)
- Positive, Neutral and Negative if the sentence concerns the Economic Perspectives (EP).

Additionally, when the content does not concern any topic, then the sentence is labeled as 'NONE'.

Table 1: Examples of Introductory Statements classified sentences

Text	Type	Clean text
We will now report on the outcome of today s m...	NONE	report outcom today meet govern council ecb al...
Following our regular economic and monetary an...	MP Neutral	follow regular econom monetari analysi continu...
The available indicators point to an ongoing e...	EP Positive	avail indic point ongo econom recoveri euro area
We will continue to carefully monitor all deve...	MP Restrictive	continu care monitor develop could affect asse...
On the external side, recent exchange rate dev...	EP Negative	extern side recent exchang rate develop negat ...
The short-term risks to this outlook remain ba...	EP Neutral	shortterm risk outlook remain balanc

Table 2: Data description for ECB Press Conferences Introductory Statements Transcripts

Observations	Transcripts	Total words	Average words per transcript
10,197	173	247,025	1,428

Figure 1 illustrates sentiments distribution. The data includes 10,197 sentences , as indicated in table 2, and it appears to be imbalanced. It is mainly dominated by utterances belonging to the 'NONE' modality. NONE

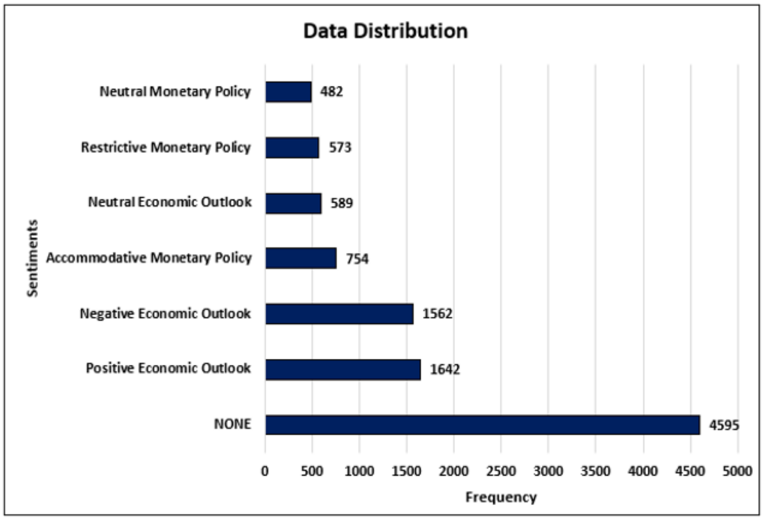

Figure 1: Sentiment distribution of the manually encoded IS sentences

presents 45.1% (4595 sentences) and aggregates repetitive statements like greetings, speech introductions and closings. While positive and negative Economic Perspectives represent respectively 16.1% (1,642 sentences) and 15.3% (1,562 sentences), accommodative and restrictive Monetary Policy are the least frequent, they represent respectively 7.4% (754 sentences) and 5.6% (573 sentences).

In our analysis, we handle the issue of the imbalanced distribution by eliminating some 'NONE' sentences and by intervening at the ML modeling level. In each classifier, we attribute the same weight to all sentiments. By doing this, we guarantee that predictions will not be assigned to the dominant label.

In order to classify Q&A set, we have to first process IS sentences, subsequently, to run various ML classifiers in order to detect which model performs better IS classification.

Figure 2 illustrates the major steps preparing IS sentences for modeling. The pre-processing step includes:

- NONE under-sampling by reducing the common repetitive and non-pertinent sentences (see Appendix, section 7.3).
- Stop words, numbers, punctuation and white spaces elimination. For the stop words, we augmented the existing list with other words that we judge irrelevant (see Appendix, section 7.4).
- Words appearing less than five times are removed.

- Text standardization by fitting lemmatization and stemming processes.

Once the text is cleaned, it needs to be numerically transformed into vectors used as features in the models. We used two techniques of Frequency-based Word Embedding approach to ensure text vectorization. The techniques correspond to CountVectorizer (called also Bag-of-Word) (BOW) with uni-gram features and Term Frequency-Inverse Document Frequency (TF-IDF) with both uni-grams and bi-grams. Another crucial step consists of one-hot encoding of the target data.

Once the data set is prepared, it is suitable to run different supervised ML classifiers. However, two issues are also arise in our analysis. The first matter reveals that the unbalanced data may strongly conduct to biased outcomes. In general, the predictions may be influenced by the importance of the most frequent label. Thus, in each ML models we attributed the same weight to each label. Specifically, we rely on class weighting as a solution to handle unbalanced data. The second concern is related to the over-fitting problem. As Statistical-Based Word Embedding approach transforms the text data into multidimensional vectors, it seems crucial to control the size of the inputs. Our analysis is then based on a pipeline of connected grid searches that find at the same time the optimal input dimensions and the optimal parameters values for the different models.

We also use the Local Interpretable Model-agnostic Explanations (LIME) technique to evaluate the quality of predictions. Such technique explains individual predictions of ML models. It allows to understand why models made a particular decision for a specific sentence. It also demonstrates how models attribute weights to each text characteristics and how they influence the final expected values. This means that LIME exhibits feature importance. It displays the most influential words determining why a model predicted a specific label.

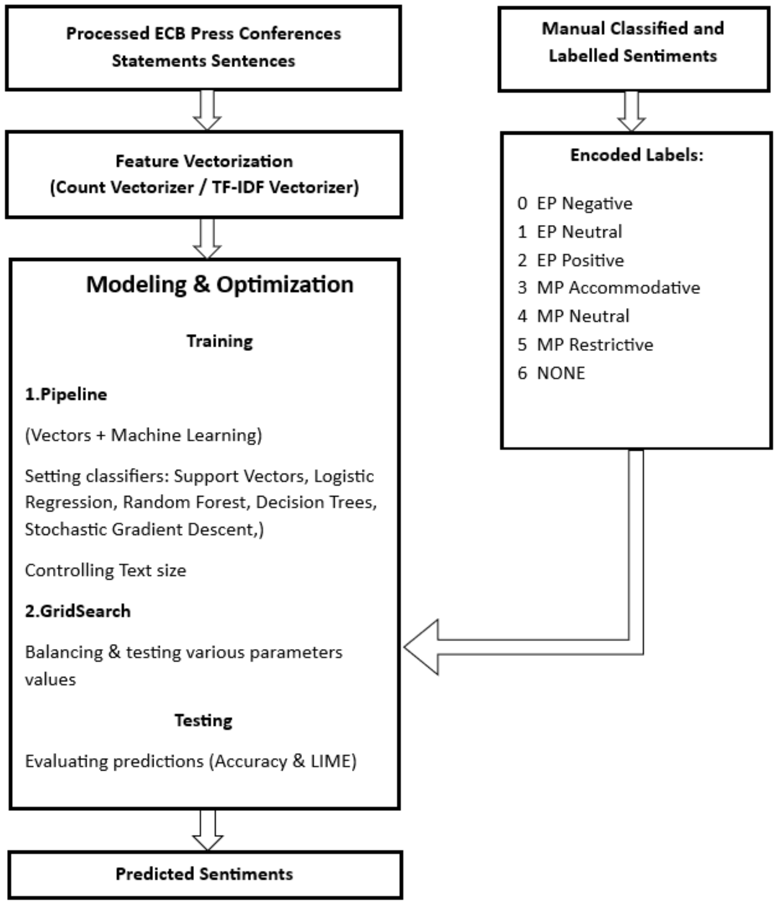

Figure 2: Quantification Framework

Table 3 displays the obtained classifiers' accuracies when the text is transformed with BOW and TF-IDF techniques (columns 2 and 3 respectively). The different classifiers are given in column 1. The results indicate that the best accuracies are obtained by Support Vector classifier (83.37% for BOW and 84.77% for TF-IDF). The worst results are given by Decision Trees (74.27% for BOW and 73.16% for TF-IDF).

Table 3: Classifiers' Accuracies

Classifiers	BOW	TF-IDF
Logistic Regression	75.89%	75.33%
Support Vector	**83.37%**	**84.77%**
Decision Trees	74.27%	73.16%
Random Forest	79.19%	80.36%
Stochastic Gradient Descent	75.61%	77.73%

Once we have computed the predicted sentiments, we aggregate them by dates and quantify a tone measure of each topic specific to ECB Press Conference contents. To our best knowledge, Q&A sentiment construction with NLP and ML techniques and models were not emphasized in previous works. Given IS and Q&A sentiments at time t, MP and EP scores are derived using the following equations:

$$MP\ Score_{i,j} = \frac{MP_{i,j}^{Rest} - MP_{i,j}^{Acco}}{MP_{i,j}^{Rest} + MP_{i,j}^{Acco}} \tag{1}$$

$$EP\ Score_{i,j} = \frac{EP_{i,j}^{Posi} - EP_{i,j}^{Nega}}{EP_{i,j}^{Posi} + EC_{i,j}^{Nega}} \tag{2}$$

Where $MP_{i,j}^{Acco}$ represents the number of Accommodative Monetary Policy sentences (Category 3) for each Introductory Statements or Q&A Transcripts j of a given Press Conference i, and $MP_{i,j}^{Rest}$ the number of Restrictive Monetary policy sentences (Category 5). $EP_{i,j}^{Posi}$ and $EP_{i,j}^{Nega}$ represent respectively the number of sentences of Negative (Category 0) or Positive Economic Policy (Category 2) for each j of i. The different catagories (encoded lablels) are indicated is Figure 2.

3.3 Effect of the ECB Communication on Intraday Assets

In our analysis, we assess the effect of IS and Q&A tones on a set of European intraday features that correspond to change in prices of different assets expressed in diverse maturities. The set encompasses Overnight Index Swap (OIS), sovereign yields and exchange rates.

Although that SVC, when sentences are numerically transformed with TF-IDF text technique as indicated in table 3, provides the highest accuracy of classification, the results peculiarly show that the same algorithm with CountVectorize contributes to better Ordinary Least Squares (OLS) estimations. This fact is justified with LIME.

For example, here is a sentence showing how the two classifier predict the sentiment based on candidate tokens and weights.

Original sentence: '*Over the medium term underlying inflation is expected to increase, supported by our monetary policy measures, the ongoing economic expansion and robust wage growth.*'

Processed sentence: *'medium term underli inflat expect increas support monetari polici measur econom expans robust wage growth'*

Observed sentiment: EP_POSI

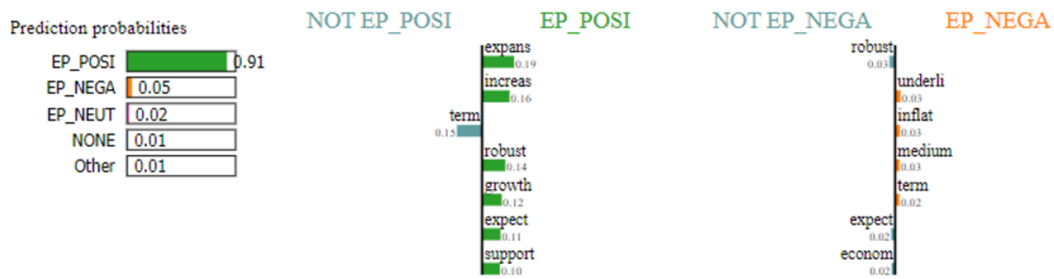

Figure 3: LIME - (BOW-SVC)

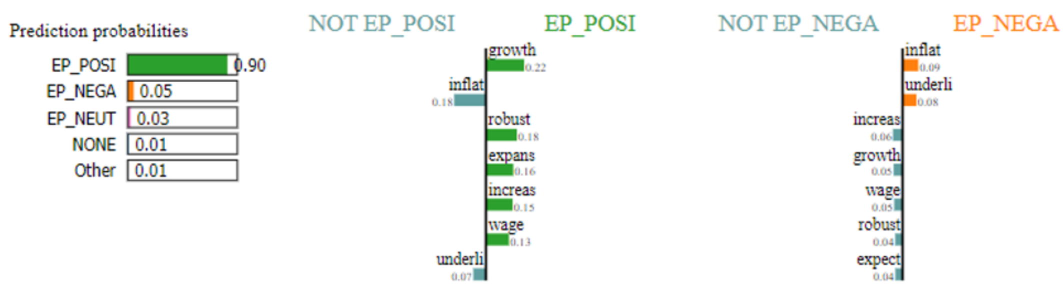

Figure 4: LIME - (TFIDF-SVC)

Both classifiers considered a set of words with relative weights that either increase or decrease the likelihood of EP_POSI (Economic Perspective = Posivite) and EP_NEGA (Economic Perspective = Negative). The words are presented in color code. Orange for EP_NEGA and Green for EP_POSI. The box length is proportional to the corresponding weight.

It appears that the classifiers successfully and correctly predicted the observed sentiment which is EP_POSI. However, the probability of BOW–SVC (figure 3) is slightly higher compared to the probability of TF-IDF–SVC (91% vs 90%) as indicated in figure 4.

Moreover, while in BOW case, the features that allow to determine EP_POSI correspond to: *expansion, increase, robust, growth, expected,* and *support*, where *expansion* and *increase* are highly important with positive impact. In case of TF-IDF, the substantial features correspond to *growth, robust, expansion, increase*, and *wage*, where feature *growth* has the strongest positive influence.

It is not easy to make a final selection as BOW with SVC appears assigning higher weight to words that are more clearly linked to positive economic indicators (*expansion* and *increase*) that predict EP_POSI class, while

TF-IDF with SVC assigns high weight to *growth* and *inflation*, where *inflation* is very likely related to a negative economic context.

Subsequently, we decided to consider SVC when the sentences are transformed with the CountVectorizer approach. Examples of the manual classified and predicted IS test sentiment and Q&A expected labels using (BOW - SVC) are given in Appendix (Tables 10, 11 and 12 respectively). Hence, in what follows, we present the results of the combination of sentiment index derivation (BOW and SVC) to model the high frequency Euro Area Monetary Database (EA-MPD) of Altavilla et al. (2019). Appendix 7.6 illustrates IS and Q&A tones curves when we consider BOW and SVC.

Many research also used this datum to investigate investors' reaction. For example, Schmeling and Wagner (2019) demonstrated that equity market returns are highly associated with positive ECB Press conferences opening statements tone, which are built with LM dictionary, and also slightly associated with volatility risk premia and credit spreads.

In our case, we consider the ECB Press conference event window. The set considers financial data about the evolution of the change in asset prices before 2:15 PM - 2:45 PM CET and after 3:40 PM - 3:50 PM CET. Knowing that ECB press conference is held between 2:30 PM CET and 3:30 PM CET. We mainly aim to see how financial markets behave following the ECB Press conferences and if they are more likely to be influenced by IS or Q&A tones.

3.4 Baseline models

ECB communication tones may highly impact asset prices. Empirically, we shed light on the most preeminent communication channel. To study the reaction of market participants after perceiving ECB Press conference communication respectively in form of IS and Q&A, we propose equations (3) and (4) respectively. Note that the full sample (Jan 2006 – Dec 2020) is considered.

$$\Delta AP_t = \alpha + \beta_1 \times MP\_IS_t + \beta_2 \times EP\_IS_t + \epsilon_t \tag{3}$$

$$\Delta AP_t = \alpha + \beta_1 \times MP\_QA_t + \beta_2 \times EP\_QA_t + \epsilon_t \tag{4}$$

Where the target variable (ΔAP_t) corresponds to the change in median price of euro area asset prices around

ECB Press conferences. Specifically, ΔAP_t corresponds to (i) Overnight Interest Rate Swap Price (OIS) at various maturities: 1, 3 and 6 months, also 1 and 2 years, (ii) Risk-free Deutsch (DE) and French (FR) Sovereign Bond Yields also at various horizons: 2, 5 and 10 years, and (iii) the EUR/USD Exchange Rate.

The explanatory features in equations (3) and (4) are :

- MP_IS_t: Introductory Statement sentiment index treating monetary policy information.
- EP_IS_t: Introductory Statement sentiment index treating economic perspective information.
- MP_QA_t: Questions and Answers sentiment index treating monetary policy information.
- EP_QA_t: Questions and Answers sentiment index treating economic perspective information.

4 Results

This section summarizes the results obtained after applying the regressions. These results are presented in Table 4 where Table 4-(a) corresponds to Introductory Statements and Table 4-(b) to Questions and Answers (Q&A).

We estimate Equations 3 and 4 with robust standard errors using scikit-learn and SciPy Python packages. The results reveal that when the ECB communicates a more restrictive monetary policy stance in its opening statements, signaling an intention to raise interest rates, OIS rates tend to rise. As market participants expect higher short-term interest rates in the future or reductions of balance sheets policies, OIS rates at maturities between 3 month to 2 year increase. Moreover, signaling a more restrictive monetary policy stance, suggests that most of sovereign bond prices tend to fall, due to the higher future interest rates that reduces the relative attractiveness of existing fixed-rate bonds, decreasing their prices and increasing their yields. A positive economic perspective (e.g., strong GDP growth, low unemployment and stable inflation) leads to higher OIS rates. As strong economy may prompt the (ECB) to consider tightening monetary policy to prevent overheating and inflation. Higher OIS rates anticipate the possibility of future rate hikes. As bond prices and yields have a contrary relationship. When prices decrease, yields increase. Hence, if the markets foresee a rise in interest rates due to positive economic prospects awareness, the sovereign bonds yields could lever up. Generally, markets appear to positively, but not significantly, respond to IS. We believe that markets already reacted to the ECB verdict at the decision policy and press release announcements.

In the second regression outcome (table 4-b), all price assets coefficients are positive and significant, indicating that Q&A contents are effective and suitable to shape financial markets dynamics. This evidence highlights the

Table 4: Estimated effect of Monetary Policy and Economic Perspective tones on Asset Prices (full sample)

(a) Introductory Statement

	OIS 3M	OIS 6M	OIS 1Y	OIS 2Y	DE 2Y	DE 5Y	DE 10Y	FR 2Y	FR 5Y	FR 10Y	EUR USD
MP_IS_t	0.307	0.293	0.508	0.365	0.048	0.161	-0.280	0.037	-0.129	-0.164	0.036
	(0.526)	(0.699)	(0.947)	(1.062)	(1.134)	(1.060)	(0.781)	(1.078)	(1.024)	(0.811)	(0.112)
EP_IS_t	1.000	0.949	1.526	1.859	2.841*	2.660*	0.799	2.161	1.149	-0.038	0.079
	(0.698)	(0.927)	(1.256)	(1.409)	(1.504)	(1.406)	(1.036)	(1.431)	(1.358)	(1.075)	(0.149)
Intercept	-0.152	-0.161	-0.180	-0.237	-0.219	-0.083	-0.027	-0.266	-0.249	0.028	-0.030
	(0.180)	(0.238)	(0.323)	(0.363)	(0.387)	(0.362)	(0.267)	(0.368)	(0.350)	(0.277)	(0.038)
Obs.	152	152	152	152	152	152	152	152	152	152	152
R^2	0.016	0.008	0.012	0.012	0.023	0.024	0.005	0.015	0.005	0.000	0.003
Adj. R^2	0.003	-0.005	-0.002	-0.001	0.010	0.010	-0.009	0.002	-0.008	-0.013	-0.011
F Stat.	1.194	0.610	0.880	0.928	1.784	1.800	0.363	1.142	0.366	0.021	0.189

(b) Questions & Answers

	OIS 3M	OIS 6M	OIS 1Y	OIS 2Y	DE 2Y	DE 5Y	DE 10Y	FR 2Y	FR 5Y	FR 10Y	EUR USD
MP_QA_t	1.133***	1.568***	2.394***	2.506***	2.355***	2.030***	0.952*	2.087***	2.149***	1.198**	0.141*
	(0.378)	(0.498)	(0.670) (	0.756)	(0.812)	(0.766)	(0.566)	(0.774)	(0.733)	(0.587)	(0.080)
EP_QA_t	1.012**	1.407**	1.977**	2.214**	2.865***	2.393**	1.787**	2.582**	1.994**	1.607**	0.343***
	(0.490)	(0.645)	(0.867)	(0.978)	(1.051)	(0.991)	(0.733)	(1.001)	(0.948)	(0.759)	(0.103)
Intercept	-0.158	-0.168	-0.190	-0.246	-0.229	-0.091	-0.033	-0.275	-0.254	0.021	-0.033
	(0.174)	(0.229)	(0.307)	(0.347)	(0.373)	(0.352)	(0.260)	(0.355)	(0.336)	(0.269)	(0.037)
Obs.	152	152	152	152	152	152	152	152	152	152	152
R^2	0.080	0.088	0.105	0.095	0.094	0.078	0.054	0.083	0.079	0.054	0.085
Adj. R^2	0.068	0.075	0.093	0.083	0.082	0.065	0.042	0.071	0.066	0.041	0.073
F Stat.	6.468***	7.156***	8.779***	7.864***	7.719***	6.265***	4.281**	6.784***	6.357***	4.217**	6.905***

Note: Results from the OLS estimation of Equation 3 for the top part and Equation 4 for the bottom part with robust standard errors for the period 2006 to 2020 (152 observations). * represents a statistical significance of 10%, ** of 5% and *** of 1%. Each column represent a financial asset with Overnight Index Swaps (OIS) from a maturity 3 month to 2 year, Sovereign bond yields of maturities 2, 5 and 10 year of Germany (DE) and France (FR) and the Euro/US dollar exchange rate. MP and EP are, repectively, the Monetary Policy and Economic Perspective of the Introductory Statement (IS) and the Questions and Answers (Q&A) part of the ECB press conferences at time t.

versatility of our created feature based on NLP and ML. We expand our initial specification to include both communications from the Introductory Statement and the Q%A session and gives the detailed results in Table 5. When considering both contents, results are practically unchanged. The utility of Q&A in providing supplementary messages about monetary and economic policies is still observed. We argue that the introductory statement provides relevant information but the Q%A can provided more detailed discussion and view of the ECB President on the path of the Euro-Area economy and monetary policy. Our findings complement the results of Baranowski et al. (2023) for the Stoxx50 as they find both the content of the Introductory Statement and the Q%A session to affect stock prices dynamics.

Table 5: Estimated effect of Monetary Policy and Economic Perspective Introductory Statements, Questions and Answers tones on Asset Prices (full sample)

	OIS 3M	OIS 6M	OIS 1Y	OIS 2Y	DE 2Y	DE 5Y	DE 10Y	FR 2Y	FR 5Y	FR 10Y	EUR USD
IS_MP_t	0.116	0.016	0.084	-0.073	-0.326	-0.156	-0.428	-0.300	-0.523	-0.386 0.017	
	(0.517)	(0.682)	(0.917)	(1.034)	(1.104)	(1.042)	(0.775)	(1.056)	(1.003)	(0.803)	(0.110)
IS_EP_t	0.706	0.525	0.880	1.187	2.248	2.157	0.552	1.626	0.545	-0.387	0.045
	(0.687)	(0.907)	(1.218)	(1.374)	(1.468)	(1.384)	(1.030)	(1.403)	(1.333)	(1.068)	(0.146)
QA_MP_t	1.054***	1.517***	2.302***	2.404***	2.183***	1.847**	0.949	1.969**	2.158***	1.278**	0.135
	(0.390)	(0.515)	(0.691)	(0.780)	(0.833)	(0.785)	(0.584)	(0.796)	(0.756)	(0.606)	(0.083)
QA_EP_t	1.020**	1.411**	1.985**	2.221**	2.874***	2.406**	1.781**	2.587**	1.986**	1.596**	0.344***
	(0.491)	(0.649)	(0.871)	(0.983)	(1.050)	(0.990)	(0.737)	(1.003)	(0.953)	(0.764)	(0.104)
Intercept	-0.158	-0.169	-0.191	-0.249	-0.237	-0.098	-0.038	-0.282	-0.260	0.018	-0.032
	(0.174)	(0.230)	(0.309)	(0.349)	(0.372)	(0.351)	(0.261)	(0.356)	(0.338)	(0.271)	(0.037)
Obs.	152	152	152	152	152	152	152	152	152	152	152
R^2	0.087	0.090	0.109	0.100	0.109	0.093	0.058	0.092	0.081	0.056	0.086
Adj. R^2	0.062	0.065	0.084	0.076	0.085	0.068	0.033	0.068	0.056	0.030	0.061
F Stat.	3.488***	3.622***	4.478***	4.088***	4.487***	3.759***	2.273*	3.741***	3.258**	2.173*	3.439**

Note: Results from the OLS estimation of our baseline model with all communication variables and with robust standard errors for the period 2006 to 2020 (152 observations). * represents a statistical significance of 10%, ** of 5% and *** of 1%. Each column represent a financial asset with Overnight Index Swaps (OIS) from a maturity 3 month to 2 year, Sovereign bond yields of maturities 2, 5 and 10 year of Germany (DE) and France (FR) and the Euro/US dollar exchange rate. MP and EP are, repectively, the Monetary Policy and Economic Perspective of the Introductory Statement (IS) and the Questions and Answers (Q&A) part of the ECB press conferences at time t.

5 Robustness

To confirm our initial findings, we perform two robustness tests. First, to confirm the added value of the information provided during the press conference, we add two macroeconomic variables to our initial specification. Second, we benchmark our sentiment obtained with a ML classification to two different approaches using either an existing financial dictionary or a pre-trained large language model.

First, in addition to equations (3) and (4), we propose to study the impact of the two types of communications (IS and Q&A) when combined with macroeconomic variables. Following Taylor (1993), we focus on the inflation ($Inflation_t$) through the flash estimate Harmonized Consumer Prices Index (HCPI) available before the press conferences and the output gap ($Output\ Gap_t$) measured with the Industrial Production.[1] Equation 5 gives the obtained model:

[1] We use an Hodrick-Prescott filter to separate the trend from the cycle with a smoothing parameter $\lambda = 1,600$.

$$\Delta AP_t = \alpha + \beta_1 \times MP\_IS_t + \beta_2 \times EP\_IS_t$$
$$+\beta_3 \times MP\_QA_t + \beta_4 \times EP\_QA_t \quad (5)$$
$$+\beta_5 \times Output\ Gap_t + \beta_6 \times Inflation_t + \epsilon_t$$

Results are provided in Table 6. Our findings confirm the previous results of Gardner et al. (2022) : central banks communication provides to financial market participants information not directly conveyed in macroeconomic data. Furthermore, as there is no release of new relevant macroeconomic information during the press conferences (or days before the conference), market participants have already priced such release before the beginning of the ECB press conference supporting the absence of statistical significance of both variables.

Table 6: Estimated effect of Monetary Policy and Economic Perspective Introductory Statements, Questions and Answers tones and Control Variables Tones on Asset Prices (full sample)

	OIS 3M	OIS 6M	OIS 1Y	OIS 2Y	DE 2Y	DE 5Y	DE 10Y	FR 2Y	FR 5Y	FR 10Y	EUR USD
IS_MP_t	0.126	0.038	0.091	-0.117	-0.366	0.214	-0.453	-0.347	-0.581	-0.404	0.017
	(0.521)	(0.687)	(0.924)	(1.040)	(1.111)	(1.046)	(0.780)	(1.061)	(1.006)	(0.809)	(0.110)
IS_EP_t	0.768	0.646	0.934	1.004	2.096	1.922	0.431	1.426	0.301	-0.442	0.037
	(0.702)	(0.926)	(1.246)	(1.402)	(1.499)	(1.410)	(1.052)	(1.432)	(1.357)	(1.092)	(0.149)
QA_MP_t	1.049***	1.508***	2.297***	2.413***	2.189***	1.859**	0.957	1.980**	2.171***	1.279**	0.136
	(0.392)	(0.517)	(0.696)	(0.783)	(0.837)	(0.788)	(0.588)	(0.800)	(0.758)	(0.610)	(0.083)
QA_EP_t	1.028**	1.429**	1.992**	2.190**	2.846***	2.365**	1.762**	2.553**	1.945**	1.584**	0.343***
	(0.495)	(0.652)	(0.878)	(0.988)	(1.056)	(0.993)	(0.741)	(1.008)	(0.956)	(0.769)	(0.105)
Inflation	0.056	0.134	0.033	-0.285	-0.270	-0.383	-0.162	-0.309	-0.382	-0.132	0.006
	(0.181)	(0.239)	(0.322)	(0.362)	(0.387)	(0.365)	(0.272)	(0.370)	(0.351)	(0.282)	(0.038)
Output gap	0.014	0.019	0.017	-0.001	0.011	0.004	-0.010	-0.002	-0.001	0.015	-0.007
	(0.056)	(0.074)	(0.099)	(0.112)	(0.120)	(0.112)	(0.084)	(0.114)	(0.108)	(0.087)	(0.012)
Intercept	-0.243	-0.373	-0.238	0.195	0.188	0.502	0.211	0.200	0.336	0.228	-0.044
	(0.338)	(0.446)	(0.601)	(0.676)	(0.722)	(0.680)	(0.507)	(0.690)	(0.654)	(0.526)	(0.072)
Obs.	152	152	152	152	152	152	152	152	152	152	152
R^2	0.088	0.093	0.109	0.105	0.112	0.100	0.061	0.097	0.090	0.057	0.088
Adj. R^2	0.050	0.056	0.072	0.067	0.075	0.063	0.023	0.060	0.052	0.018	0.050
F. Stat	2.338**	2.483**	2.956***	2.821**	3.047***	2.699**	1.579	2.609**	2.390**	1.467	2.318*

Note: Results from the OLS estimation Equation 5 with robust standard errors for the period 2006 to 2020 (152 observations). * represents a statistical significance of 10%, ** of 5% and *** of 1%. Each column represent a financial asset with Overnight Index Swaps (OIS) from a maturity 3 month to 2 year, Sovereign bond yields of maturities 2, 5 and 10 year of Germany (DE) and France (FR) and the Euro/US dollar exchange rate. MP and EP are, repectively, the Monetary Policy and Economic Perspective of the Introductory Statement (IS) and the Questions and Answers (Q&A) part of the ECB press conferences at time t.

Second, we compare our methodology to other models and techniques. We consider the Loughran and McDonald (2011) financial dictionary (LM) and the pre-trained model FinBERT. Both methods ensure automatic text classification into positive and negative polarities. Note that a positive or negative sentiment means that the sentence (lexical content) expresses an overall tone classified as positive or negative depending on the words and their intensities. Additionally, we cluster sentiments of both approach by dates and quantify the ECB Press Conference contents tonality.

Given IS and Q&A sentiments at time t, the LM score is derived using the following equation:

$$LM\ sentiment_t = \frac{Positive\ words - Negative\ words}{Positive\ words + Negative\ words} \tag{6}$$

where $Positive\ words$ ($Negative\ words$) is the number of occurences of words classified as positive (negative) in the LM dictionary.[2] Equation 6 shows the normalized net balance between aggregated positive and negative sentiments, and we use these alternative measures as regressors to explain the asset prices set. The FinBERT sentiment score $Fin\ sentiment_t$ is obtained by aggregating the polarity[3] of each sentence inside a given text so that:

$$Fin\ sentiment_t = \sum (SentencePosi.Score - SentenceNega.Score) \tag{7}$$

Tables 7 and 8 report the OLS results when we consider the indexes separately for each content and when we combine both of them.

Using the LM dictionary on introductory statements, OIS and sovereign yields react positively and significantly for short term maturities. Although no effect is observed when considering Q&A sessions. This result remains consistent when we consider simultaneously the effect of Introductory Statement and Q&A sentiments on asset prices (Part c of Table 7). While previous study already discussed the use of the LM dictionary for monetary policy communication, Picault and Renault (2017) showed the limits of this approach as it might lead to wrong (opposite) classification of words toward a positive or a negative inclination. In contrast, using the FinBERT algorithm to infer complementary information to the markets shows that the markets positively and significantly behave to both

[2] The dictionary is available at https://sraf.nd.edu/loughranmcdonald-master-dictionary/.

[3] The FinBert sentiment is measured using HuggingFace with Python Transformers package. The parameters and characteristics of FinBert are available at https://huggingface.co/ProsusAI/finbert

Table 7: Estimated effect of Positive and Negative LM dictionary tones of Introductory Statements, Questions and Answers on Asset Prices (full sample)

(a) Introductory Statement

	OIS 3M	OIS 6M	OIS 1Y	OIS 2Y	DE 2Y	DE 5Y	DE 10Y	FR 2Y	FR 5Y	FR 10Y	EUR USD
LM_IS_Sentiment	0.008**	0.009**	0.013**	0.014**	0.017**	0.013**	0.006	0.015**	0.006	0.001	0.001
	(0.003)	(0.004)	(0.006)	(0.006)	(0.007)	(0.006)	(0.005)	(0.007)	(0.006)	(0.005)	(0.001)
Intercept	-0.153	-0.166	-0.191	-0.252	-0.226	-0.174	-0.032	-0.276	-0.264	0.017	-0.031
	(0.178)	(0.236)	(0.320)	(0.359)	(0.384)	(0.347)	(0.267)	(0.364)	(0.349)	(0.277)	(0.038)
Obs.	152	152	152	152	152	152	152	152	152	152	152
R^2	0.042	0.031	0.034	0.030	0.040	0.028	0.009	0.036	0.007	0.000	0.016
Adj. R^2	0.036	0.024	0.028	0.024	0.034	0.021	0.002	0.030	0.000	-0.007	0.009

(b) Questions & Answers

	OIS 3M	OIS 6M	OIS 1Y	OIS 2Y	DE 2Y	DE 5Y	DE 10Y	FR 2Y	FR 5Y	FR 10Y	EUR USD
LM_QA_sentiment	-0.001	-0.000	-0.001	-0.000	0.000	0.001	0.002	0.000	0.001	0.002	0.000
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.000)
Intercept	-0.158	-0.172	-0.200	-0.262	-0.240	-0.186	-0.039	-0.288	-0.271	0.013	-0.032
	(0.181)	(0.240)	(0.325)	(0.365)	(0.392)	(0.351)	(0.266)	(0.371)	(0.350)	(0.275)	(0.038)
Obs.	152	152	152	152	152	152	152	152	152	152	152
R^2	0.003	0.001	0.001	0.000	0.001	0.003	0.011	0.000	0.003	0.018	0.003
Adj. R^2	-0.004	-0.005	-0.006	-0.007	-0.006	-0.004	0.005	-0.007	-0.004	0.011	-0.003
F.Stat	0.453	0.203	0.146	0.022	0.082	0.400	1.700	0.008	0.408	2.739	0.506

(c) Introductory Statements and Questions & Answers

	OIS 3M	OIS 6M	OIS 1Y	OIS 2Y	DE 2Y	DE 5Y	DE 10Y	FR 2Y	FR 5Y	FR 10Y	EUR USD
LM_IS_sentiment	0.008***	0.009**	0.013**	0.014**	0.017**	0.013**	0.005	0.016**	0.006	-0.000	0.001
	(0.003)	(0.004)	(0.006)	(0.006)	(0.007)	(0.006)	(0.005)	(0.007)	(0.006)	(0.005)	(0.001)
LM_QA_sentiment	-0.001	-0.001	-0.001	-0.000	0.000	0.001	0.001	-0.000	0.001	0.002	0.000
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.000)
Intercept	-0.151	-0.164	-0.189	-0.251	-0.226	-0.176	-0.035	-0.276	-0.266	0.012	-0.031
	(0.178)	(0.237)	(0.321)	(0.361)	(0.385)	(0.348)	(0.266)	(0.366)	(0.350)	(0.276)	(0.038)
Obs.	152	152	152	152	152	152	152	152	152	152	152
R^2	0.047	0.033	0.036	0.031	0.040	0.029	0.019	0.036	0.009	0.018	0.018
Adj. R^2	0.034	0.020	0.023	0.018	0.027	0.016	0.006	0.023	-0.004	0.005	0.005
F.Stat	3.655**	2.548*	2.794*	2.358*	3.116**	2.239	1.432	2.803*	0.681	1.360	1.376

Note: Results from the OLS estimation of Equations 3 -top-, 4 -middle-, and both part of the press conference -bottom-. The estimation is performed with robust standard errors for the period 2006 to 2020 (152 observations). * represents a statistical significance of 10%, ** of 5% and *** of 1%. Each column represent a financial asset with Overnight Index Swaps (OIS) from a maturity 3 month to 2 year, Sovereign bond yields of maturities 2, 5 and 10 year of Germany (DE) and France (FR) and the Euro/US dollar exchange rate. The sentiment is measured using the LM alternative lexicon defined in Equation 6 for the Introductory Statement (IS) and the Questions and Answers (Q&A) part of the ECB press conferences at time t.

Table 8: Estimated effect of Positive and Negative FinBERT tones of Introductory Statements, Questions and Answers on Asset Prices (full sample)

(a) Introductory Statement

	OIS 3M	OIS 6M	OIS 1Y	OIS 2Y	DE 2Y	DE 5Y	DE 10Y	FR 2Y	FR 5Y	FR 10Y	EUR USD
Fin_IS_sentiment	2.227**	2.352*	3.203*	3.476*	4.574**	4.026**	1.011	3.606*	2.856	0.335	0.337*
	(0.912)	(1.215)	(1.648)	(1.849)	(1.974)	(1.772)	(1.370)	(1.879)	(1.782)	(1.421)	(0.195)
Intercept	-0.156	-0.170	-0.197	-0.258	-0.233	-0.178	-0.035	-0.283	-0.265	0.017	-0.031
	(0.178)	(0.237)	(0.321)	(0.361)	(0.385)	(0.346)	(0.267)	(0.367)	(0.348)	(0.277)	(0.038)
Obs.	152	152	152	152	152	152	152	152	152	152	152
R^2	0.038	0.025	0.025	0.023	0.035	0.033	0.004	0.024	0.017	0.000	0.020
Adj. R^2	0.032	0.018	0.018	0.017	0.028	0.027	-0.003	0.018	0.010	-0.006	0.013
F.Stat	6.556**	4.737**	5.303**	4.651**	6.260**	4.260**	1.364	5.636**	1.047	0.010	2.398

(b) Questions & Answers

	OIS 3M	OIS 6M	OIS 1Y	OIS 2Y	DE 2Y	DE 5Y	DE 10Y	FR 2Y	FR 5Y	FR 10Y	EUR USD
Fin_QA_sentiment	1.339*	2.040**	2.639*	3.209**	4.014**	2.937*	1.897	3.283**	1.570	0.795	0.057
	(0.779)	(1.026)	(1.394)	(1.560)	(1.667)	(1.505)	(1.150)	(1.586)	(1.514)	(1.200)	(0.167)
Intercept	-0.159	-0.173	-0.201	-0.262	-0.239	-0.184	-0.036	-0.288	-0.269	0.016	-0.032
	(0.180)	(0.237)	(0.322)	(0.360)	(0.385)	(0.347)	(0.265)	(0.366)	(0.349)	(0.277)	(0.038)
Obs.	152	152	152	152	152	152	152	152	152	152	152
R^2	0.019	0.026	0.023	0.028	0.037	0.025	0.018	0.028	0.007	0.003	0.001
Adj. R^2	0.013	0.019	0.017	0.021	0.031	0.018	0.011	0.021	0.001	-0.004	-0.006
F.Stat	2.954*	3.950*	3.584*	4.232*	5.799*	3.808*	2.721	4.284*	1.076	0.439	0.117

(c) Introductory Statements and Questions & Answers

	OIS 3M	OIS 6M	OIS 1Y	OIS 2Y	DE 2Y	DE 5Y	DE 10Y	FR 2Y	FR 5Y	FR 10Y	EUR USD
Fin_IS_sentiment	2.102**	2.152*	2.946*	3.160*	4.180**	3.743**	0.816	3.284*	2.711	0.252	0.334*
	(0.912)	(1.210)	(1.643)	(1.841)	(1.956)	(1.767)	(1.369	(1.870)	(1.790)	(1.430)	(0.197)
Fin_QA_sentiment	1.179	1.876*	2.415*	2.969*	3.696**	2.653*	1.835	3.033*	1.364	0.776	0.032
	(0.771)	(1.023)	(1.390)	(1.556)	(1.654)	(1.494)	(1.157)	(1.581)	(1.514)	(1.209)	(0.166)
Intercept	-0.156	-0.170	-0.197	-0.258	-0.233	-0.179	-0.035	-0.284	-0.265	0.017	-0.031
	(0.177)	(0.235)	(0.319)	(0.358)	(0.380)	(0.343)	(0.266)	(0.363)	(0.348)	(0.278)	(0.038)
Obs.	152	152	152	152	152	152	152	152	152	152	152
R^2	0.053	0.046	0.044	0.047	0.066	0.054	0.020	0.048	0.022	0.003	0.020
Adj. R^2	0.041	0.033	0.031	0.034	0.054	0.041	0.007	0.035	0.009	-0.010	0.007
F.Stat	4.176**	3.585**	3.425**	3.617**	5.252***	4.192**	1.533	3.713**	1.689	0.234	1.502

Note: Results from the OLS estimation of Equations 3 -top-, 4 -middle-, and both part of the press conference -bottom-. The estimation is performed with robust standard errors for the period 2006 to 2020 (152 observations). * represents a statistical significance of 10%, ** of 5% and *** of 1%. Each column represent a financial asset with Overnight Index Swaps (OIS) from a maturity 3 month to 2 year, Sovereign bond yields of maturities 2, 5 and 10 year of Germany (DE) and France (FR) and the Euro/US dollar exchange rate. The sentiment is measured using FinBert defined in Equation 7 for the Introductory Statement (IS) and the Questions and Answers (Q&A) part of the ECB press conferences at time t.

contents. FinBERT not only contribute to powerful effect when examining the introductory statement, but also adds information with questions and answers and successfully help to predict financial markets expectations. As the FinBert training considers effectively both negations and amplifiers, it avoids several limits of the initial LM specification. However, both methods fail to decompose the content of the press conference between sentences referring to monetary policy (MP) and economic perspective (EP) limiting our understanding of the relevant part of the central bank communication to model asset prices dynamics.

6 Conclusion

Text mining is a valuable approach to effectively handle central banks textual announcements. By delving into the language patterns, sentiments and tones, using various linguistic tools and Machine Learning modeling, researchers have been able to uncover valuable insights from such communications.

We considered textual data from ECB press conferences transcripts covering a period that runs from 2004 until 2020. These transcripts include introductory statements and Q&A contents and are available on the ECB website. The corpus contains decisions about monetary policy directions and economic prospects during three ECB presidencies of Jean-Claude Trichet (2004-2011), Mario Draghi (2011-2019), and Christine Lagarde (2019-2020).

Introductory statements details the decision taken by the Governing Council and during Q&A hearings, the ECB president engages in real-time interactions with journalists to respond to their questions. We analyzed the contents by employing Natural Language Processing techniques to process and transform the data into multidimensional numerical representations and made it ready to ensure computational efficiency and interpretability of supervised Machine Learning classifiers in order to build monetary policy and economic outlook sentiments.

To our best knowledge, Q&A classification and sentiment index construction using Machine Learning models was not accurately considered in previous works. In our study, opening statements train set is used to identify the best classifier for Q&A sentences. Sentiment scores are determined from classified sentences. They correspond to the proportion of the difference between restrictive and accommodative sentiments and the proportion of the difference between positive and negative sentiments. These tones are then used to determine if it is worth exploring ECB Press conferences Q&A informativeness in explaining asset prices dynamics in the Euro Area.

The main contribution of this paper consists in underlining the impact of ECB information tones on various asset prices. The study reveals, thanks to OLS regression analysis, that OIS, sovereign yields and the EUR/USD exchange rate are influenced by the monetary and economic policies of the Q&A contents.

In a future work, it will be interesting to study more specifically misalignment between the content of the introductory statement and the content of the Q&A session. In the carefully drafted introductory statement, each words is weighted during the Governing Council meeting. The Q&A gives the President of the ECB more room to use his or her own terms to discuss the central bank actions, potentially creating differences between the two messages.

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7 Appendix

7.1 Data exploration

The analysis of the distribution of IS sentences revealed that when the ECB communicates, it always uses some of the same sentences. This allowed us to deduce that the ECB does not tend to change its communication style. The analysis helps also to detect the presence of sentences having no added value and are then classified as 'NONE' in our models. Table 9 shows an extract of the most repetitive sentences.

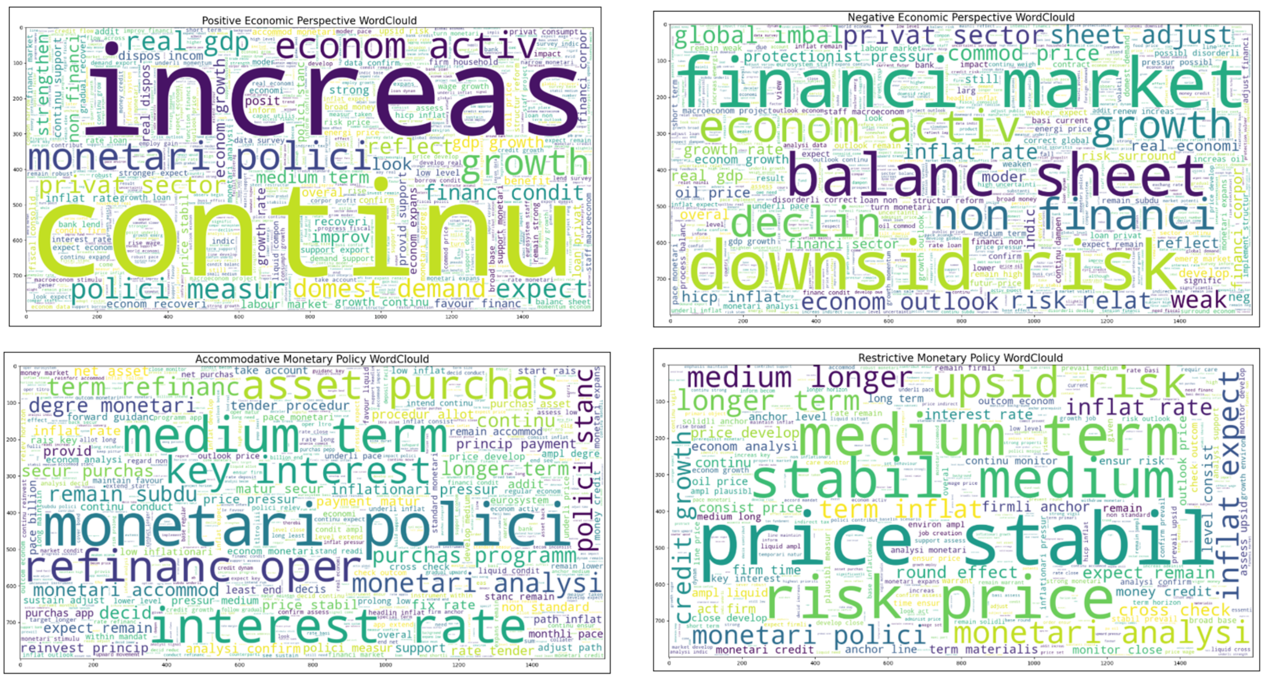
Table 9: Extract of most repetitive Introductory Statements sentences

Sentence	Occurrence
'We are now at your disposal for questions.	150
Jump to the transcript of the questions and answers.	129
'Let me now explain our assessment in greater detail, starting with the economic analysis.	109
Ladies and gentlemen, the Vice-President and I are very pleased to welcome you to our press conference.	77
Introductory statement to the press conference (with Q A)	62
Introductory statement with Q A	56
Based on our regular economic and monetary analyses, we decided to keep the key ECB interest rates unchanged.	47
We will now report on the outcome of today s meeting of the Governing Council.	27
A cross-check with the signals from the monetary analysis confirms this picture.	26
Allow me to explain our assessment in greater detail, starting with the economic analysis.	24
Accordingly, we will continue to monitor very closely all developments over the period ahead.	21
We will now report on the outcome ... which was also attended by the Commission Vice-President, Mr Dombrovskis.	21
On the basis of our regular economic and monetary analyses, we decided ... to leave the key ECB interest rates unchanged.	17

7.2 Word clouds of main sentiments

Figure 5 indicates some word clouds for the main sentiments (Positive EP, Negative EP, Accommodative MP and Restrictive MP) that appear in the ECB opening statement. Such visualization allows to identify the most frequent words, key grams and patterns in any monetary and economic contexts.

Figure 5: Word cloud for the main sentiments



7.3 NONE elimination

ECB opening statements are quiet concentrated with irrelevant information that we classified as 'NONE' since it does not reveal any news about monetary and economic policies. To minimize its weight, we removed these NONE sentences. Below, some examples of NONE classified phrases that we removed from the analysis:

- Ladies and gentlemen, the Vice-President and I are very pleased to welcome you to our press conference today.
- The Vice-President and I are very pleased to welcome you to our press conference.
- Ladies and gentlemen, allow me to welcome you to our press conference and report on the outcome of today s meeting of the ECB s Governing Council.
- This is my last press conference following a meeting of the Governing Council.
- Let me now explain our decision in more detail.
- Allow me to explain our assessment in greater detail.
- We are now ready to take your questions.
- We are now at your disposal for questions.

- We will now report on the outcome of this meeting.
- We will now report on the outcome of today's meeting of the Governing Council, which was also attended by Commissioner Rehn.
- We will report on the outcome of today's meeting of the Governing Council.
- Ladies and gentlemen, welcome to our press conference.
- Today is the first time that I have had the privilege and pleasure of chairing the meeting of the Governing Council of the ECB.
- Ladies and gentlemen, the Vice-President and I are very pleased to welcome you to our press conference here in Berlin.
- Let me take the opportunity to warmly thank President Weidmann for his invitation and kind hospitality.
- I would also like to express our special gratitude to the staff of the Deutsche Bundesbank for the excellent organisation of our meeting.
- I will now report on the outcome of today s meeting of the Governing Council, which was also attended by the Commission Vice-President, Mr Rehn.
- I would like to thank Governor Visco for his kind hospitality and express our special gratitude to his staff for the excellent organisation of today s meeting of the Governing Council.
- Introductory statement to the press conference (with QA).
- We will now report on the outcome of today s meeting of the Governing Council, which was also attended by the Commission Vice-President, Mr. Rehn.
- The meeting was also attended by the Commission Vice-President, Mr Rehn.

7.4 Stop words

Removing stop word is an important step that serves to clean the text. Here is the list of stop words usually used by researchers:

['i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves', 'you', "you're", "you've", "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he', 'him', 'his', 'himself', 'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself', 'they', 'them', 'their', 'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that', "that'll", 'these', 'those', 'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has', 'had', 'having', 'do', 'does', 'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', 'as', 'until', 'while', 'of', 'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'through', 'during', 'before', 'after', 'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', 'over', 'under', 'again', 'further', 'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'any', 'both', 'each', 'few', 'more', 'most', 'other', 'some', 'such', 'no', 'nor', 'not', 'only', 'own', 'same', 'so', 'than', 'too', 'very', 's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've", 'now', 'd', 'll', 'm', 'o', 're', 've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "didn't", 'doesn', "doesn't", 'hadn', "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', 'mightn', "mightn't", 'mustn', "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't", 'wasn', "wasn't", 'weren', "weren't", 'won', "won't", 'wouldn', "wouldn't"]

We also extended the stop words list by adding other common ECB-related words that we judged non-pertinent so that their presence and weight will not influence the classification. The list is as follows:

["ecb", "ecb", "governing", "government", "council", "vicepresident", "vice-president", "vice president", "president", "chair", "chairman", "executive", "almunia", "member", "euro", "area", "eurogroup", "prime", "minister", "commission", "commissioner", "governor", "governors", "ecofin", "eurostat", "introductory", "press", "conference", "transcript", "statement", "meeting", "question", "questions", "answer", "answers", " q a", " q&a", "welcome", ’thank’, "thanks", "today", "year", "please", "pleased", "let", "new", "best", "express", "own", "wishes", "mr", "ms", "mrs", "madam", ’would’, "mario", "draghi", "jeanclaude", "jean", "claude", "jean-claude", "trichet", "christine", "lagarde", "bonnici", "caruana", "chair", "coene", "constancio", "v tor", "const ncio", "de guindos", "fazio", "garganas", "georghadji", "graeff", "hansson", "hurley", "ignazio visco", "korber", "kranjec", "liebscher", "liikanen", "luis de guindos", "nwotny", "noyer", "lucas", "papademos", "tumpel gugerell", "vasiliauskas", "weber", "weidmann", "duisenberg", "juncker", "rehn", "mccreevy","solbes", "zalm" , "barroso", "weber", "willem f duisenberg", "hein luoma", "steinbr ck", "gaspari", "bajuk", "orphanides", "bonello", "ramko", "const ncio", "lipstok", "katainen", "rim vi s", "Vasiliauskas", "dijsselbloem", "dombrovskis", "helsinki", "centeno", "ladies", "gentlemen","january", "february", "march", "april", "may", "june", "july", "august", "september", "october", "november" ,"december", "moment", "past", "present", "future", "recent", "month", "months", "period", "periods", "date", "dates", "current", "currently", "previous", "previously", "early", "towards", "last", "next", "half", "year", "annual", "years", "quarter", "quarters", "since", "mid", "latest", "newest", "late", "new", "back", "ago", "time", "ongoing", "meantime", "available", "context", "moreover", "besides", "point", "likely", "already", "ahead", "aim", "finally", "final", "understood", "particular", "particularly", "partly", "partially", "point", "points", "regard", "therefore", "range", "like", "in order", "beyond", "considerably", "main", "part", "whereas", "allow", "ask", "asked", "say", "said", "mention", "mentioned", "talk", "told", "suggest", "suggested", "think", "thought", "wonder", "wondered", "mean", "meant", "understand", "know", "knew", "seem", "seemed", "see", "saw", "look", "looked", "consider", "considered", "include", "included", "hear", "heard", "believe", "believed", "feel", "felt", "make", "made", "going", "go", "goes", "come", "came", "give", "gave", "using", "use", "used", "also", "must", "should", "maybe", "perhaps", "however", "notably", "whereas", "case", "well", "kind", "full", "necessary", "lot", "bit", "little", "furthermore", "yes", "no", "fact", "accordingly", "according", "appropriate", "broadly ", "following", "follow", "manner", "flash", "outside", "one", "two", "three", "four", "five", "six", "seven", "eight", "nine", "ten", "first", "second", "third", "fourth", "firstly", "secondly", "thirdly", "fourthly", "frankfurt", "brussels", "berlin", "athens", "paris", "madrid", "dublin", "venice", "lisbon", "greece","luxembourg", "venice","vienna"]

7.5 Classification

Tables 10 - 12 report sentences extracted from the IS and Q&A sets. They contain the observed sentiments in the "Sentiment encoded" column and the predicted ones in the "Sentiment predicted" column with the associated probabilities of each numerical label. Columns p_0 to p_6 refer to the probability distribution over the encoded labels set and indicate the most likely class the sentence should belong to. Codes 0 to 6 are those indicated in the framework of Figure 2 (0 = EP Negative, 1 = EP Neutral, 2 = EP Positive, 3 = MP Accommodative, 4 = MP Neutral, 5 = MP restrictive, 6 = NONE)).

For example, in table 10 , for the first sentence, the observed class is "EP_POSI" and the predicted label is 2, since the greatest probability is obtained for p_2 (0.95).

Table 10: Extract from IS of ECB Press conferences test set, that are classified with SVC model when the sentences are transformed with BOW

Date	Text	Sentiment	Sentiment encoded	Sentiment predicted	p_0	p_1	p_2	p_3	p_4	p_5	p_6
03/02/2011	...the positive underlying momentum of economic activity in the euro area,...	EP_POSI	2	2	0,02	0,02	**0,95**	0,00	0,00	0,00	0,01
08/09/2011	...inflation rates are likely to stay clearly above 2% ...	MP_REST	5	5	0,01	0,01	0,01	0,00	0,00	**0,91**	0,06

Table 11: Extract from IS of ECB Press conferences test set, that are mis-classified with SVC model when the sentences are transformed with BOW

Date	Text	Sentiment	Sentiment encoded	Sentiment predicted	p_0	p_1	p_2	p_3	p_4	p_5	p_6
03/02/2011	... the fiscal stance in the euro area will be broadly neutral in 2017.	EP_NEUT	1	6	0,01	0,01	0,12	0,01	0,00	0,00	**0,86**
08/09/2011	... reiterates its position that it is crucial to avoid the mistakes of the past.	NONE	6	2	0,01	0,01	**0,51**	0,02	0,00	0,01	0,43

Table 12: Extract from Q&A of ECB Press conferences set that are classified with SVC when the sentences are transformed with BOW

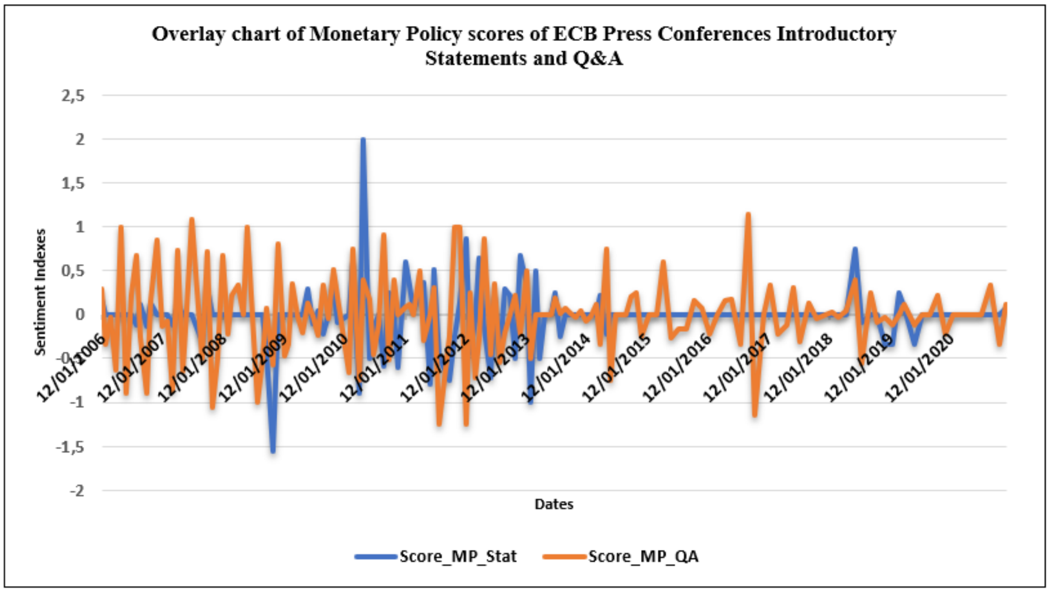
Date	Text	Type	Sentiment predicted	Sentiment predicted_encoded
02/03/2006	As regards the reason why we increase rates today, ...	Answer	MP_REST	5
07/07/2011	... I said we have taken the decision to increase rates by 25 basis points.	Answer	MP_REST	5

7.6 Scores of the ECB Introductory Statement and Q&A Sessions

The figures 6 - (a) and (b) display MP and EP tones of IS and Q&A that are transformed with BOW and classified with SVC. Obviously, the MP (EP) tones for IS and Q&A seem having the same trends , but with significant deviations at specific time periods. The gaps indicate differences in communication style. IS corresponds to the official written speech but in the (Q&A) sessions, the presidents use their own vocabulary mixed with several emotions.

Figure 6: Scores of the ECB Introductory Statement and Q&A Sessions.

(a) Monetary Policy (MP) scores



(b) Economic Perspectives (EP) scores