Unified Voice or Cacophony? A Discordance Index of the European Central Bank Governing Council Members

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Abstract

This paper investigates media perceptions of communications by members of the European Central Bank (ECB) Governing Council. It employs large language models (LLMs) to understand the media's perception on public statements by ECB Governing Council members. A cacophony index is developed to quantify member discordance from the official ECB stance. The first contribution to research involves the application of advanced LLMs to a novel dataset comprising media coverage on members of the Governing Council. Throughout the observation period from July 21, 2022, to March 10, 2024, the findings showed that 78% of the articles were perceived as hawkish. The second contribution to research is the analysis of the dataset after applying LLMs. We utilised an interquartile range (IQR) approach to measure the diversity of opinions among ECB Governing Council members. This analysis revealed that the National Competent Bank Governor from Germany was consistently seen as the most hawkish across several periods, whereas the governors from Portugal, Greece, Italy, and France appeared more dovish. Our findings contribute to the growing literature on applying advanced sentiment analysis to central banking communications, including the use of fine-tuned RoBERTa models, and offers insights into media perceptions of the dynamics within the ECB Governing Council during a period of rising interest rates.

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1 Introduction

For many years, central banks were shrouded in secrecy. Central bankers believed that the effectiveness of monetary policy hinged on their ability to surprise markets. Montagu Norman, Governor of the Bank of England (1920–1944), aptly summarised monetary policy communication, with the motto: ”never explain, never excuse” International Monetary Fund (2022) . This approach began to change during the 1990s with the adoption of inflation targeting. Central banks aimed to make monetary policy more predictable Blinder et al. (2024) and in this new regime, communication was seen as a core tool to do this. Regular press conferences, interviews and published official documents pushed monetary policy firmly into the public domain. The 2007-2008 financial crisis posed an enormous challenge for central banks and their communications teams. As a result of this increased media scrutiny, central bank communications was even weaponised as an active policy tool once conventional monetary policy was exhausted. In 2012, Mario Draghi, President of the European Central Bank (ECB) (2011-2019) ”whatever it takes” Blinder et al. (2008) speech on his plans to save the Euro, raised confidence in monetary policy action and arguably was the turning point of the European debt crisis.

The ECB faces additional complexities on communication due to its governance structure Jansen and de Haan (2006). The ECB Governing Council consists of six members from the Executive Board and 20 National Governors, each from the central banks of the Eurozone member states. Given the ECB’s supranational structure, it is unsurprising that there are diverging cases of communication between Governing Council members Tillmann and Walter (2019). For example, the President of the ECB, the Governor of Banco de España and the President of the Bundesbank are unlikely to communicate the same views on monetary policy and bias towards a position typically increases when speaking from their home country Bennani and Neuenkirch (2016). Communications of the ECB Governing Council also has an extensive influence on financial markets Istrefi et al. (2021) and also the personal finances of millions of borrowers and lenders in the Eurozone. It is important for the ECB to understand how the media perceives sentiment from the Governing Council. Do the members speak with one voice? If there is indeed a cacophony, which member states are least aligned and how can the discordance be quantified?

The goal of this paper is to measure how the media perceives the communication of the ECB Governing Council members. The focus will be on their commentary related to status of inflation and monetary policy of the ECB. The aim of this research is to highlight and define the perceived discordance via a numerical index.

Our research benefited from a database developed by the Strategy Communications Team at the ECB, using resources from Ruepoint, a firm that specialises in media clippings. This database contains statements made by members of the Governing Council, sourced from worldwide news articles. This resource provided significant added value to our research. It offered access to a broad array of media reports that are typically difficult to obtain.

Our first contribution to literature is that we applied state-of-the-art natural language processing (NLP) techniques, starting with simple benchmarks and gradually advancing in complexity. The methodology involved using manual labelling to establish a baseline, followed by employing the OpenAI API with Chat-GPT4, testing to find the optimum prompt and then classifying the sentiment of a subset of articles. To scale the project, we utilised a pre-trained RoBERTa model to label all articles based on the initial classifications by Chat-GPT4. The result was a comprehensive sentiment analysis of the entire dataset.

The objective of the ECB is, as far as possible, communicate coherently and give price predictability to European citizens and promote stability in the financial markets. Our second contribution to research is significant because it measures the perception whether the ECB Governing Council is able to speak with one voice. Our results, as calculated by the fine-tuned RoBERTa model shows that the vast majority of sentiment in the time period, 2022-07-21 to 2024-03-10, is classified as hawkish. After matching with the correspondent speakers, it was found also that throughout this period, the media tended to perceive the positions taken by the Southern European central bank governors as more dovish than the baseline sentiment of the ECB Governing Council.

This research is structured as follows: Chapter 1 introduces the study and outlines its significance. Chapter 2 provides a literature review on the subject. Chapter 3 presents the data, detailing the dataset of articles and the representation of ECB Governing Council members. Chapter 4 describes the methodology used, including human labelling, OpenAI API usage, and model predictions. Chapter 5 outlines the models used, including the dictionary benchmark and the pretrained BERT model. Chapter 6 explores the results derived from these models. Chapter 7 introduces the development of the cacophony index and its results. The final chapter presents the conclusion.

2 Literature Review

The surge in interest in central banking communications since the turn of the millennium has coincided with significant advancements in technology for analysing such data.

Early attempts to analyse the consistency of ECB communications date back to the central bank's inception in 1998 (Jansen and de Haan, 2006). Initially, researchers employed theoretical approaches, focusing on keyword searches and frequency counts. Early findings revealed contradictions in policy statements and the dominance of national banks in monetary policy communications. As research became more sophisticated, an more complex method involving word counts contributed to a creation of a consistency indexJansen and de Haan (2010). The index used a word-scores approach which assessed policy consistency, by measuring word frequency across texts. This study found noticeable coherence within ECB communications.

Further advancements were made by incorporating n-grams, which consider sequences of words, enriching context in textual analysis (Amaya and Filbien, 2015). This study analysed the similarity of ECB monetary policy statements, making a significant step in capturing the nuanced financial lexicon of central bank communications. Additionally, Gorodnichenko et al. (2023) developed a financial word dictionary to detect emotions embedded in central banking press conferences, categorising sentences as dovish or hawkish based on combinations of financial-related nouns and verbs.

Innovative research by Bennani and Neuenkirch (2016), developed a classification method which went beyond the focus on word counts and considered the conceptual meanings of words in relation to monetary policy. They created a hawkish-dovish index, calculated as the ratio of the difference to the sum of hawkish and dovish terms. This study also revealed evidence of biases, whereby some statements by Governing Council members were linked to their country's political interests. This methodology was further refined in Picault and Renault (2017) by incorporating term-weighting along with n-grams. This enhancement allowed for a more sophisticated analysis of the subtleties in central bank communications. The research highlighted significant advancements in communication analysis, demonstrating how these methods can be applied to predict future ECB monetary policy decisions.

The major breakthrough in text analysis came with Vaswani et al. (2017) who applied the new technology of new large language models (LLMs). Following this research, word counts were largely abandoned as LLMs offered a deeper understanding of context and semantics. LLM could capture the meaning of entire sentences, recognised complex relationships between words, and understood nuances, providing a more comprehensive analysis of text.

Now, evident that technology and LLMs can be used to effectively decipher complex language, (Hansen and Kazinnik (2023)) examined how effectively GPT models, particurlay GPT-4, can understand and analyse central bank communication. Focusing on Fedspeak,lexicon used by the Federal Reserve for monetary policy discussions, it evaluated the model's ability to classify the policy direction from Federal Open Market Committee announcements. The study found that GPT models significantly surpass other methods in classification accuracy. Furthermore, the paper by Leek et al. (2024) developed new indices to gauge the relationships between the monetary policies of central banks, governmental actions, and financial markets, drawing on speeches from 118 central banks from 1997 to mid-2023. The study used LLM, ChatGPT 3.5-0301, and empahsised the importance of accurate and efficient prompt-engineering. The study examined model enhancements, trend analyses over time, and correlations with political-economic variables across banks. Notably, by providing clear prompts even with this older version of ChatGPT, this research offered a method for deciphering ECBspeak, the language and communication style used by the ECB in public statements and publications.

Building on this foundation, we will utilize state-of-the-art benchmarks for analyzing financial text through dictionary-based models and large language models (LLMs). Initially, we will employ ChatGPT-4, an enhanced version of the model used in Leek et al. (2024), as a fine-tuner for a pre-trained model on financial data that has demonstrated robust results Shah et al. (2023). To ensure the robustness of our findings, we will also test our model using the established benchmark by Gorodnichenko et al. (2023). By building on this literature, we aim to create a reliable classifier for our text, which will significantly contribute to the development of our index.

3 Data

3.1 Dataset of Articles

In this paper, we used a dataset provided by the Strategic Communications Team of the European Central Bank. Consisting of 35,076 articles ranging from 2nd September 2022 to 10th March 2024, the data was collected by Ruepoint, a media intelligence firm, and curated to only include articles containing commentary by a Governing Council member. Figure 1 shows the daily count of articles over the time period in this study. The cyclical peaks in articles likely correspond to the releases in ECB Monetary Statements, which occur every six weeks.

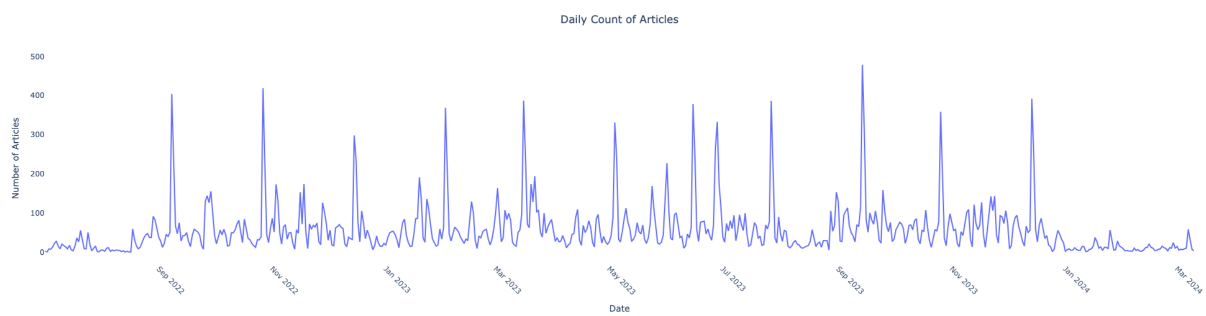

Figure 1: Daily Count of Articles

The dataset was populated with the article displayed in the original language, coupled with a corresponding manual summary written in English. These manual summaries were populated by human professionals specialising in financial media and this text will be the source of our sentiment analysis. Manual summaries were populated for 89.47% of all the articles, corresponding to 31,384 in which we are able to work with in this study

The data contains news articles written in various languages. The majority of articles are in Italian, totaling 6860 articles (19.55%). This is followed by German with 5819 articles (16.59%), Spanish with 5794 articles (16.51%), and English with 4303 articles (12.27%). French articles account for 3333 entries (9.50%), while Greek and Portuguese have 2654 (7.56%) and 1804 (5.14%) articles, respectively. These seven languages together account for a total of 30567 articles, representing 87.14% of the dataset, reflecting the diverse linguistics of the media sources.

The news articles came from various counties. The top 10 countries with the highest number of articles are as follows: Italy with 6908 articles (19.70%), Spain with 5803 articles, Germany with 4120 articles, France with 2804 articles (7.99%), the United States with 2545 articles (7.25%), Greece with 2118 articles (6.03%), Portugal with 1802 articles (5.14%), Belgium with 932 articles (2.66%), Austria with 902 articles (2.57%), and Ireland with 857 articles (2.44%). Collectively, these top 10 countries account for a total of 32,791 articles, which represents 93.49% of the entire dataset.

The data also contains news from various sources. The majority are from the Web, corresponding 22828 articles (65.08%), Print has 10936 articles (31.11%), TV has 827 articles (2.35%) and Radio

442 articles (1.26%). Table 1 shows the breakdown of the sites where the data was sourced:

Sitename	Count	Percentage (%)	Sitename	Count	Percentage (%)
Bloomberg	1229	3.51	Frankfurter Allgemeine Zeitung	490	1.40
Reuters	998	2.85	La Repubblica	467	1.33
Handelsblatt	928	2.65	Tgcom24	462	1.32
Milano Finanza	896	2.55	IL SOLE 24 ORE	417	1.19
Expansión	728	2.08	Naftemporiki	404	1.15
Börsen-Zeitung	728	2.08	El Pais	401	1.14
Dagens Industri	576	1.64	LaVanguardia	395	1.13
Finanzen.ch	517	1.47	Il Sole 24 Ore	387	1.10
La Stampa	497	1.42	Expresso	381	1.09
La Tribune	491	1.40	El Economista	379	1.08

Table 1: Article Counts and Percentages by Sitename

From the analysis of the data, it is apparent that the dataset reflects media coverage across the financial world, with a particular emphasis on European major economies and languages.

3.2 ECB Governing Council Members representation on the Dataset

After examining the data, we matched the manual summaries with the corresponding names of the ECB Governing Council members. To achieve a match the surname or full name of each respective member had to appear in an article.

31384 articles had a manual summary and we successfully matched 30154, achieving a match rate of 96% where data was available. The biggest challenge encountered was matching the Latvian Governor, Mārtiņš Kazāks, whose name required a different search approach due to variations in name spelling. Upon further research, we confirmed that the unmatched 4% of articles were related to the ECB but did not specifically mention any individual. Table 2 shows the match rate per ECB Governing Coucil member.

ECB Governing Council Member	Count	Percentage (%)	NCB Country or Position in the Executive Council
Christine Lagarde	18483	61.30	President of the ECB
Luis de Guindos	1752	5.81	Vice-President of the ECB
Isabel Schnabel	1137	3.77	Member of the Executive Council
Joachim Nagel	1084	3.59	Germany
Philip Lane	1080	3.58	Chief Economist and Member of the Executive Council
François Villeroy de Galhau	951	3.15	France
Fabio Panetta	838	2.78	Member of the Executive Council until 2023-11, Governor of Banca d'Italia since then
Pablo Hernandez de Cos	633	2.10	Spain
Mario Centeno	591	1.96	Portugal
Ignazio Visco	552	1.83	Italy
Yannis Stournaras	403	1.34	Greece
Klaas Knot	352	1.17	Netherlands
Robert Holzmann	344	1.14	Austria
Martins Kazaks	340	1.13	Latvia
Pierre Wunsch	261	0.87	Belgium
Piero Cipollone	205	0.68	Member of the Executive Council since 2023-11
Gediminas Simkus	200	0.66	Lithuania
Frank Elderson	167	0.55	Member of the Executive Council
Gabriel Makhlouf	162	0.54	Republic of Ireland
Peter Kazimir	153	0.51	Slovakia
Olli Rehn	130	0.43	Finland
Constantinos Herodotou	108	0.36	Cyprus
Bostjan Vasle	82	0.27	Slovenia
Boris Vujcic	71	0.24	Croatia
Madis Muller	62	0.21	Estonia
Edward Scicluna	10	0.03	Malta
Gaston Reinesch	3	0.01	Luxembourg
Total	**30154**	**100.00**	

Table 2: Counts and Percentages of Mentions of ECB Governing Council Members with NCB Representatives

From the analysis of Table 2, Christine Lagarde accounts for nearly two-thirds of all matches. She is followed by the Vice President, who holds approximately 5.81% of the total, and Isabel Schnabel with 3.77%. It is notable that governors from smaller countries, such as Gaston Reinesch with only three articles and Edward Scicluna with only ten articles, are positioned at the lower end of the table.

It is evident that the dataset is unbalanced and disproportionately skewed towards Christine Lagarde. Additionally, it can be observed that the Executive Council Members maintain a significant representation, alongside notable representation from the governors of Germany, France, and Spain.

4 Methodology

4.1 Index and Human Labelling

To establish a baseline for the classifier models, it was necessary to manually label articles. The articles were categorised as either "Hawkish", "Dovish", or "Neutral" (see Table 3). In binary terms, "Dovish" is represented as -1, "Neutral" as 0 and "Hawkish" as 1. As a baseline, we established a scoring system: 'Hawkish' denotes a strong stance on reducing inflation, 'Neutral' indicates ambiguity towards their monetary policy stance or that they are talking about something else, and 'Dovish' signifies criticism of inflation-reducing efforts and support for more relaxed measures.

A random sample of 100 articles was selected from the dataset and labelled by each of us. The purpose of this randomisation was to capture the inherent bias in the dataset, as explained in section 3.2.

Manual Summary	**Joaquin**	**Rui**	**Ed**
Speaking at the IMF in Washington, ECB President Christine Lagarde reaffirmed her commitment...	Hawkish	Hawkish	Hawkish
Starting in October, the ECB wants to use a new climate score...	Neutral	Neutral	Neutral
ECB Chief Economist Philip Lane has proposed taxing high incomes or corporate profits...	Hawkish	Neutral	Hawkish
Former German Chancellor Angela Merkel has received the State Prize of...	Neutral	Neutral	Neutral
The ECB has raised its interest rates again by 0.25 percentage points...	Hawkish	Hawkish	Hawkish
Banco de España Governor Pablo Hernández de Cos defended the full implementation of...	Neutral	Neutral	Neutral

Table 3: Manual Labelling

Once the human labelling was completed, summary statistics were added to the manually labelled articles. The statistics were then summed up, creating an average sentiment score for each of the manual classifiers (see Table 4).

Classifier	Standard Deviation	Median	Average	Counts_Dovish	Counts_Neutral	Counts_Hawkish
Joaquin	0.658971	1.0	0.49	9	33	58
Rui	0.658741	1.0	0.52	9	30	61
Ed	0.666667	0.5	0.40	10	40	50

Table 4: Manual Labelling Statistics

The average value of the 'Average' column is 0.47. This figure will be used to assess the ability of each prompt to classify the articles in the dataset.

4.2 OpenAI API

4.2.1 Prompt Selection

According to the reviewed literature, the OpenAI model: Chat-GPT4 stands out as the best LLM for understanding financial concepts from a human perspective. To evaluate its performance, we created five distinct prompts and used the OpenAI API to label the same 100 rows that were previously labelled manually. The prompts were as follows:

1. "Discard all the previous instructions. Behave like you are an expert sentence classifier. Classify the following statement from an ECB member into 'HAWKISH', 'DOVISH', or 'NEUTRAL'. Label it 'HAWKISH' if it suggests tightening monetary policy, 'DOVISH' if it suggests easing monetary policy, or 'NEUTRAL' if the stance is ambiguous or not directly related to monetary policy:"

2. "Discard all the previous instructions. Behave like you are an expert sentence classifier. Assess the following statement from an ECB member in the context of maintaining price stability and promoting maximum employment. Determine whether it reflects a HAWKISH (tightening), DOVISH (easing), or NEUTRAL stance on monetary policy or is ambiguous:"

3. "Discard all the previous instructions. Behave like you are an expert sentence classifier. Analyze the following statement from an ECB member and identify the likely impact on interest rates, economic growth, and inflation. Based on your analysis, classify the sentence as HAWKISH, DOVISH, or NEUTRAL:"

4. "Discard all the previous instructions. Behave like you are an expert economist. Evaluate the following statement from an ECB member from the perspective of how the media reader might interpret it. Would it likely be perceived as HAWKISH (signaling higher rates), DOVISH (signaling lower rates), or NEUTRAL (ambiguous):"

5. "Discard all the previous instructions. Behave like you are an expert economist. Given current economic conditions, determine whether the following statement from an ECB member suggests a HAWKISH (concerned about inflation), DOVISH (concerned about growth), or NEUTRAL stance on monetary policy or ambiguous:"

The prompt most similar to manual classifiers was OpenAI Prompt 4 with a difference of 0.015 from the manual average.

Prompt	Counts_Dovish	Counts_Neutral	Counts_Hawkish	Standard Deviation	Average
openai_prompt_1	17	24	58	0.769443	**0.414141**
openai_prompt_2	13	5	81	0.694680	**0.686869**
openai_prompt_3	13	17	65	0.725939	**0.547368**
openai_prompt_4	21	9	69	0.825161	**0.484848**
openai_prompt_5	16	2	81	0.744526	**0.656566**

Table 5: Performance metrics for different OpenAI prompts

4.2.2 Classify Sample Dataset: Chat-GPT4

Now the objective was to use OpenAI Prompt 4 to classify sentiment. Due to resource limitations, it was not possible to classify all articles with Chat-GPT4. The decision was taken to use OpenAI Prompt 4 to classify a sample set, 10% (3000 articles) of the articles. Following a similar process as we did with the prompt selection we randomly selected a new set of 3000 articles.

Manual Summary	OpenAI Score
Speaking at the IMF in Washington, ECB President Christine Lagarde reaffirmed her commitment...	1
Starting in October, the ECB wants to use a new climate score...	0
ECB Chief Economist Philip Lane has proposed taxing high incomes or corporate profits...	-1
Former German Chancellor Angela Merkel has received the State Prize of...	0
The ECB has raised its interest rates again by 0.25 percentage points...	1

Table 6: OpenAI Scores on Training Set

4.3 Models prediction

With 3000 articles now classified, we explored models that could scale up on the work done by OpenAI and accurately classify the 30,000 articles in the ECB dataset. Through researching academic papers, we identified prediction models best suited for this type of financial text analysis.

5 Models

5.1 Dictionary benchmark

Rule-based classification is common practice in financial natural language processing. This technique works by classifying financial text based on certain keyword combinations. Gorodnichenko et al. (2023) demonstrated the effectiveness of this approach by categorising sentences as dovish or hawkish, depending on the combination of financial-related nouns and verbs within predefined panels in each sentence. We used this method as our benchmark classification, applying Gorodnichenko's financial word dictionary, on the ECB manual summaries. As seen in Table 8, a sentence is classified as dovish if it includes words from panels A1 and A2 or B1 and B2. Conversely, it is classified as hawkish if it contains words from A1 and B2 or A2 and B1. If a sentence contains a word from panel C, we reverse the initial classification—dovish becomes hawkish and vice versa.

Panel A1	**Panel A2**
inflation expectation, interest rate, bank rate, fund rate, price, economic activity, inflation, employment, price stability, asset prices, consumer prices, producer prices	anchor, cut, subdue, decline, decrease, reduce, low, drop, fall, fell, decelerate, slow, pause, pausing, stable, non-accelerating, downward, tighten, stimulate, support, accommodative, dovish tilt, gradualism, patient, cautious, easing bias

Panel B1	**Panel B2**
unemployment, growth, exchange rate, productivity, deficit, demand, job market, monetary policy, labor market, wage growth, output gap, trade balance	ease, easing, rise, rising, increase, expand, improve, strong, upward, raise, high, rapid, tightening, restrictive, constrain, hawkish tilt, aggressive, tightening bias, overheated economy

Panel C (Handling Contractions)
weren't, were not, wasn't, was not, did not, didn't, do not, don't, will not, won't

Table 7: Rule-based dictionary used by Gorodnichenko et al. (2023)

5.2 Pretrained BERT Model

For our main model of classification, we decided to use a pre-trained RoBERTa model from Hugging Face (Shah et al. (2023)). This model has already been pre-trained on data related to Federal Open Market Committee (FOMC) news, including meeting minutes, press conferences, and speeches from FOMC members, highlighting its familiarity with the nuances of financial language.

BERT (Bidirectional Encoder Representations from Transformers) models are designed to understand the context of a word in search queries. Unlike traditional models that read text input sequentially (left-to-right or right-to-left), BERT reads the entire sequence of words at once. This bidirectional approach allows BERT to understand the meaning of a word based on surrounding words, providing a deeper understanding of language context.

5.3 Pretrained BERT Model Fine-Tuned

We fine-tuned the pre-trained RoBERTa model with the expectation of further enhancing the performance of the model. This fine-tuning process involved adapting the model specifically to our dataset, by inserting the articles already classified by OpenAI (see chapter 4.2.2). By fine-tuning, the BERT model became more adept at recognising central banking language and context specific to the ECB articles. Thus, the model was able to more accurately identify sentiment linked to the ECB governors and effectively classify the articles, as hawish, dovish or neutral.

6 Results

6.1 Dictionary-Based Classification

Our baseline, the dictionary-based classification method yielded relatively poor results. Given the simple structure of the model this was unsurprising; the F1-score was approximately 0.40. We believe this score was the result of the complexity of the news expression across the member states. This consisted of diverse languages, idiomatic nuances, and considerable variations in article lengths. These challenges collectively hindered the accuracy and reliability of the baseline classification approach and highlights the need of a more complex and tailored model to accurately classify the ECB articles.

6.2 BERT Models

A grid search was used to find the best hyperparameters for each model. The models were run both with and without text preprocessing (removing stop-words, lemmatising, etc.) and the results were compared. The results were similar, and we believe that this is because BERT models are designed to capture the contextual information in the input text. The model is able to effectively handle noise, such as punctuation or stopwords.

Table 8: Comparison of Classification Models Performance

Metric	Dictionary-based	FOMC-RoBERTa	Ft/FOMC-RoBERTa
		Dovish (0)	
Precision	0.23	0.60	0.57
Recall	0.70	0.31	0.51
F1-Score	0.34	0.41	0.54
		Hawkish (1)	
Precision	0.83	0.83	0.79
Recall	0.29	0.78	0.89
F1-Score	0.43	0.80	0.84
		Neutral (2)	
Precision	0.35	0.32	0.39
Recall	0.69	0.75	0.15
F1-Score	0.47	0.45	0.21
		Overall Metrics	
Accuracy	0.40	0.60	0.74
Macro Avg	0.41	0.55	0.53
Weighted Avg	0.42	0.69	0.72

Table 8 shows the performance results of all models. The fine-tuned RoBERTa model shows significant improvement both in overall accuracy and weighted average metrics. This confirms that the fine-tuning has enhanced the model's ability to classify the articles correctly. However, there is a trade-off. The slightly lower macro average metric, suggests that while the fine-tuned model performs better overall, its performance on individual classes like ”Neutral” has decreased. This trade-off is common in fine-tuning processes. We suspect that the imbalance in our dataset is a significant factor contributing to this issue. Additionally, the increased complexity of classifying articles with a ”Neutral” label introduces further nuances, complicating the task for the model.

7 Creating the Cacophony Index

7.1 Sentiment Per Governor

The next step is to develop the cacophony index. We apply our most effective model, the Ft/FOMC-RoBERTa, across all articles. Below presents the classification results for each article paired with the corresponding speaker throughout the entire observation period.

Examining Table 9, we observe that despite the majority of speakers having more than half of their articles labeled as hawkish, governors from Southern European central banks tend to occupy lower positions. This includes Pablo Hernandez de Cos from Spain, Mario Centeno from Portugal,

Name of Speaker	**Dovish %**	**Neutral%**	**Hawkish%**	**Total**
Gaston Reinesch	0.0	0.0	100.0	3
Boris Vujcic	9.9	0.0	90.1	71
Edward Scicluna	10.0	0.0	90.0	10
Joachim Nagel	9.1	1.6	89.3	1084
Olli Rehn	4.6	6.9	88.5	130
Martins Kazaks	10.0	2.4	87.6	340
Robert Holzmann	9.3	3.2	87.5	344
Gabriel Makhlouf	7.4	6.8	85.8	162
Piero Cipollone	4.4	11.2	84.4	205
Philip Lane	15.6	1.0	83.3	1080
Bostjan Vasle	17.1	0.0	82.9	82
Pierre Wunsch	14.6	3.1	82.4	261
Peter Kazimir	13.1	5.9	81.0	153
Christine Lagarde	16.6	3.5	79.9	18483
Klaas Knot	17.9	2.8	79.3	352
Madis Muller	19.4	1.6	79.0	62
Constantinos Herodotou	14.8	9.3	75.9	108
Isabel Schnabel	21.4	2.7	75.9	1137
Luis de Guindos	18.5	5.7	75.9	1752
Gediminas Simkus	19.0	7.5	73.5	200
Fabio Panetta	17.5	9.9	72.6	838
Pablo Hernandez de Cos	19.9	9.6	70.5	633
Mario Centeno	23.9	10.2	66.0	591
François Villeroy de Galhau	29.1	5.3	65.6	951
Ignazio Visco	29.5	6.5	64.0	552
Yannis Stournaras	33.0	8.2	58.8	403
Frank Elderson	5.4	43.1	51.5	167
Total Count	**5200**	**1320**	**23634**	**30154**

Table 9: Sentiment percentages for each speaker (sorted by % of Hawkish)

Ignazio Visco from Italy, and Yannis Stournaras from Greece. François Villeroy de Galhau, Governor of Banque de France, and Fabio Panetta, a member of the Executive Board for most of our observation period, also appears in this group.

The model identifies a distinct neutral pattern in the speeches of Executive Board member Frank Elderson, who often discusses climate change as Vice-Chair of the ECB Supervisory Board, rather than focusing solely on monetary policy.

At the top of the table, Gaston Reinesch, Boris Vujcic, and Edward Sciluna rank noticeably, though this may be influenced by the limited number of observations available to accurately assess their stance. Joachim Nagel, the Governor of Bundesbank, follows immediately afterwards with nearly 89.3% of articles labeled as hawkish. Close to him are Olli Rehn from Finland and Martins Kazaks from Latvia.

Christine Lagarde, the ECB President, stands near the middle of the table despite the highest number of observations (18,483), with approximately 79.9% of her articles labeled as hawkish.

In order to develop the Cacophony Index, we need to establish a timeframe that allows for meaningful comparisons, with the data available.

7.2 Determining the Index Timeframe Aggregation

First, we aimed to determine the appropriate timeframe for analysing sentiment. To ensure that we would be able to have at least a representative of each ECB Governing Council Member, we started to analyse the aggregated counts of the articles mentioning each member. We decided to aggregate the data based on monetary policy statements, which are produced every six weeks. We chose this approach because:

- Monetary policy statements are the primary communication tool of the ECB.
- They influence the perception of the ECB's overall stance, affecting the positions of Governing Council Members.
- There was sufficient representation in our timeline to capture the sentiment of most Executive Council Members.

Upon analysing the different timelines, we discovered that the data became significantly skewed and reduced after the monetary policy statement of 2023-12-14. This resulted in the exclusion of many governors included in previous statements. Additionally, during this period, there were two monetary policy statements (2024-01-25 and 2024-03-07), leading to fewer articles to analyse. To ensure data quality, we excluded these two statements from the results of this paper, although the same methodology can be applied in future studies. To contextualise below are the dates of the ECB Monetary Policy Statement and respective interest rate raise.

Date	Interest Rate Raise
2022-07-21	0.50
2022-09-08	0.75
2022-10-27	0.75
2022-12-15	0.50
2023-02-02	0.50
2023-03-16	0.50
2023-05-04	0.25
2023-06-15	0.25
2023-07-27	0.25
2023-09-14	0.25
2023-10-26	0.00

Table 10: Chronology of Monetary Policy Statements

Lastly, we found that averaging the sentiment indicated in these articles provides a reliable measure to condense the overall sentiment portrayed by the speaker. Using the average is effective because it offers a balanced and representative view of the speaker's sentiment over time, while taking into account possible outliers, capturing the general trend.

7.3 Baseline

The purpose of the cacophony index is to determine if there are differences in sentiment among the ECB Governing Members. To build the index, we need a representative of the official position of the ECB. We decided to use Christine Lagarde as the baseline for the following reasons:

- As the President of the ECB, she is closest to the official position of the institution.
- We have comprehensive data on her for this timeline.
- Her sentiment aligns with the official interest rate trends, with a more hawkish sentiment during periods of interest rate rises and more dovish sentiment towards the end of the research period, when interest rates stop rising.

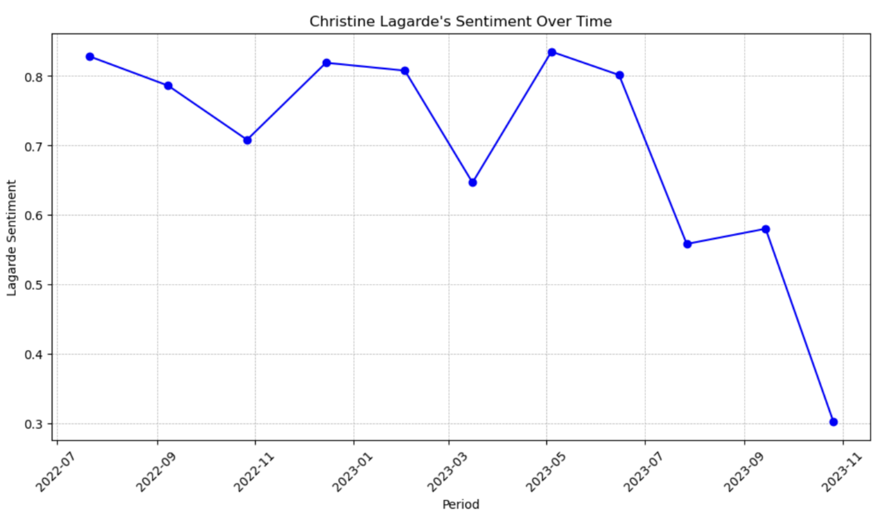

Figure 2: Sentiment Graph of Christine Lagarde, ECB President

To investigate if the relationship between interest rate increases and Christine Lagarde's sentiment was merely apparent or statisically significant, we examined if her sentiment following a monetary policy statement could explain the decisions made at that time.

The regression reveals a statistically significant correlation at the 5% level, indicating that Christine Lagarde's sentiment following the monetary policy statement has a statistical relationship to previous interest rate raises. The significance level shows that this relationship is statistically supported,

Table 11: OLS Regression Results with Interest Rate as Dependent Variable

Variable	**Coefficient (P.Value)**
Christine Lagarde's Sentiment	0.8275 (0.048)

although it would not be significant at the more stringent 1% level. Moreover, the coefficient of 0.8275 implies that at the maximum level of our sentiment indicator (1), the previous raise in the interest rate would be, on average, 0.8275. This suggests that a higher sentiment of hawkishness on the Lagarde sentiment is correlated with a higher interest rate increase.

7.4 Difference of the ECB Governing Council Members Sentiment

To observe the differences between the various governors of the ECB, we constructed table 12 showing the observed sentiment for each member of the Executive Council. We calculated an overall "Weighted Difference" which accounts for the different Capital Keys of the countries[1]. This was done to weigh the importance of each ECB governing member in the overall cacophony. We redistributed the remaining capital key of the non-eurozone members, through the Executive Board Members, excluding Lagarde. Finally, it is important to mention that Gaston Reinesch, Edward Scicluna and Boris Vujcic, the NCB Governors of Luxembourg, Malta and Croatia, respectively, were excluded from these calculations because they did not have significant interventions in all periods, making calculation infeasible.

Looking at Table 12, we observe distinct tendencies amongst the governors representing the major economies of the Eurozone. For instance, Joachim Nagel consistently appears more hawkish than Christine Lagarde in all periods except one. Conversely, Ignazio Visco and François de Villeroy de Galhau are consistently perceived as more dovish, with only occasional exceptions. These patterns, first reflected in Table 9, are now displayed more granularly across the periods.

Turning to other major economies, Spanish Governor Pablo Hernandez de Cos and Dutch Governor Klaas Knot show contrasting stances. Hernandez de Cos is more dovish in seven periods compared to Lagarde, whereas Knot is more hawkish in eight periods.

Among Executive Council Members, Luis de Guindos initially appears more dovish than Lagarde overall but shifts to a more hawkish stance in the last three periods. Fabio Panetta consistently maintains a dovish stance across seven periods. Isabel Schnabel closely aligns with Lagarde throughout most periods, except the last. Philip Lane shows a balanced view with five periods more hawkish and six more dovish. Frank Elderson, is perceived as more dovish in seven periods and more hawkish in four, with his index influenced more by ambiguity than by straightforward dovishness, as seen in table 9.

To examine the trend of the weighted difference, we plotted it to analyse its trajectory over time.

[1]The allocation of shares for National Central Banks (NCBs) within the capital structure of the ECB is determined by a formula that considers each country's proportionate contribution based on both its population and gross domestic product (GDP) within the European Union.

Name of Speaker	**2022-07-21**	**2022-09-08**	**2022-10-27**	**2022-12-15**	**2023-02-02**	**2023-03-16**	**2023-05-04**	**2023-06-15**	**2023-07-27**	**2023-09-14**	**2023-10-26**	**Weight**
Joachim Nagel	0.105	0.180	0.125	0.021	-0.008	0.248	0.124	-0.099	0.160	0.148	0.403	0.218
François Villeroy de Galhau	0.172	-0.031	-0.141	-0.183	-0.161	0.056	-0.430	-0.449	-0.089	-0.292	-0.366	0.164
Ignazio Visco	-0.428	-0.504	-0.262	-0.597	-0.445	-0.103	-0.429	-0.704	-0.558	-0.239	0.554	0.131
Pablo Hernandez de Cos	0.172	-0.173	-0.382	0.050	-0.359	0.050	-0.132	-0.301	-0.121	-0.131	0.187	0.097
Klaas Knot	0.172	0.093	-0.128	0.044	0.049	0.245	0.095	-1.041	-0.225	0.109	0.164	0.048
Luis de Guindos	-0.384	-0.127	-0.310	0.009	-0.030	-0.123	-0.203	-0.126	0.158	0.116	0.198	0.039
Fabio Panetta	-1.213	0.066	-0.483	-0.123	-0.492	0.125	-0.328	-0.086	-0.127	0.271	0.005	0.039
Frank Elderson	-0.186	-0.186	-0.458	-0.819	0.192	0.020	-0.224	-0.176	-0.114	0.039	0.114	0.039
Isabel Schnabel	-0.002	0.058	0.042	-0.047	0.047	0.174	-0.197	-0.046	-0.047	0.059	-0.617	0.039
Philip Lane	0.038	-0.186	-0.001	0.092	0.031	0.206	-0.277	-0.066	-0.519	-0.080	0.241	0.039
Pierre Wunsch	0.172	0.214	0.292	-0.486	0.044	0.313	0.022	-0.529	0.442	-0.639	0.338	0.030
Robert Holzmann	-0.064	0.214	0.083	-0.105	0.046	0.035	-0.391	0.199	0.386	0.115	0.371	0.024
Mario Centeno	-0.328	-0.196	-0.384	-0.281	-0.517	-0.128	-0.323	-0.438	-0.480	-0.269	0.156	0.019
Yannis Stournaras	-0.828	-0.186	-0.708	-0.242	-0.281	-0.285	-0.554	-0.461	-0.500	-0.557	-0.063	0.018
Gabriel Makhlouf	0.172	-0.358	0.070	-0.041	0.192	0.171	-0.094	-0.301	-0.301	0.170	0.524	0.018
Olli Rehn	0.172	-0.248	0.292	0.181	-0.016	0.059	0.165	0.122	0.442	0.420	-0.303	0.015
Peter Kazimir	0.172	0.214	0.292	0.181	0.192	0.123	0.165	0.032	0.134	-0.493	-0.017	0.009
Gediminas Simkus	0.172	-0.000	0.292	-0.194	-0.016	-0.202	-0.057	-0.201	-0.669	-0.152	0.180	0.005
Bostjan Vasle	0.172	0.214	0.292	0.181	0.192	0.353	0.165	-0.135	0.442	-0.247	-0.103	0.004
Martins Kazaks	0.023	0.142	-0.170	0.070	-0.262	0.195	-0.008	-0.024	0.042	0.300	0.297	0.003
Madis Muller	0.172	0.214	0.292	-0.819	-0.058	0.020	0.165	-0.087	0.442	-0.469	-0.636	0.002
Constantinos Herodotou	-0.072	-0.072	-0.170	-0.152	-0.208	0.171	-0.085	-0.051	-0.892	-0.174	0.697	0.002
Weighted Difference	-0.057	-0.061	-0.119	-0.156	-0.137	0.091	-0.177	-0.319	-0.095	-0.068	0.151	

Table 12: Difference of sentiment between the different members of the Executive Council and Christine Lagarde

Looking at Figure 3, we observe that for most periods (8 out of 10), the weighted difference from Lagarde ranges between 0.1 and -0.1. However, on dates such as 2023-05-04 and 2023-06-15, the Governing Council appears more dovish, with the weighted difference reaching values higher than 0.1 only in the last date observed. This indicates a tilt towards hawkishness.

Nevertheless, the weighted difference does not fully capture cacophony because it overlooks the dispersion within the Executive Council. To better understand this dispersion, a more detailed analysis of each period's variation is necessary.

7.5 Cacophony of the ECB Governing Council

To assess the cacophony within the ECB Governing Council, we utilised the InterQuartile Range (IQR) as our method of analysis. This statistical approach helps identify which speakers frequently occupy the more extreme quartiles, indicating perceived divergence from the ECB's official stance. Additionally, the IQR provides insights into the central range where most speakers are positioned and their deviation from the baseline. By examining changes in the Q3 and Q1 boundaries, we gain a comprehensive understanding of trends and dynamics, making the IQR an ideal tool for our analysis.
Table 13 provides valuable insights into the dynamics within the ECB Governing Council. Notably, the periods with the lowest InterQuartile Range (IQR), 2023-02-02 and 2023-03-16, coincide with the ECB's interest rate increases. This suggests a more unified perception of the ECB's stance in the media during this time. Additionally, on 2023-03-16, we observe a unique instance where the Q1 boundary reached higher values, indicating fewer dovish voices than usual.

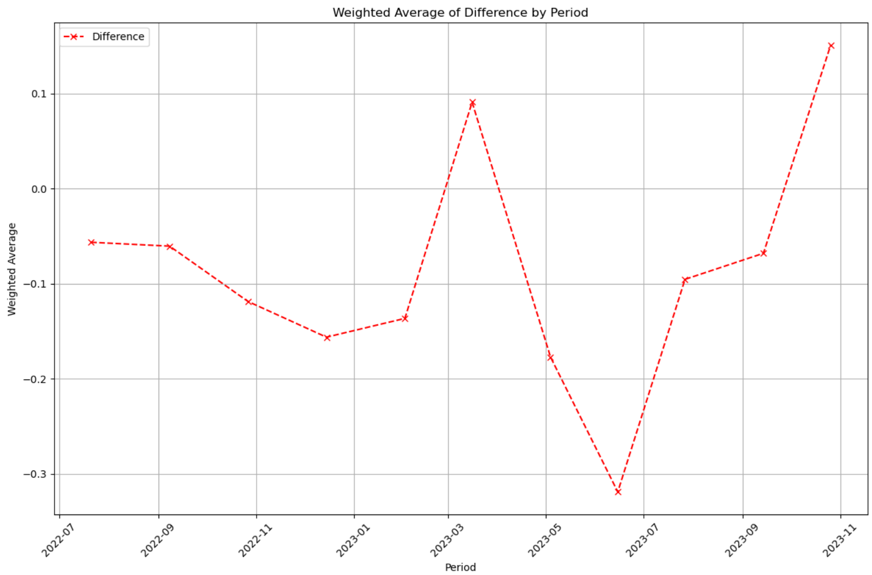

Figure 3: Weighted Difference of the Governing Council Members to Lagarde

Period	IQR	Q3 Boundary	Q1 Boundary
2022-07-21	0.329	0.172	-0.158
2022-09-08	0.357	0.171	-0.186
2022-10-27	0.548	0.250	-0.298
2022-12-15	0.279	0.049	-0.230
2023-02-02	0.296	0.047	-0.249
2023-03-16	0.170	0.190	0.020
2023-05-04	0.389	0.077	-0.312
2023-06-15	0.349	-0.055	-0.404
2023-07-27	0.595	0.160	-0.435
2023-09-14	0.379	0.116	-0.264
2023-10-26	0.379	0.328	-0.052

Table 13: Summary of IQR, Q3, and Q1 boundaries for each period

Significant divergences are evident on 2022-09-08 and 2023-07-27, with IQRs of 0.548 and 0.595, respectively. These periods likely experienced the greatest cacophony. On 2022-09-08, the quartile boundaries were relatively balanced, with a Q3 value of 0.250 and a Q1 value of -0.298. However, the divergence was more stark on 2023-07-27, where the Q1 boundary fell to its lowest at -0.435, suggesting a pronounced disparity in opinions among the council members during that time.

These fluctuations indicate an initial hawkish alignment with ECB President Lagarde's sentiment, which matched the council's trend of raising interest rates. Over time, however, as rates continued to rise, a shift toward a more dovish sentiment emerged, evidenced by the Q1 value decreasing markedly from -0.404 to -0.052 in the time period of 2023-06-15 to 2023-10-26. This shift brought the baseline closer to more dovish positions. Changes in Q3 towards the end of the observed period do not necessarily reflect a change in stance from the more hawkish members but rather a softening in the perceived hawkishness of Lagarde herself. This analysis underscores the evolving consensus and dissent within the ECB Governing Council. Economic policies and external conditions influence the collective and individual stances of its members.

To identify which members of the ECB Governing Council are perceived as having more diverging views, we can analyse how frequently certain speakers appear in either Q1 or Q4. Q1 indicates that a speaker is perceived as being more dovish compared to the baseline. Conversely, appearing in Q4 suggests that a speaker is perceived as more hawkish than the baseline on that period. By counting the occurrences of each speaker in these quartiles, we can understand whether there are certain voices that are constantly perceived with a certain perspective. The full analysis for each period is in the Appendix in the Tables 15,16,17 and in 18.

Rank	Speaker Counts on Q1	Speaker Counts on Q4
1	Mario Centeno: 10	Bostjan Vasle: 7
2	Yannis Stournaras: 10	Joachim Nagel: 6
3	Ignazio Visco: 8	Peter Kazimir: 6
4	Fabio Panetta: 4	Olli Rehn: 6
5	François Villeroy de Galhau: 4	Pierre Wunsch: 5

Table 14: Top 5 Speakers in Q1 and Q4 over the period observed

Table 14 corroborates the findings in Table 9, particularly regarding the positioning of various central bank governors in Q1 and Q4. In Q1, which represents a more dovish stance compared to the baseline, we find the governors from Portugal, Greece, Italy, and France. Notably, the Portuguese and Greek governors appear in this quartile in almost every period, but one. Additionally, Executive Board Member Fabio Panetta stands out as the only member of the Executive Board ranked in these quartiles.

In Q4, which identifies those with a more hawkish stance than the baseline, the rankings include the governors from Slovenia, Germany, Slovakia, Finland, and Belgium. The position of German Governor, Joachim Nagel, is particularly noteworthy. Representing the country with the largest capital key in the Eurozone, Germany's consistent placement within this quartile carries significant weight.

8 Conclusion

The goal of this paper is to measure how the media perceives the communication of the ECB Governing Council members. In order to do this, a cacophony index was created to identify and quantify discordance from the official position of the institution. The analysis focused on governor comments related to the status of inflation and the monetary policy of the ECB.

The data source for this research was a broad array of media articles provided by the ECB Strategy Communications Team. The manual summary of the articles populated by human professionals, served as the basis of the sentiment analysis. A total of 30,154 articles were successfully matched with corresponding names of ECB Governing Council Members, achieving a 96% match rate.

After reviewing the latest techniques for classifying central bank texts, articles were categorised as dovish, hawkish, or neutral. Initial benchmarks were created through manual labelling and rule-based classifications. An iterative approach using natural language processing techniques of gradually increasing complexity was applied. An optimal Chat-GPT4 prompt was selected by comparing performance against benchmarks, which then labelled 10% of the dataset using the OpenAI API. The Chat-GPT4 classification was used to fine-tune a pre-trained RoBERTa model on financial text, which enhanced its performance on the specific types of articles used in this paper. This fine-tuning proved to be more effective compared to both a dictionary-based classification and an untuned RoBERTa model.

The fine-tuned RoBERTa model labelled all articles. The result was that, on average, 78% of articles were classified as hawkish. Notably, governors from Southern European central banks tended to occupy more dovish positions.

A cacophony index was created to quantify discordance, with sentiment aggregated around the release dates of ECB monetary policy statements. Christine Lagarde's sentiment was defined as the baseline, given her proximity to the institution's official position. A overall weighted-difference index was created accounting for the varying capital keys for each member-state. Bundesbank Governor Joachim Nagel consistently appeared more hawkish than Lagarde, while Ignazio Visco and François Villeroy de Galhau of Italy and France, respectively, were regularly perceived as more dovish. It was noted that the weighted difference did not fully capture cacophony due to the inability to fully capture dispersion of sentiment within the Executive Council.

An inter quartile range (IQR) statistical approach more effectively identified speakers frequently occupying extreme quartiles, indicating higher perceived divergence from the ECB's official stance. In Q1, the quartile representing an extremely dovish stance, we found the governors from Portugal, Greece, Italy, and France. In Q4, identifying those with a more hawkish stance, the rankings included governors from Germany, Slovenia, Slovakia, Finland, and Belgium. The IQR analysis supported the initial observation from the pre-trained RoBERTa model that Southern European central bank governors were perceived as the most dovish, whereas the consistent placement of the German central bank governor within the hawkish quartile carries significant weight given the size of their population and economy.

We contribute to the literature in two key ways: first, by employing state-of-the-art NLP techniques on a new and comprehensive dataset that capture public statements made by the ECB Governing Council Members, throughout a period of rising interest rates. Secondly, by providing meaningful insights that could stimulate further studies on the dissidence of the ECB Governing Council Members. We believe that one of the limitations we encountered was the low representation of some NCB Governors, which may have resulted in slightly skewed results in our aggregated analysis. This could be due to these governors either not often speaking publicly or not being covered extensively by media. Furthermore, testing the whole dataset on more state-of-art LLM's could also improve the robustness of our results.

There are several extensions to our research that warrant further exploration. One potential avenue is to investigate whether the sentiment of specific ECB Governing Council members can be used to forecast possible interest rate changes. Another area of interest is examining whether dissidence within the Council could lead to less effective policy outcomes. Additionally, the study of sentiment could be used to understand the anchoring of inflation expectations both among the general public and within financial markets. While the sentiment analysis of Council members has been explored in previous literature, the advent of large language models (LLMs) has significantly enhanced the quality and accuracy of these analyses.

In conclusion, we aim for this research to inspire greater interest in utilising large language models (LLMs) to analyse statements from high-profile monetary policy leaders, thereby contributing to the growing trend of research in the field of monetary policy communication.

References

Amaya, D. and Filbien, J.-Y. (2015). The similarity of ecb's communication. *Finance Research Letters*, 13:234–242.

Bennani, H. and Neuenkirch, M. (2016). The (home) bias of european central bankers: New evidence based on speeches. *Applied Economics*, 49(11):1114–1131.

Blinder, A. S., Ehrmann, M., de Haan, J., and Jansen, D.-J. (2024). Central bank communication with the general public: Promise or false hope? *Journal of Economic Literature*. Forthcoming.

Blinder, A. S., Ehrmann, M., Fratzscher, M., De Haan, J., and Jansen, D.-J. (2008). Central bank communication and monetary policy: A survey of theory and evidence. *Journal of Economic Literature*, 46(4):910–45.

Gorodnichenko, Y., Pham, T., and Talavera, O. (2023). The voice of monetary policy. *American Economic Review*, 113(2):548–84.

Hansen, A. L. and Kazinnik, S. (2023). Can chatgpt decipher fedspeak? *Available at SSRN*.

International Monetary Fund (2022). Central bank communications: A technical assistance handbook.

Istrefi, K., Odendahl, F., and Sestieri, G. (2021). Ecb communication and its impact on financial markets. *Working Paper*, (859).

Jansen, D.-J. and de Haan, J. (2006). Look who's talking: Ecb communication during the first years of emu. *International Journal of Finance & Economics*, 11(3):219–228.

Jansen, D.-J. and de Haan, J. (2010). An assessment of the consistency of ecb communication using wordscores. *DNB Working Paper*, 259.

Leek, L. C., Bischl, S., and Freier, M. (2024). Introducing textual measures of central bank policy-linkages using chatgpt.

Picault, M. and Renault, T. (2017). Words are not all created equal: A new measure of ecb communication. *Journal of International Money and Finance*, 79:136–156.

Shah, A., Paturi, S., and Chava, S. (2023). Trillion dollar words: A new financial dataset, task & market analysis. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 6664–6679, Toronto, Canada. Association for Computational Linguistics.

Tillmann, P. and Walter, A. (2019). The effect of diverging communication: The case of the ecb and the bundesbank. *Economics Letters*, 176:68–74.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L., and Polosukhin, I. (2017). Attention is all you need. In *Advances in Neural Information Processing Systems*, Long Beach, CA, USA. NIPS.

Appendix

	2022-07-21	2022-09-08	2022-10-27
Q4	No speaker goes over the threshold	Joachim Nagel (0.180) Pierre Wunsch (0.214) Robert Holzmann (0.214) Peter Kazimir (0.214) Bostjan Vasle (0.214) Madis Muller (0.214)	Pierre Wunsch (0.292) Olli Rehn (0.292) Peter Kazimir (0.292) Gediminas Simkus (0.292) Bostjan Vasle (0.292) Madis Muller (0.292)
Q1	Yannis Stournaras (-0.828) Fabio Panetta (-1.213) Luis de Guindos (-0.384) Ignazio Visco (-0.428) Frank Elderson (-0.186) Mario Centeno (-0.328)	Gabriel Makhlouf (-0.358) Olli Rehn (-0.248) Mario Centeno (-0.196) Ignazio Visco (-0.504)	Yannis Stournaras (-0.708) Fabio Panetta (-0.483) Luis de Guindos (-0.310) Frank Elderson (-0.458) Mario Centeno (-0.384) Pablo Hernandez de Cos (-0.382)

Table 15: Q4 and Q1 Speakers for the 2022-07-21, 2022-09-08, and 2022-10-27

	2022-12-15	2023-02-02	2023-03-16
Q4	Pablo Hernandez de Cos (0.050) Philip Lane (0.092) Olli Rehn (0.181) Peter Kazimir (0.181) Bostjan Vasle (0.181) Martins Kazaks (0.070)	Klaas Knot (0.049) Frank Elderson (0.192) Isabel Schnabel (0.047) Gabriel Makhlouf (0.192) Peter Kazimir (0.192) Bostjan Vasle (0.192)	Joachim Nagel (0.248) Klaas Knot (0.245) Philip Lane (0.206) Pierre Wunsch (0.313) Bostjan Vasle (0.353) Martins Kazaks (0.195)
Q1	Ignazio Visco (-0.597) Frank Elderson (-0.819) Pierre Wunsch (-0.486) Mario Centeno (-0.281) Yannis Stournaras (-0.242) Madis Muller (-0.819)	Ignazio Visco (-0.445) Pablo Hernandez de Cos (-0.359) Fabio Panetta (-0.492) Mario Centeno (-0.517) Yannis Stournaras (-0.281) Martins Kazaks (-0.262)	Ignazio Visco (-0.103) Luis de Guindos (-0.123) Mario Centeno (-0.128) Yannis Stournaras (-0.285) Gediminas Simkus (-0.202)

Table 16: Q4 and Q1 Speakers for the Periods 2022-12-15, 2023-02-02, and 2023-03-16

	2023-05-04	2023-06-15	2023-07-27
Q4	Joachim Nagel (0.124)	Isabel Schnabel (-0.046)	Joachim Nagel (0.160)
	Klaas Knot (0.095)	Robert Holzmann (0.199)	Pierre Wunsch (0.442)
	Olli Rehn (0.165)	Olli Rehn (0.122)	Robert Holzmann (0.386)
	Peter Kazimir (0.165)	Peter Kazimir (0.032)	Olli Rehn (0.442)
	Bostjan Vasle (0.165)	Martins Kazaks (-0.024)	Bostjan Vasle (0.442)
	Madis Muller (0.165)	Constantinos Herodotou (-0.051)	Madis Muller (0.442)
Q1	François Villeroy de Galhau (-0.430)	François Villeroy de Galhau (-0.449)	Ignazio Visco (-0.558)
	Ignazio Visco (-0.429)	Ignazio Visco (-0.704)	Philip Lane (-0.519)
	Fabio Panetta (-0.328)	Klaas Knot (-1.041)	Mario Centeno (-0.480)
	Robert Holzmann (-0.391)	Pierre Wunsch (-0.529)	Yannis Stournaras (-0.500)
	Mario Centeno (-0.323)	Mario Centeno (-0.438)	Gediminas Simkus (-0.669)
	Yannis Stournaras (-0.554)	Yannis Stournaras (-0.461)	Constantinos Herodotou (-0.892)

Table 17: Q4 and Q1 Speakers for the Periods 2023-05-04, 2023-06-15, and 2023-07-27

	2023-09-14	2023-10-26
Q4	Joachim Nagel (0.148)	Joachim Nagel (0.403)
	Luis de Guindos (0.116)	Ignazio Visco (0.554)
	Fabio Panetta (0.271)	Pierre Wunsch (0.338)
	Gabriel Makhlouf (0.170)	Robert Holzmann (0.371)
	Olli Rehn (0.420)	Gabriel Makhlouf (0.524)
	Martins Kazaks (0.300)	Constantinos Herodotou (0.697)
Q1	François Villeroy de Galhau (-0.292)	François Villeroy de Galhau (-0.366)
	Pierre Wunsch (-0.639)	Isabel Schnabel (-0.617)
	Mario Centeno (-0.269)	Yannis Stournaras (-0.063)
	Yannis Stournaras (-0.557)	Olli Rehn (-0.303)
	Peter Kazimir (-0.493)	Bostjan Vasle (-0.103)
	Madis Muller (-0.469)	Madis Muller (-0.636)

Table 18: Q4 and Q1 Speakers for the Periods 2023-09-14 and 2023-10-26