Information in Central Bank Sentiment: An analysis of Fed and ECB Communication

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Abstract

This paper uses modern data analysis tools to measure sentiment overtime of published Central Bank communications. We employ natural language processing and FinBERT techniques (machine learning models adapted to analyze financial news) to construct sentiment based on FOMC minutes, and ECB press conferences. We also construct sentiment based on speeches, statements and CB overviews of economic conditions, and find high correlation across communications. Fed and ECB sentiment tends to move together, but there is little evidence of one leading the other. Using local projection analysis, we find that CB sentiment leads policy rates and the Taylor rule. In turn, stock market returns tend to lead Central Bank sentiment. Our findings imply that there is important information in CB communication sentiment, which could be used to identify monetary policy shocks.

1 Introduction

In recent years, central banks have been confronted with various crises, including financial turmoil and the pandemic-induced inflation surge in both the US and the EU. As a result, they have deployed measures to stabilize economies and markets. Central bank communication is usually defined as the provision of information by the central bank to the public on the objective of monetary policy, the strategy to achieve these objectives, the economic outlook, and the outlook for future policy decisions (Blinder et al., 2008). CB communication has emerged as a cornerstone tool for shaping the monetary policy sentiments of all financial market participants. Its role has transformed from supporting the conventional monetary policy framework to actively guiding financial markets and aiding central banks in attaining their macroeconomic objectives (Niţoi et al., 2023).

Central banks communicate through various channels, including policy statements, post-meeting press conferences, economic forecasts, monetary policy reports, speeches, interviews, and testimonies to parliament (Blinder et al., 2008). These communications are supposed to help reinforce key messages and provide additional clarity on the central bank's policy intentions (de Haan and Hoogduin, 2024; Blinder et al., 2008; Benchimol et al., 2021). Communication practices for both the Federal Reserve and the ECB (European Central Bank) have evolved over the past decades. Prior to 1990s, central banks followed a practice of little communication that was indirect in its messaging (de Haan and Hoogduin, 2024).

Over time communications and transparency of central banks evolved dramatically and have become more complicated. While tools and methods of communication used by the Fed and the ECB were relatively different in the past, there is evidence that they have converged over time de Haan and Hoogduin (2024). For example, the FOMC began publishing minutes of its meetings in 1993, while the ECB started publishing its minutes in 2015. On the other hand, the ECB has had press conferences after each policy meeting since its start in 1999, while the Fed introduced press conferences after each meeting in 2019.

While the communication tools and techniques of both the ECB and the Fed have become more similar, an open question is the relationship between the monetary policy which is adopted by each central bank and the corresponding communication. Do the two banks react similarly to the state of the global economy? Are there feedback effects where the policy of one leads the other? For example, as of April 2024, the ECB plans to reduce interest rates in light of a continued fall in inflation in the Eurozone. In contrast, the Fed is expected to keep rates on hold. According to Reuters, ECB President Christine Lagarde insisted her institution was "data-dependent, not Fed-dependent." However, analysts and policymakers remark that high US inflation and interest rates were bound to have an impact on the ECB's plans via financial markets and trade.[1]

In this paper we explore the relationship between the Fed and the ECB monetary policy by constructing and analyzing sentiment of Fed and ECB communications. While there is a large and growing literature aimed at quantifying sentiment from central banks announcement and speeches, we extend this analysis by developing a measure for sentiment over time for both the ECB and the Fed and study the relationship between these two measures.

For the purpose of sentiment calculation, we utilized the FinBERT pre-trained Natural Language Processing (NLP) model. FinBert is an open source model that has been specifically trained on financial data, and outperforms almost all other NLP techniques for financial sentiment analysis.

We proceed in four steps. First, we construct sentiment for different modes of central bank communication – minutes/press conferences, statements, beige book/economic bulletin and speeches. The sample periods over which these are available is quite different. In particular, only speeches go back farther for the ECB. We then filter the time series data in order to focus on lower-frequency movements in sentiment. While sentiment tends to move together across measures, overall we find quite varied correlations of sentiment across communications. Fed statements tend of have the highest correlation with minutes, but it changes over time. We therefore use Fed minutes and ECB press conference sentiment for our analysis.

Second, using local projection analysis, we check if the Fed or the ECB leads the other

[1] See: "ECB cannot ignore Fed as it goes down its rate cut path" by Francesco Canepa and Balazs Koranyi in: https://www.reuters.com/markets/europe/solo-minded-ecb-may-find-itself-singing-feds-hymn-sheet-after-all-2024-04-11/

central bank. We find some contemporaneous correlation, but there is little evidence of policy predictability.

Third, we explore the effect of Fed and ECB sentiment on monetary policy stance and the state of the economy. We use local projection analysis to check if sentiment can predict policy rates as well as the Taylor rule. We find that for both the Fed and the Euroarea, sentiment leads economic conditions as measured by the Taylor rule, i.e. the output gap and the deviation of inflation from its target. Similarly, sentiment leads policy interest rates for both the Fed and the ECB. We check that the central bank sentiment is not simply a measure of overall consumer sentiment but contains additional information. Indeed, we find that Fed sentiment is a more informative predictor of the federal funds rate as compared to the Michigan sentiment measure.

Fourth, we check if stock market returns lead central bank sentiment. One might hypothesize that financial markets reflect all available information. Indeed, when returns are high, sentiment at the next meeting tends to be higher. This is true both for the Fed and for the ECB.

Overall, we find that sentiment of central bank publications are a strong leading indicator for key variables related to central banks' monetary policy stance. A negative central bank sentiment indicates potential cuts in interest rates, while positive sentiment tends to predict interest rate increases. This additional tool allows increased accuracy in the forecasting of funds rates and helps market observers predict potential future policy changes.

1.1 Methods for Sentiment Analysis

Analyzing central bank communications and annotating sentiment of every sentence published is a time-consuming task. In that past, this has limited sentiment analysis projects to only one document base, or to look at a narrow range of publications. As computing technology has improved, so have potential applications in many areas, including financial market analysis. Initially, many papers translated textual information from central bank communications into quantitative measures through the utilization of lexicon-based approaches.

This method relies on predefined lists of words, known as lexicons or dictionaries, where each word is assigned a score indicating its sentiment. For instance, a lexicon might include words categorized as positive, neutral, or negative, with corresponding scores of 1, 0, and -1 respectively.

Word-matching methods are often termed as bag-of-words (BOW) techniques.[2] This is because they disregard contextual characteristics such as word order, part-of-speech, and co-occurrence with other words, focusing solely on the individual words themselves (Shapiro et al., 2022a). Loughran and McDonald (2011) find that general dictionaries do not provide sufficient accuracy for tonality in finance contexts and create a dictionary tailored to the context of 10-K reports. They find that almost three-fourths of the words in the Harvard dictionary have a different connotation in finance.

The main limitation of lexicon based methods are their inability to account for the context of the keywords (Niţoi et al., 2023). Therefore, a second generation of Machine Learning (ML) methods have been developed. These methods construct complex models for probabilistically predicting the sentiment of a given set of text. However, this type of model ignores the order of words and the small training sets can pose modeling challenges (Shapiro et al., 2022a). The third generation of models are the deep learning models that extracts sentiments from a text by relying on similar labeled text data to learn and tune its embeddings parameters. The main shortfall of these models is the need for a large amount of human labeled text data for training.

In this paper, we use a third generation model - the FinBERT for sentiment analysis. Bidirectional Encoder Representations from Transformers, or BERT, is a transformer deep learning model developed by Google in 2017 and was made open source in 2018. The big advancement that BERT made in the field of machine learning is its ability to be trained on large datasets. This is due to BERT not requiring as much preprocessing as previous models such as Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) did.

Building on top of the BERT model, FinBERT, that was first developed by Araci (2019),

[2] Althought it is rare, lexicon can be a list of n-grams rather than just unigrams (single words). Similarly, some lexicons use word stems to match all inflected variants of a given word.(Shapiro et al., 2022a)

builds a transformer model that designed to analyze financial documents. Since FinBERT was tranied on financial sentiment lexicons,it can predict the sentiment of financial documents with a higher accuracy than BERT and other similar models. Further improvements have been made to both the model and prepossessing of the data used in the model. By training the model on central bank communications the model was able to better identify the sentiment of announcements made by these bodies.(Gössi et al., 2023).

1.2 Related Literature

Our paper is mostly related to two strands of the economic and financial literature. The first, is textual analysis techniques to capture how the sentiment of central banks communication affects and market behavior. The earliest method employed for applying natural language processing techniques to sentiment analysis of central bank publications involved the use of keyword lexicons or word bank (i.e., a vocabulary bank). This method entailed creating a work banks that categorize words as either good or bad, or as hawkish or dovish. Documents are then fed through a natural language processor and each block of text is given a count for the number of appearances a word for each list appears. This keyword identification is refined by identifying keywords relative to other keywords, such as looking for the appearance of raise or lower within a few words of the word interest rate. The earliest example of this approach is done by de Haan et al. (2007) that analyze how ECB communications would influence Euro area inflation expectations.

Loughran and McDonald (2011) used a financial dictionary that utilized 10-K reports to measure sentiment for financial documents. While the dictionary developed by Loughran and McDonald (2011) is widely used to measure central banks' sentiment, it has been claimed that in the context of central banks, the interpretation of words as negative or positive may be biased. As a result, Correa et al. (2021) refined and improved the dictionary, classifying the words in a manner that better fits the style of central bank communication.

This work expanded out to the effects sentiment had on other markets and key macroeconomic indicators. These measurements of sentiment have been used to analyse a range of market aspects. This included analysis of the stock market performance and trade volume (Gu et al., 2022), sentiment's predictive power of the Taylor Rule (Picault and Renault, 2017), and market interest rates (Tadle, 2022). Work has also been done to assess the effect sentiment has on market stability (Correa et al., 2017). Work is also done to analyse not only how the information within the publications has an effect but also how Central bank publication changes in communication methods and transparency have changed their ability to stabilize the market and effect public perception (Oosterloo et al., 2007). This is especially relevant over the past two decades in the US and Europe as their communication methods and transparency has converged. This came to ahead in 2015 when the ECB overhauled their communication strategy to mimic the publication style and schedule of the Fed (Gardt et al., 2022).

The second strand of literature study the relationship between the ECB and Federal Reserve monetary policy. Belke and Gros (2005) find that the ECB is indeed often influenced by the Fed, but the reverse is true at least as often if one considers longer sample periods. There is empirically little support for the proposition that there has for a long time been a systematic asymmetric leader-follower relationship between the ECB and the Fed. Chinn and Frankel (2007) argue that nominal US interest rates influence the European rates unilaterally even after the European Monetary Union (EMU).

The synchronized behavior of central banks is also measured by deviations from the Taylor Rule. Hofmann and Bogdanova (2012) have argued that deviations from the Taylor rule can be best interpreted as a change in the global equilibrium real interest rate. Taylor (1993) argues that a further transmission channel for international spillovers stems from the fact that central banks no longer decide on policy rates independently.

2 Data

Both The Federal Reserve and The ECB have a number of publications that convey information relevant to the economy. For this analysis we will be focusing on Speeches, Statements, Minutes, and Beige Books. For The ECB, we will be looking at Speeches, Monetary Policy

Accounts, Economic Bulletin, and Press Conferences.

Speeches by Federal Reserve officials, such as the Chair or Board of Governors members, give insights into their views on the economy, monetary policy, and financial markets. These speeches can signal potential policy changes or provide updates on the central bank's assessment of the economic outlook. For example, a speech by the Fed Chair indicating concern about rising inflation could signal a possible interest rate hike in the future. Statements, released after meetings of the Federal Open Market Committee (FOMC), convey the Fed's policy decisions and forward guidance. The Fed is the policy-making body of the Federal Reserve, and its decisions have a significant impact on the economy. For example, the Fed's decision to raise or lower interest rates can have a major impact on borrowing costs, investment, and economic growth. Minutes of FOMC meetings provide a detailed account of the discussions and considerations that led to policy decisions. They offer transparency into the central bank's decision-making process and can help investors and economists understand the rationale behind policy changes. For example, the minutes of an Fed meeting might reveal that the central bank was divided on the decision to raise interest rates, and that some members expressed concerns about the potential impact on economic growth. Beige Books, published eight times a year, summarize economic conditions in each Federal Reserve district. They provide qualitative and quantitative information on employment, production, spending, and credit conditions, contributing to a comprehensive understanding of regional economic activity. For example, a Beige Book might report that manufacturing activity in the Midwest is expanding, while consumer spending in the Northeast is slowing down.

The European Central Bank (ECB) also publishes a number of publications that provide insights into its assessment of the economic situation and its policy decisions. Speeches by ECB officials, such as the President or Executive Board members, offer a unique opportunity to gain insights into their views on the economy, monetary policy, and financial markets. These speeches often signal potential policy changes or provide updates on the central bank's assessment of the economic outlook. Monetary Policy Accounts summarize the discussions and decisions of the ECB's Governing Council, which is the policy-making body of the ECB.

These accounts provide a detailed account of the central bank's decision-making process and can help investors and economists understand the rationale behind policy changes. The Economic Bulletin, published four times a year, provides in-depth analysis of economic and monetary developments in the euro area. It includes articles on a wide range of topics, such as inflation, economic growth, and financial stability. Press conferences, held after Governing Council meetings, provide an opportunity for ECB officials to explain the central bank's policy decisions and to answer questions from journalists. These press conferences can provide valuable insights into the ECB's thinking and its assessment of the economic situation.

Table 1: Central Bank Publications Used in Sentiment Analysis.

Dataset	Start Date	End Date	Num. of Docs.	Docs/Year	Words Per Doc
Fed Documents					
Speeches	01-2000	05-2023	1225	52	3,698
Statements	02-2000	05-2023	199	8	475
Minutes	02-2000	05-2023	188	8	13,692
Beige Books	01-2006	05-2023	140	8	20,435
ECB Documents					
Speeches	01-2000	06-2023	1788	76	4,502
Monetary Policy Accounts	02-2015	06-2023	69	8	5,704
Economic Bulletin	02-2015	05-2023	67	8	61,710
Press Conferences	01-2000	05-2023	241	8	1,634

Over time, the communication, and transparency of The FOMC and The ECB has changed. As identified by (Middeldorp, 2011) over time, the FOMC has become or transparent and has increased communication over time. This was done to increase monetary policy predictability. Menno identifies FOMC communication reforms in the early 1990s and in 2003 that significantly improved monetary policy predictability.

3 Sentiment Analysis

To obtain a accurate sentiment classification of publications, we must process, classify, and filter these texts. While this may be achieved in the future, currently we are unable to feed an entire raw document into a machine learning model and receive an accurate result. Instead we must process the data into sentences that can then be classified. Once we have results for every sentence in every document we can then group and filter these results to further improve the accuracy of our sentiment measure. To measure sentiment we implement a modified version of FinBERT, a pre-trained NLP model. The original FinBERT model is used to analyse financial texts and is built on Googles BERT model. We used (Gössi et al., 2023) version of the model that has been fine-tuned on FOMC minute publication sentiment to improve its accuracy in identifying the sentiment of Central Bank publications. After sentiment classification of our processed texts, we apply The Hodrick-Prescott filter to our data before running time series analysis.

This sentiment analysis is looking at overall sentiment of each sentence as opposed to classifying them with a certain characteristic such as in (Tadle, 2022) who labels sentences as either hawkish or dovish. In our analysis positive is considered a sentence that is positive in a general financial context not as it relates to a specific aspect of the economy. This general sentiment classification allows us to use these results on a variety of questions related to CB sentiment not just a specific area such as inflation.

3.1 Data Processing and Sentiment Classification

For the NLP filtering of the data, the Python library Natural Language Toolkit (Bird et al., 2009) is leveraged to read and break up each publication. The texts are broken up into the detected sentence sub-strings using the sentence tokenizer API. Once the text is broken up into sentences, the texts are further refined in preparation for sentiment analysis. We accomplish this by removing punctuation symbols and and stop words. This makes it easier for FinBERT to analyse the essence of the sentence and have a higher chance of accurately identifying it. Our first step in sentiment classification was preprocessing the data. We prepared the Central Bank publications for sentiment analysis using a series of preprocessing steps that would standardise our data. Our first step was to take all of the various forms the data was in and standardise them into sentences in a CSV format. For this we imported all of the data out of the PDFs, CSVs, or JSON files that they were previously in and converted them into CSVs. We then broke up every text block that was naturally identified into sentences using the NLTK toolkit sentence tokenizer API (Bird et al., 2009).

After standardizing our data, we applied the techniques described in (Gössi et al., 2023). This involved removing unnecessary commas and condensing sentences to their essential components. By removing commas we improve sentence clarity by identifying and eliminating commas that precede conjunctions or root verbs, which helps maintain the overall sentiment of the sentence. It achieves this by analyzing the dependency tags of each word in the sentence. When a comma is followed by a token with the dependency tag "ROOT" (main verb) or "conj" (conjunction), it is considered extraneous and is removed. The resulting sentence structure is cleaner and more coherent, which can improve sentiment analysis accuracy. Refining the sentence is achieved by adjusting the focus of sentences based on specific conjunctions like "but," "although," and "though," as well as the position of commas. This function isolates the most sentimentally relevant part of a sentence, especially in complex sentences with contrasting clauses. For example, in sentences beginning with "but," the text following "but" is isolated as it likely contains the crux of the sentiment. Similarly, for sentences containing "although" or "though," the function extracts the most sentimentally significant portion by navigating the commas that typically demarcate shifts in sentiment.

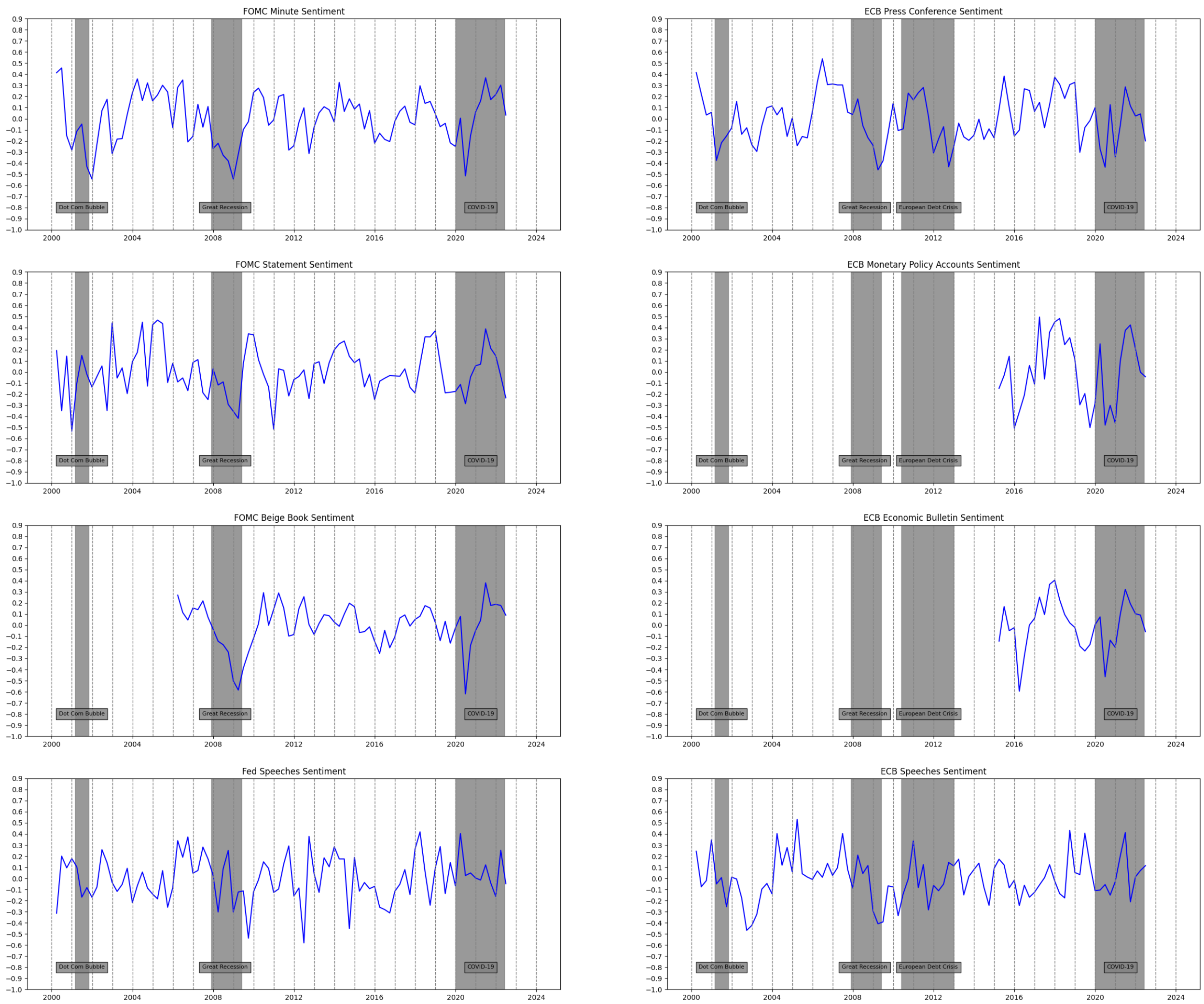
Table 2: Summary Statistics of Central Bank Sentiment

Dataset	Mean	SD	Min	Max	Num. of Docs.
		Fed Documents			
Speeches	-0.03	0.139	-0.40	0.53	1225
Statements	-0.04	0.18	-0.83	0.31	199
Minutes	-0.14	0.11	-0.42	0.16	188
Beige Books	-0.04	0.14	-0.46	0.18	140
		ECB Documents			
Speeches	-0.01	0.11	-0.40	0.43	1788
Monetary Policy Accounts	-0.12	0.12	-0.36	0.11	69
Economic Bulletin	0.03	0.04	-0.10	0.10	67
Press Conferences	0.07	0.16	-0.32	0.45	241

3.2 Lower frequency sentiment: HP Filter

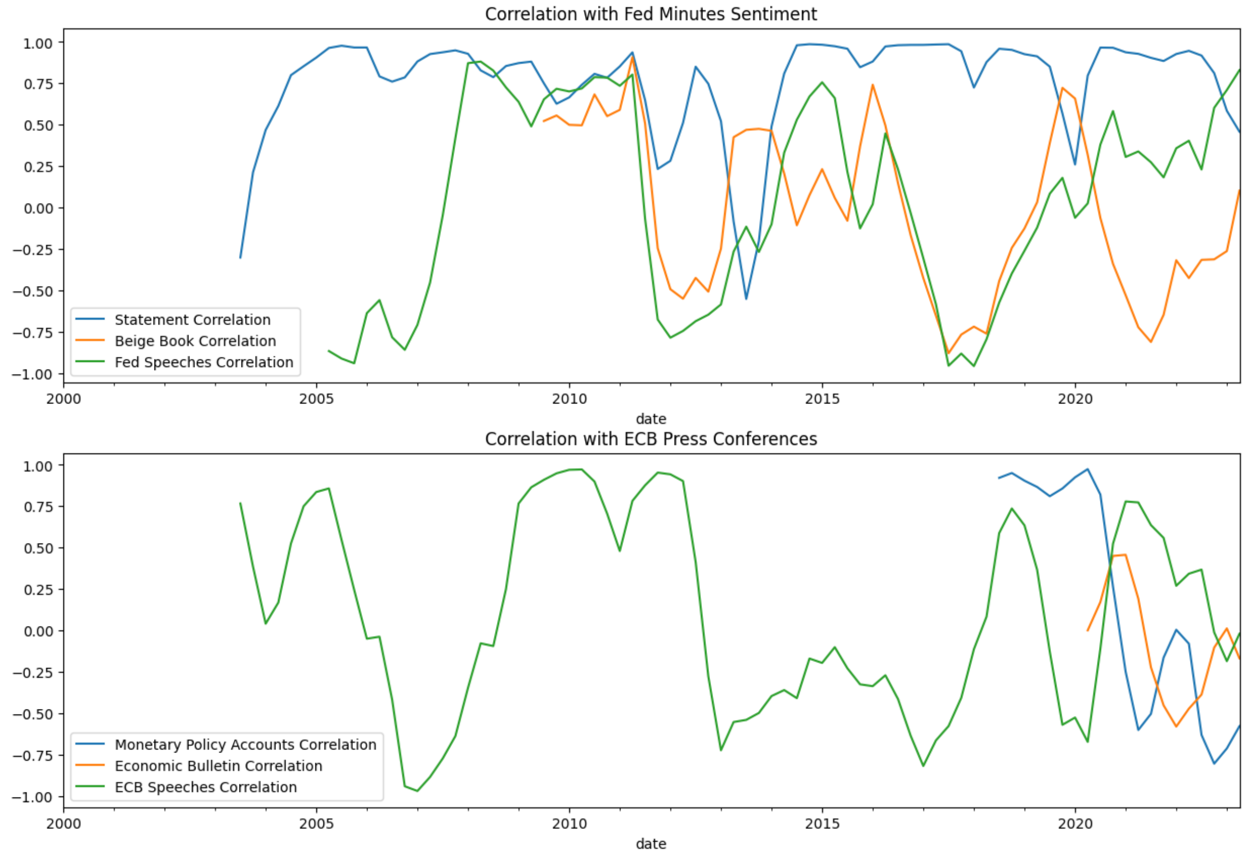
To smooth our Time series data we implement a Hodrick Prescott (HP) filter.Hodrick and Prescott (1997) We use an HP filter due to its ability to isolate the underlying sentiment trend from short term fluctuations. Central Bank communications, while structured and consistent, are subject to inherent volatility arising from economic events, policy announcements, and, as highlighted in your study, changes in communication policies themselves. The HP filter addresses this challenge by smoothing the sentiment score series, thus enhancing the effects of long-term sentiment trends that are necessary in economic analysis. This smoothing process for eliminating noise induced by temporary events or policy shifts, ensuring that the extracted sentiment trends accurately reflect the overarching message of Central Bank communications over time(Fernandez et al., 2021).

Figure 1: Central Bank Sentiment Over Time. Sentiment measurements for Central Bank publications grouped by quarter and low frequency filtered using a Hodrick–Prescott filter.



Comparing the sentiment of the various publication, the sentiment across documents within a Central Bank and Across The Fed and ECB cycle in step with each other. Correlation Between our primary sentiment reference and general speech sentiment for both The Fed and ECB cycle over the years with Fed Beige Books correlation moving with speech correlation. This reflections the difference in messaging that Central Banks have for different communication methods. Fed minutes and ECB press conferences are scheduled planned events that each party knows will be analysed in depth by the public. Given that speeches are have a higher frequency and given by a range of speakers, the sentiment of these transcripts are not going to be as carefully planned and will differ across speaker and topic.

Figure 2: Correlation of Sentiment Measurements. Two year moving correlation of Central Bank publications relative to reference publication sentiment.



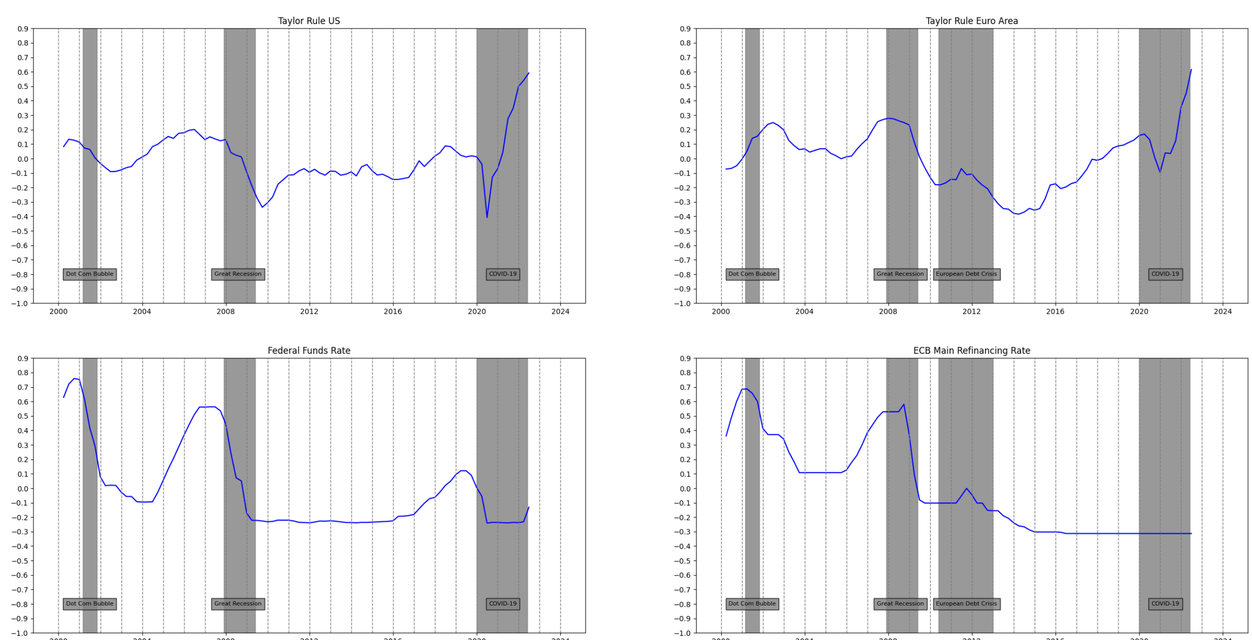
4 Analysis and Results

For our analysis we will be focusing on FOMC Minutes and ECB Press Conferences. FOMC Minutes were chosen because they cover a large time span, and have been used in previous sentiment analysis. For the ECB we will use press conference data as the representative for Europe. ECB Monetary Policy Accounts may be a better comparison to FOMC minutes but given we are looking at quarterly data and Monetary Policy Accounts only have existed since 2015 they were not ideal to use. In future work once more data has accumulated or under a different analysis method these may be better to use.

The goal of these regressions to see if sentiment is a leading indicator for key macroeconomic variables. To do this we will regress these key variables against the filtered sentiment of Central Bank publications. To account for any spurious regression that may occur we include a lagged variable as a independent variable (Granger and Newbold, 1974). Additionally, we will implement Whites standard errors to correct for homoscedasticity within our data (White, 1980).

Local projection analysis is a statistical technique that can be used to analyze the relationship between two variables, taking into account the possibility of non-linearity(Jordà, 2005). We apply this in our analysis to assess the magnitude of which Central Bank sentiment affects interest rates and Taylor Rule. This allows for detailed and nuanced analysis of the relationship between the sentiment of these publications and our key macroeconomic variables. Local projection analysis can capture any non-linearity in the relationship between our dependent and independent variables. In many cases, the relationship between variables is not linear, and using local projection analysis can provide a more accurate and informative analysis. Data in this analysis is grouped by quarter to account for differences in meetings across Central Banks

Figure 3: Interest Rate and Taylor Rule for Fed and ECB



4.1 Federal Reserve vs. European Central Bank sentiment

Given that Central Banks have taken steps to align their publication and meeting strategies, logically the information and sentiment of these publications will also start reflecting each other. Our results show that sentiment in one bank's communications can be predictive of sentiment in the other. A key finding is that current ECB sentiment has a positive correlation with future Fed sentiment, and vice versa, though the strength and significance of these correlations vary over time. This could imply that there is some degree of synchronization in the policy outlooks of the two banks, possibly due to shared economic challenges or global economic conditions that affect both the Eurozone and the United States. The lagged variables in the regressions suggest that the sentiment in one bank's communications can influence the sentiment in the other bank's communications in subsequent periods.

These results demonstrate how policy outlook in one major economy can have ripple effects on others. For instance, an optimistic sentiment in the ECB's communications about the Eurozone's economic recovery might be followed by a similar sentiment in the Fed's communications, as improved conditions in the Eurozone could positively impact the global and US economies. The results suggest a certain degree of alignment or at least responsiveness between the Fed and ECB, which is crucial for global economic stability. In a highly interconnected global economy, coordinated Central Bank policies can help mitigate international financial turbulence. Market participants can use this information to anticipate shifts in monetary policy and adjust their investment strategies accordingly. The analysis underscores the importance of central bank communications as a policy tool. By analyzing the sentiment in these communications, researchers and market participants can gain deeper insights into the central banks' views on economic conditions, their policy inclinations, and the potential direction of future monetary policy moves.

Table 3: **FOMC Minute Sentiment Regressed on ECB PC Sentiment.**

	Fed(t)	Fed(t+1)	Fed(t+2)	Fed(t+3)	Fed(t+4)
ECB(t)	0.184**	0.186**	0.097	0.021	-0.157**
	(0.081)	(0.086)	(0.090)	(0.092)	(0.074)
ECB(t-1)	-0.056	-0.161*	-0.236**	-0.329***	-0.203**
	(0.077)	(0.090)	(0.097)	(0.087)	(0.082)
Fed(t-1)	0.478***	0.219**	0.207**	0.242**	0.067
	(0.087)	(0.096)	(0.101)	(0.101)	(0.099)
Observations	89	89	89	89	89
R^2	0.310	0.095	0.085	0.170	0.156

Note: *p<0.1; **p<0.05; ***p<0.01

Note: White Standard Errors in parentheses

Table 4: **ECB Press Conference Sentiment Regressed on FOMC Minute Sentiment.**

	ECB(t)	ECB(t+1)	ECB(t+2)	ECB(t+3)	ECB(t+4)
Fed(t)	0.294**	0.160	0.230	0.198	0.169
	(0.116)	(0.161)	(0.155)	(0.149)	(0.155)
Fed(t-1)	-0.060	0.139	0.066	0.094	0.190
	(0.142)	(0.154)	(0.164)	(0.163)	(0.153)
ECB(t-1)	0.481***	0.163	0.112	-0.055	-0.166
	(0.082)	(0.102)	(0.101)	(0.114)	(0.113)
Observations	89	89	89	89	89
R^2	0.315	0.092	0.072	0.039	0.065

Note: *p<0.1; **p<0.05; ***p<0.01

Note: White Standard Errors in parentheses

4.2 Taylor Rule

Taylor Rule data for the US is sourced from calculations preformed by FRED and our Euro Area Results are sourced from Bloomberg. Taylor Rule is a calculation of that captures the interest rate relationship with inflation rates and economic growth with the following formula(Taylor, 1993).

$$r = p + 0.5y + 0.5(p - 2) + 2 \tag{1}$$

where

r is interest rate

p is rate of inflation over the previous four quarters

y is percent deviation of real GDP from a target

$$y = \frac{100(Y - Y^*)}{Y^*}$$

where

Y is real GDP

Y^* is trend in real GDP

Results indicate a significant relationship between the sentiment of Fed and ECB communications and the application of the Taylor Rule. Positive sentiment in the communications is associated with an increase in the predicted interest rate based on the Taylor Rule, suggesting that optimistic central bank sentiment can signal a tightening monetary policy in response to expected inflation or economic growth. Conversely, negative sentiment might indicate a relaxed policy stance. These findings are significant as they highlight the predictive power of central bank sentiment on key policy instruments like the interest rate as guided by the Taylor Rule. It suggests that central bank communications carry crucial information not just about current economic conditions, but also about future policy directions. This demonstrates the importance of textual analysis and sentiment measurement in understanding monetary policy and its implications for the financial markets.

Table 5: Taylor Rule US Regressed on FOMC Minute Sentiment

	Taylor US(t)	Taylor US(t+1)	Taylor US(t+2)	Taylor US(t+3)	Taylor US(t+4)
Fed(t)	6.033***	7.206***	10.656***	12.444***	11.736***
	(2.310)	(1.651)	(2.278)	(3.078)	(4.088)
Fed(t-1)	-0.073	3.078	3.172	2.277	1.969
	(1.767)	(2.284)	(2.408)	(3.105)	(3.552)
Taylor US(t-1)	0.957***	0.865***	0.733***	0.560***	0.373***
	(0.055)	(0.074)	(0.092)	(0.116)	(0.122)
Observations	89	89	89	89	89
R^2	0.865	0.741	0.607	0.433	0.268

Note: *p<0.1; **p<0.05; ***p<0.01

Note: White Standard Errors in parentheses

Table 6: Taylor Rule EU Regressed on ECB PC Sentiment

	Taylor EA(t)	Taylor EA(t+1)	Taylor EA(t+2)	Taylor EA(t+3)	Taylor EA(t+4)
ECB(t)	1.019*	1.962**	4.280***	4.855***	4.794**
	(0.570)	(0.927)	(1.252)	(1.627)	(2.126)
ECB(t-1)	1.367**	3.123***	2.760**	2.925	3.498
	(0.681)	(1.055)	(1.258)	(1.783)	(2.150)
Taylor EA(t-1)	1.018***	1.003***	0.989***	0.945***	0.889***
	(0.030)	(0.055)	(0.084)	(0.110)	(0.129)
Observations	89	89	89	89	89
R^2	0.939	0.846	0.725	0.585	0.466

Note: *p<0.1; **p<0.05; ***p<0.01

Note: White Standard Errors in parentheses

4.3 Interest Rates

A key role that Central Banks play in policy making is setting rates. Speeches and publications can have explicit indicators regarding future changes in monetary policy(Shapiro and

Wilson, 2021), but less obvious indicators like sentiment and tone can also have an effect on the market (Gu et al., 2022). To assess this we regress rates set by The Central Bank on their respective sentiment. In both Europe and The US, sentiment has a strong positive relationship with their respective rates (Niţoi et al., 2023). This positive sentiment indicating interest rate hikes supports findings by (Shapiro and Wilson, 2021) who showed that FOMC sentiment is an indicator of target rate cuts.

Table 7: US Federal Funds Rate Regressed on Fed Sentiment

	Fed Rate(t)	Fed Rate(t+1)	Fed Rate(t+2)	Fed Rate(t+3)	Fed Rate(t+4)
Fed(t)	2.334***	3.835***	4.953***	5.518***	6.311***
	(0.596)	(0.915)	(1.260)	(1.526)	(1.762)
Fed(t-1)	1.511***	2.983***	4.134***	5.238***	5.715***
	(0.511)	(1.020)	(1.416)	(1.712)	(1.880)
Fed Rate(t-1)	0.969***	0.884***	0.760***	0.610***	0.464***
	(0.023)	(0.041)	(0.058)	(0.070)	(0.073)
Observations	89	89	89	89	89
R^2	0.971	0.896	0.770	0.620	0.486

Note: *p<0.1; **p<0.05; ***p<0.01

Note: White Standard Errors in parentheses

Table 8: EU Refinancing Rate Regressed on ECB Sentiment

	ECB Rate(t)	ECB Rate(t+1)	ECB Rate(t+2)	ECB Rate(t+3)	ECB Rate(t+4)
ECB(t)	0.784***	1.540***	2.089***	2.526***	2.306**
	(0.279)	(0.465)	(0.631)	(0.802)	(0.990)
ECB(t-1)	0.936***	1.616***	1.986***	1.827***	1.952**
	(0.218)	(0.385)	(0.534)	(0.684)	(0.845)
ECB Rate(t-1)	0.989***	0.948***	0.884***	0.807***	0.719***
	(0.020)	(0.036)	(0.049)	(0.059)	(0.068)
Observations	89	89	89	89	89
R^2	0.979	0.934	0.865	0.767	0.641

Note: *p<0.1; **p<0.05; ***p<0.01

Note: White Standard Errors in parentheses

Michigan Consumer Sentiment Index is a survey of American households to gauge consumer expectations. This survey focuses on three pieces of information. How consumers view their personal finances, the economy as a whole in the short run, and the economy as a whole in the long run. From the results below we see a that FOMC minute sentiment has is a strong short run indicator of consumer sentiment.

Utilising FOMC Minute and Consumer sentiment, observe a strong indicator Federal Funds Rates. A positive outlook from the FOMC and consumers indicates that rate increases are likely to occur in the coming quarters. The primary distinction between FOMC and consumer sentiment appears in when looking two or more quarters into the future. FOMC sentiment maintains high statistical significance when looking two to four quarters out whereas Consumer sentiment has a high drop off rate two quarters out and beyond.

Table 9: FedFunds Regressed on FOMC Minute Sentiment and Michigan Sentiment

	Fed Rate(t)	Fed Rate(t+1)	Fed Rate(t+2)	Fed Rate(t+3)	Fed Rate(t+4)
Fed(t)	1.368***	2.799***	4.005***	4.829***	6.195***
	(0.455)	(0.948)	(1.339)	(1.764)	(2.047)
Fed(t-1)	2.284***	3.790***	4.955***	5.954***	5.940***
	(0.510)	(1.125)	(1.531)	(1.930)	(2.131)
Michigan(t)	0.029***	0.031***	0.029*	0.022	0.005
	(0.006)	(0.011)	(0.017)	(0.023)	(0.026)
Michigan(t-1)	-0.025***	-0.026**	-0.026	-0.023	-0.007
	(0.006)	(0.012)	(0.017)	(0.022)	(0.025)
Fed Rate(t-1)	0.968***	0.882***	0.763***	0.621***	0.472***
	(0.023)	(0.043)	(0.063)	(0.077)	(0.083)
Observations	89	89	89	89	89
R^2	0.976	0.903	0.776	0.624	0.486

Note: *p<0.1; **p<0.05; ***p<0.01

Note: White Standard Errors in parentheses

These results expand on, and support the findings of (Shapiro et al., 2022b) find that new sentiment and sentiment shocks from measurements including Michigan Consumer Sentiment are indicators for consumer sentiment and the federal funds rate. We see a similar effect with Fed and ECB sentiment indicating that sentiment, especially when combined with other variables can be a strong indicator for key macroeconomic variables including interest rates.

4.4 Exchange Rates

A key market variable that is heavily affected by central bank policy is interest rates (Candian, 2021). Our regression results indicate ECB sentiment increases lead increase in the value of the Euro (relative to the USD). We also find that Fed sentiment increases lead to an increase in the value of the dollar relative to the Euro. Since we measure the exchange rate as dollars per euro, the latter effect shows up as a negative coefficient since the a lower exchange rate reflects an appreciating dollar. We note that the immediate effect of central bank communications is more pronounced for the ECB; the coefficient is positive and statistically significant. For the Fed, it is lagged sentiment that is negative (higher sentiment leads an appreciating dollar). There is such a bit of an asymmetry between responses.

These results are consistent with our results when assessing the effects of sentiment on interest rates, where central bank sentiment significantly influences interest rates. Positive sentiment from both the Fed and the ECB was associated with higher interest rates, reflecting a tighter monetary policy stance. This relationship between sentiment and interest rates likely transmits to exchange rates, as expectations of higher interest rates can attract foreign capital, leading to currency appreciation. However, the lagged effects seen in exchange rates suggest that market participants may take time to fully incorporate central bank sentiment into their expectations, or that other factors, such as economic data releases and geopolitical events, might effect this impact over time.

Table 10: USD to EU Regressed on FOMC Minute and ECB PC Sentiment

	USD to 1 Euro(t)	USD to 1 Euro(t+1)	USD to 1 Euro(t+2)	USD to 1 Euro(t+3)	USD to 1 Euro(t+4)
Fed(t)	0.083	0.057	-0.032	-0.022	-0.103
	(0.079)	(0.129)	(0.157)	(0.159)	(0.168)
Fed(t-1)	-0.134**	-0.217**	-0.213	-0.309**	-0.362**
	(0.063)	(0.109)	(0.132)	(0.157)	(0.160)
ECB(t)	0.087**	0.155**	0.124	0.095	0.151
	(0.044)	(0.078)	(0.096)	(0.114)	(0.119)
ECB(t-1)	-0.019	-0.068	-0.041	0.042	0.054
	(0.053)	(0.081)	(0.101)	(0.118)	(0.117)
USD to 1 Euro(t-1)	0.950***	0.867***	0.788***	0.719***	0.677***
	(0.041)	(0.065)	(0.073)	(0.071)	(0.069)
Observations	89	89	89	89	89
R^2	0.914	0.775	0.651	0.572	0.538
Adjusted R^2	0.909	0.761	0.630	0.546	0.510
Residual Std. Error	0.047 (df=83)	0.076 (df=83)	0.094 (df=83)	0.101 (df=83)	0.104 (df=83)
F Statistic	189.016*** (df=5; 83)	49.521*** (df=5; 83)	28.109*** (df=5; 83)	22.047*** (df=5; 83)	20.801*** (df=5; 83)

Note: *p<0.1; **p<0.05; ***p<0.01

4.5 Stock Market Analysis

For analysing the market and the interaction between market performance and Central Bank sentiment, we modify our approach from our previous method. Instead of breaking the data up into quarters, we use the publication dates. This doubles our frequency of observations and allows us to see a direct effect between market returns and announcements.This change in frequency means a change in the filtering of our data. When we previously used HP filter we used a quarterly lambda value of 1600. For a frequency of eight times per year we will use the findings of (Ravn and Uhlig, 2002) to calculate a new lambda value.

$$\lambda = 1600 * (Frequency\,per\,year/4)^4 = 1600 * (8/4)^4 = 25600 \tag{2}$$

When stock markets perform well, indicating investor confidence and potentially foretelling economic growth, central bank communications may reflect this positive outlook, which can further reassure markets and sustain investor sentiment. Conversely, when markets are in distress, the tone of central bank communications may become more cautious or pessimistic, mirroring these market conditions. This effect has a two meeting lag to it indicating that central bank sentiment is slow to respond to market performance. This observation underscores the non-instantaneous nature of sentiment adjustments in central bank communications relative to market dynamics. These insights are useful for understanding the dynamics between market performances and central bank sentiment, highlighting a reactionary rather than anticipatory nature in central bank communications.

These findings support (Shapiro and Wilson, 2021) who finds that The Fed cares about stock market returns. This supports the need to identify what Central Banks weigh when measuring economics health and understand why those variables have a strong influence over Central Bank sentiment and the decisions that they make.

Table 11: Regressing Fed Sentiment on S&P 500 Returns and Regressing ECB Sentiment on STOXX 600 Returns Market returns for the Fed are based on S&P 500 returns. Market returns for the ECB are based on STOXX 600 returns.The unit for t is the time between a given meeting and two meetings ago for the given Central Bank.

	Fed(t)	ECB(t)
Market Returns(t)	0.013	-0.044
	(0.039)	(0.039)
Market Returns(t-1)	0.168^{***}	0.121^{***}
	(0.040)	(0.031)
Market Returns(t-2)	0.168^{***}	0.013
	(0.037)	(0.035)
Market Returns(t-3)	0.110^{**}	0.079^{**}
	(0.043)	(0.031)
Fed(t-1)	0.337^{***}	
	(0.080)	
ECB(t-1)		0.427^{***}
		(0.087)
Observations	177	87
R^2	0.396	0.392

Note: *p<0.1; **p<0.05; ***p<0.01

Note: White Standard Errors in parentheses

5 Discussion

5.1 Improvement of Data Accuracy and Availability

A common problem when attempting to assess Central Bank communications is the availability of these publications and their structure. While most publications are available there can be in forms that are have to consolidate and accurately break up into texts. A common publishing structure for Central Banks is to have a separate page for every meeting or publication. This makes consolidating the data difficult and time consuming. This also mean that even when data is collected it is usually in a format that is hard to parse and can obscure sentence structure. An example of a step in the right direction is ECB speeches. The ECB has published a CSV containing all speeches given by A Central Bank Member with clear labels of title, speaker, and location. While the text formatting is not perfect, doing this with all publications would vastly improve data accessibility.

5.2 Incomplete Information

While we can perform analysis on the information published by Central Banks, we do not have access to all information or the private opinions of bank members. This lack of complete information poses a challenge to accurately predicting monetary policy decisions. Central Bank's policymakers may have internal discussions and considerations that are not publicly disclosed, which can lead to gaps in our understanding of their policy stance and decision-making processes. For instance, the minutes and statements published by these institutions often summarize decisions and provide some context, but they do not reveal the full scope of the deliberations or the diverse views of the committee members. This incomplete picture of Central Bank Sentiment can lead to misinterpretations or oversights when conducting sentiment analysis or forecasting future policy actions.

The private communications and planning of formal communications between central bank officials can also play a crucial role in shaping monetary policy. Given how much attention these reports get and the effect they have on the market, there is extensive planning that goes into writing these reports. Planned messages may not accurately reflect the market or future macroeconomic shocks, for example because the Central Bank may be trying to downplay potentially bad news. This could cause situations where the sentiment measurement is positive, but officials may privately have a less positive view of economic conditions.

6 Conclusion

In this paper, we have leveraged the capabilities of modern data analysis tools, including natural language processing and FinBERT sentiment classification techniques, to capture the effects of Central Bank communications on financial markets. Our analysis, of Federal Reserve and ECB publications, demonstrates the significant role that sentiment embedded within these communications plays in predicting future market variables and measures of economic conditions including the Taylor Rule and policy interest rates. Using local projection analysis, we find long and short term impacts of sentiment, offering insights into the relationship between Central Bank communications and financial market movements. We demonstrate that modern automated analysis techniques can complement previous potentially time consuming work of sentiment labelling. These automated results not only support previous findings of sentiment effects on market variables, but give us the ability to increase our sample size with little variable cost leading to increased robustness in our results.

Since our sentiment measure captures effects of central bank communications on monetary policy, it may be possible to use it to identify monetary policy shocks. Using this measure of sentiment allows for increased robustness in the analysis of (Romer and Romer, 1989) and (Romer and Romer, 2023). By automating the analysis of sentiment and doing it in a way that allows for the understanding of nuanced policy publications allows for the expansion of data used in identifying shocks and increasing model accuracy.

References

Araci, D. (2019). Finbert: Financial sentiment analysis with pre-trained language models.

Belke, A. and Gros, D. (2005). Asymmetries in transatlantic monetary policy-making: Does the ecb follow the fed? *JCMS: Journal of Common Market Studies*, 43(5):921–946.

Benchimol, J., Kazinnik, S., and Saadon, Y. (2021). Federal reserve communication and the covid-19 pandemic. *Covid Economics*, 79:218–256.

Bird, S., Klein, E., and Loper, E. (2009). *Natural Language Processing with Python*.

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):910–945.

Candian, G. (2021). Central bank transparency, exchange rates, and demand imbalances. *Journal of Monetary Economics*, 119(C):90–107.

Chinn, M. and Frankel, J. A. (2007). Will the euro eventually surpass the dollar as leading international reserve currency? In *G7 Current account imbalances: sustainability and adjustment*, pages 283–338. University of Chicago Press.

Correa, R., Garud, K., Londono, J., and Mislang, N. (2017). Sentiment in central bank's financial stability reports. *International Finance Discussion Paper*, 2017:1–46.

Correa, R., Garud, K., Londono, J. M., and Mislang, N. (2021). Sentiment in central banks' financial stability reports. *Review of Finance*, 25(1):85–120.

de Haan, J. and Hoogduin, L. (2024). Ecb communication policies: An overview and comparison with the federal reserve. *Journal of International Money and Finance*, 142:103050.

de Haan, J., Jansen, D.-J., and de Haan, J. (2007). The Importance of Being Vigilant: Has ECB Communication Influenced Euro Area Inflation Expectations? CESifo Working Paper Series 2134, CESifo.

Fernandez, R., Palma Guizar, B., and Rho, C. (2021). A sentiment-based risk indicator for the mexican financial sector. *Latin American Journal of Central Banking*, 2(3):100036.

Gardt, M., Angino, S., Mee, S., and Glöckler, G. (2022). ECB Communication with the wider public. *Economic Bulletin Articles*, 8.

Gössi, S., Chen, Z., Kim, W., Bermeitinger, B., and Handschuh, S. (2023). Finbert-fomc: Fine-tuned finbert model with sentiment focus method for enhancing sentiment analysis of fomc minutes. In *Proceedings of the Fourth ACM International Conference on AI in Finance*, ICAIF '23, page 357–364, New York, NY, USA. Association for Computing Machinery.

Granger, C. and Newbold, P. (1974). Spurious regressions in econometrics. *Journal of Econometrics*, 2(2):111–120.

Gu, C., Chen, D., Stan, R., and Shen, A. (2022). It is not just what you say, but how you say it: Why tonality matters in central bank communication. *Journal of Empirical Finance*, 68:216–231.

Hodrick, R. J. and Prescott, E. C. (1997). Postwar u.s. business cycles: An empirical investigation. *Journal of Money, Credit and Banking*, 29(1):1–16.

Hofmann, B. and Bogdanova, B. (2012). Taylor rules and monetary policy: A global'great deviation'? *BIS quarterly review September*.

Jordà, (2005). Estimation and inference of impulse responses by local projections. *American Economic Review*, 95(1):161–182.

Loughran, T. and McDonald, B. (2011). When is a liability not a liability? textual analysis, dictionaries, and 10-ks. *The Journal of Finance*, 66(1):35–65.

Middeldorp, M. (2011). Central bank transparency, the accuracy of professional forecasts, and interest rate volatility. Staff Reports 496, Federal Reserve Bank of New York.

Niţoi, M., Pochea, M.-M., and Radu, Ş.-C. (2023). Unveiling the sentiment behind central bank narratives: A novel deep learning index. *Journal of Behavioral and Experimental Finance*, 38:100809.

Oosterloo, S., de Haan, J., and Jong-A-Pin, R. (2007). Financial stability reviews: A first empirical analysis. *Journal of Financial Stability*, 2(4):337–355.

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.

Ravn, M. O. and Uhlig, H. (2002). On adjusting the hodrick-prescott filter for the frequency of observations. *The Review of Economics and Statistics*, 84(2):371–376.

Romer, C. D. and Romer, D. H. (1989). Does monetary policy matter? a new test in the spirit of friedman and schwartz. *NBER Macroeconomics Annual*, 4:121–170.

Romer, C. D. and Romer, D. H. (2023). Presidential address: Does monetary policy matter? the narrative approach after 35 years. *American Economic Review*, 113(6):1395–1423.

Shapiro, A. H., Sudhof, M., and Wilson, D. J. (2022a). Measuring news sentiment. *Journal of econometrics*, 228(2):221–243.

Shapiro, A. H., Sudhof, M., and Wilson, D. J. (2022b). Measuring news sentiment. *Journal of Econometrics*, 228(2):221–243.

Shapiro, A. H. and Wilson, D. J. (2021). Taking the Fed at its Word: A New Approach to Estimating Central Bank Objectives using Text Analysis. *The Review of Economic Studies*, 89(5):2768–2805.

Tadle, R. C. (2022). Fomc minutes sentiments and their impact on financial markets. *Journal of Economics and Business*, 118:106021.

Taylor, J. B. (1993). Discretion versus policy rules in practice. *Carnegie-Rochester Conference Series on Public Policy*, 39:195–214.

White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica*, 48(4):817–838.

A Market Data

Data	Source
US Taylor Rule Quarterly	FRED
EU Taylor Rule Quarterly	Bloomberg
US Federal Funds Rate Quarterly	FRED
ECB Main Refinancing Operations Announcement Rate Quarterly	Bloomberg
SP500 Value weighted returns including dividends Quarterly	CRSP
STOXX600 Returns Gross Dividends Quarterly	Bloomberg