LSE_DA401_Employer_Project_Assignment_3

Employer Project Team 5

Bank of England (BOE) Sentiment Analysis of Central Bank Speeches

Assignment 3: Final Report

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Word Count: 1,453

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1. Introduction and Problem Statement

The Bank of England (BOE) plays a critical role in maintaining economic stability and market confidence. Central to this function is the Bank's strategic use of speeches its representatives deliver at public forums. Indeed, central bank communication influences financial markets and increases the predictability of monetary policy.[1]

This report examines the relationship between BOE speeches and the broader economic landscape. By analysing speech content and aligning it with economic events, including global crises, potential opportunities, and key economic indicators, our objective is to address the following business questions:

- How has sentiment changed over time?
- How does sentiment correlate with events?
- How does sentiment correlate with economic indicators?
- Does sentiment have the power to predict market behaviour?

Principally, we analyse the sentiments expressed in these speeches delivered by the BOE. Understanding how sentiments correlate with subsequent market behaviours can help us discover whether the BOE's communication is reactive or if it exhibits proactive, predictive, or even prescriptive qualities. This could reveal how the BOE influences the economic narrative, potentially shaping policy outcomes and market reactions. Prior research has shown that central bank communication reveals information about their views on current and future economic conditions, thereby affecting economic outcomes.[2]

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[1] Nakamura, E. & Steinsson, J. (2018). High-Frequency Identification of Monetary Non-Neutrality. The Quarterly Journal of Economics, 133(3), 1283–1330

[2] Ter Ellen, S., Larsen, V. H., & Thorsrud, L. A. (2020). How Central Banks Reach the General Public. BI Norwegian Business School.

2. Methodology

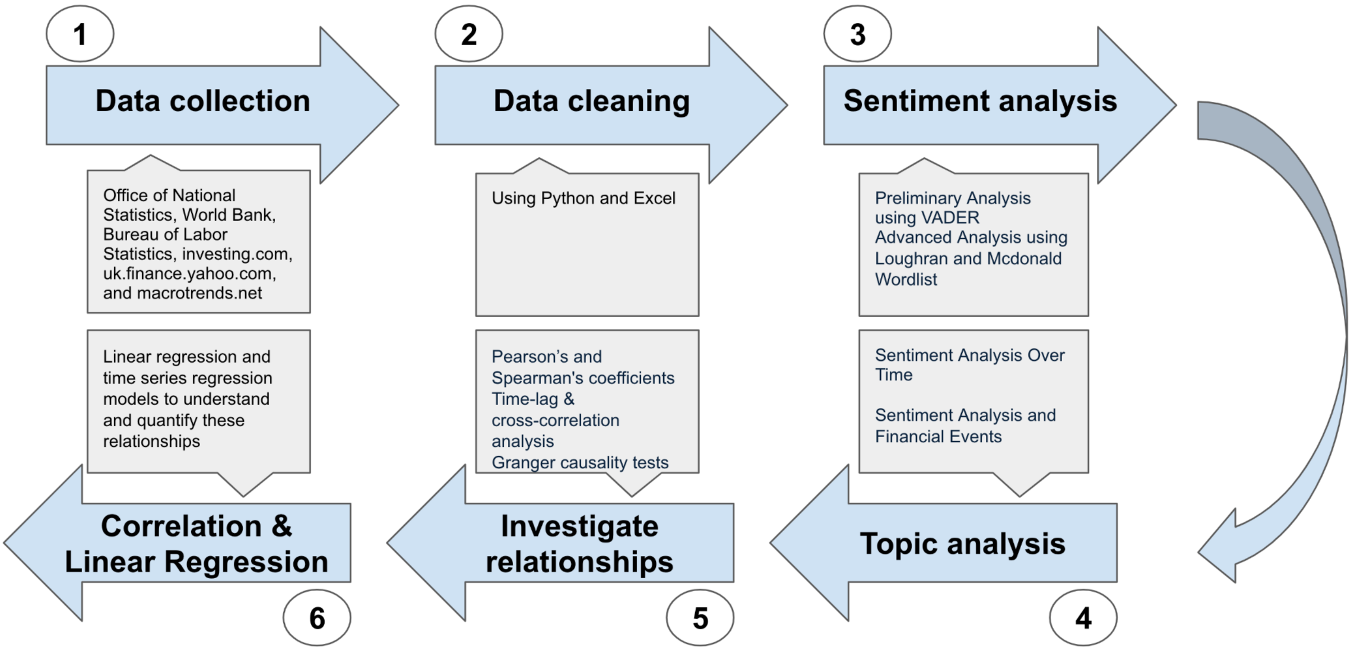

Figure 1: Flowchart of the methodology for the project.

Figure 1 maps our methodology for analysing the BOE speeches and their correlation with economic indicators, which we can categorise more broadly into data sourcing, cleaning, and analysis. The economic indicators we explored in this analysis are:

1. GDP
2. GDP Growth
3. Unemployment
4. Inflation Indices (CPI and RPI)
5. Bank Rate/ Interest Rate
6. FTSE 100 Index

Data Sourcing

Data Source	**Methodology**
Economic Metrics	• Sourced economic indicators from reputable platforms, including the ONS, World Bank, investing.com, etc. • GDP data in US dollars for standardisation and ease of international comparison. • Data collection spanned from 1997 to 2022, aligning with the availability and relevance of BOE speeches.
Speeches	• Acquired speeches directly from the BOE, spanning the same period, formatted in Excel.

Data Cleaning

Analysis Type	**Methodology**
Economic Metrics	• Utilised Excel for initial processing, addressing missing values and inaccuracies through functions and filtering techniques. • Python used to standardise date formats to YYYY-MM and facilitate data export to GitHub, ensuring collaborative efficiency.
Speeches	• Python was employed to filter the dataset, focusing on speeches relevant to the UK. • We checked for duplicates, missing data, and consistency in data and date formats.

Data Analysis

Analysis Type	Methodology
Sentiment Analysis	• Applied Valence Aware Dictionary and Sentiment Reasoner (VADER) for initial sentiment assessment, establishing a baseline sentiment. • Advanced the analysis with the Loughran and McDonald Words List (LMW), which is a sentiment lexicon for financial text mining.[3]
Topic Analysis	• Utilised Latent Dirichlet Allocation (LDA) for its efficiency in revealing latent themes within the speeches.[4]
Correlation Analysis	• Conducted correlation analysis (Pearson's and Spearman's coefficients) to identify relationships between sentiment and economic indicators. • Performed time-lag and cross-correlation analysis, along with Granger causality tests and seasonal decomposition to explore causal relationships. • Utilised linear and time series regression models to understand and quantify these relationships.

3. Sentiment Analysis

Valence Aware Dictionary and Sentiment Reasoner (VADER)

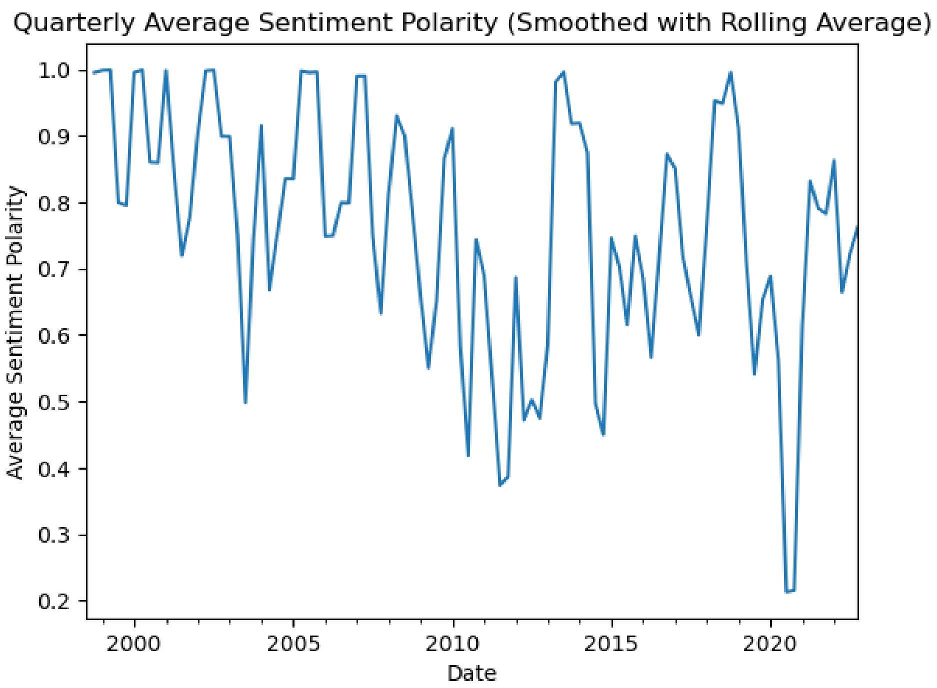

Figure 2: Plot of sentiment polarity over time, smoothed using a rolling average and analysed with VADER.

We initially applied VADER, a tool specifically tuned to analyse sentiments expressed in social media.[3] As Figure 2 illustrates, it yielded a positive average score of 0.73. However, VADER's limitations in capturing the nuances of financial terminology meant this was only the starting point.

[3] Al-Shabi, M. A. (2020). Evaluating the performance of the most important Lexicons used to Sentiment analysis and opinions Mining. International Journal of Computer Science and Network Security, 20(1), 51.

Loughran and McDonald Words List (LMW)

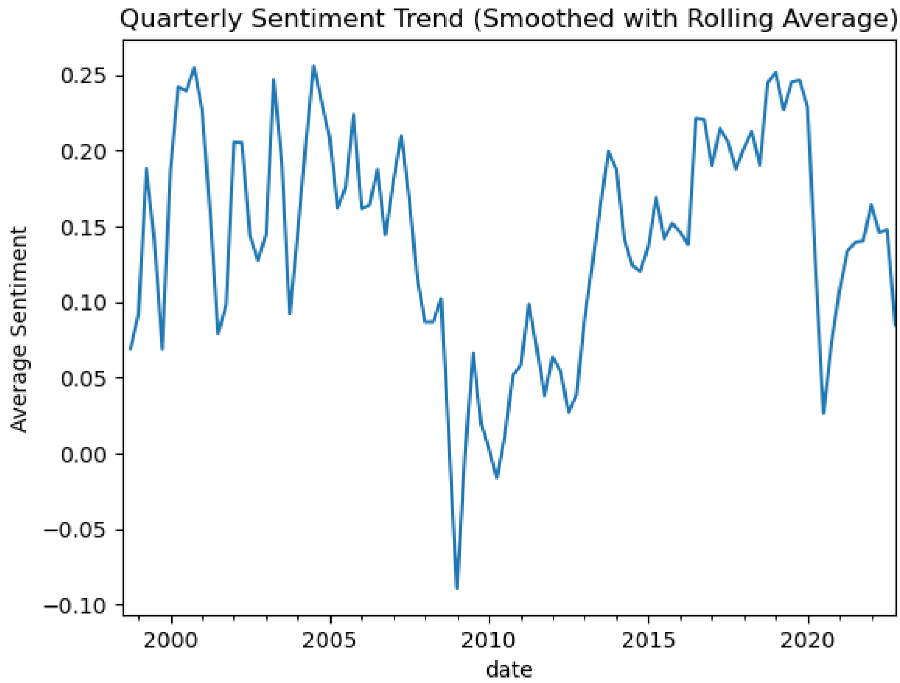

Figure 3: Plot of sentiment trend using the LMW.

We employed the LMW to gain deeper insight tailored to financial contexts. This lexicon pre-scores the sentiment of approximately 3,000 financial words. We add or subtract different sentiment scores based on their impact on a word's emotional tone, including categories like positive, negative, strong, weak, uncertainty, and litigious. We accounted for negation and normalised scores based on speech length. Finally, we tested the use of MinMaxScaler but deprecated it due to its inversive effect. The mean normalised sentiment score was 0.141, indicating a positive sentiment but closer to neutrality. This approach, though time-intensive, improved the accuracy of our sentiment analysis.

Economic Crises

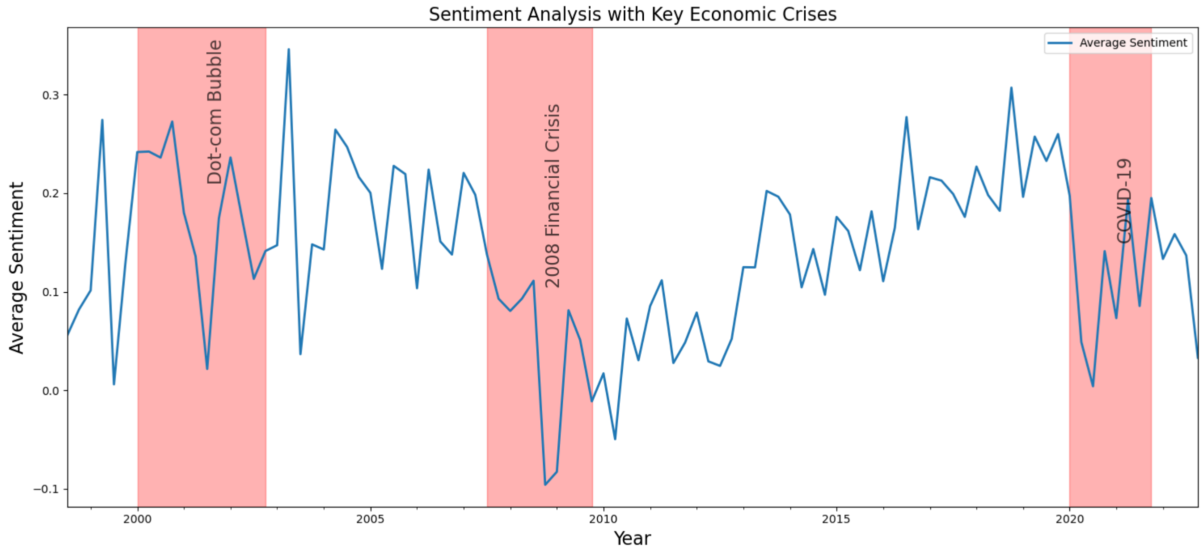

Figure 4: Plot of sentiment trend during economic crises — Analysing the Dotcom Bubble, 2008 Financial Crisis, and COVID-19.

Figure 4 plots sentiment against major economic events to visualise how the Bank's strategy adapts to economic shocks. The red-shaded boxes in Figure 4 denote the start and finish of each crisis, illustrating a decrease in sentiment for each. The 2008 crash shows a steeper decline than the Dot-com bubble, suggesting a more intense reaction with a greater economic impact. The initial sentiment drop at the start of COVID-19 is sharp but quickly reverses, reflecting the rapid policy responses.

Brexit

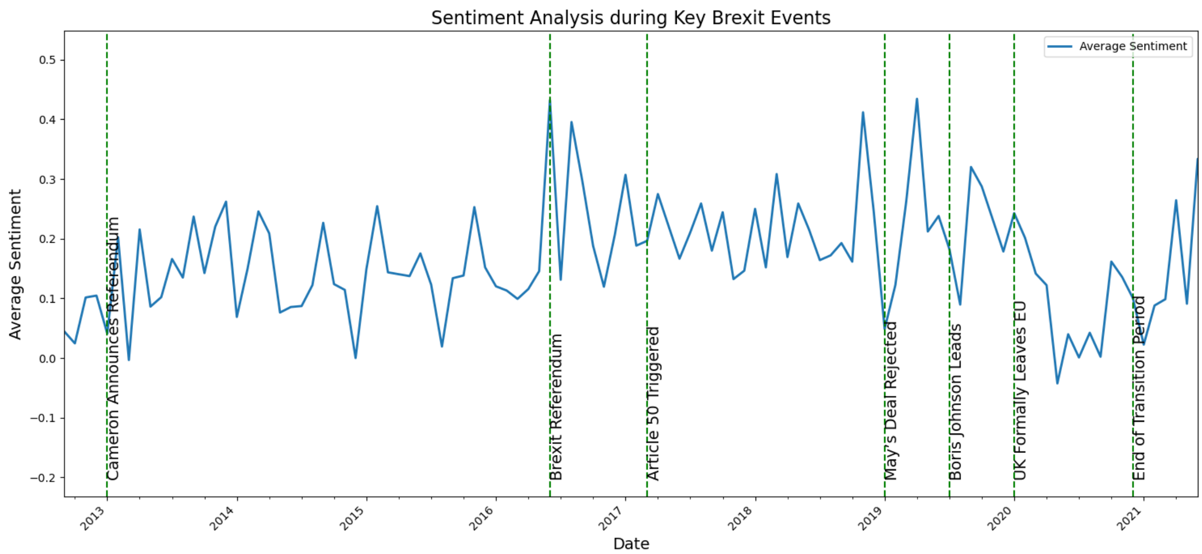

Figure 5: Plot showing the BOE's sentiment at critical junctures in the Brexit process.

We examined sentiment trends during Brexit separately, annotating notable milestones. Figure 5 captures the shift from initial optimism to increasing complexity as negotiations progressed.

The UK government's optimistic portrayal of the potential benefits of Brexit,[4] juxtaposed with the BOE's more variable outlook, indicates that economic outcomes may deviate from socio-political ambitions.

4. Topic Analysis

Topic Analysis using LDA

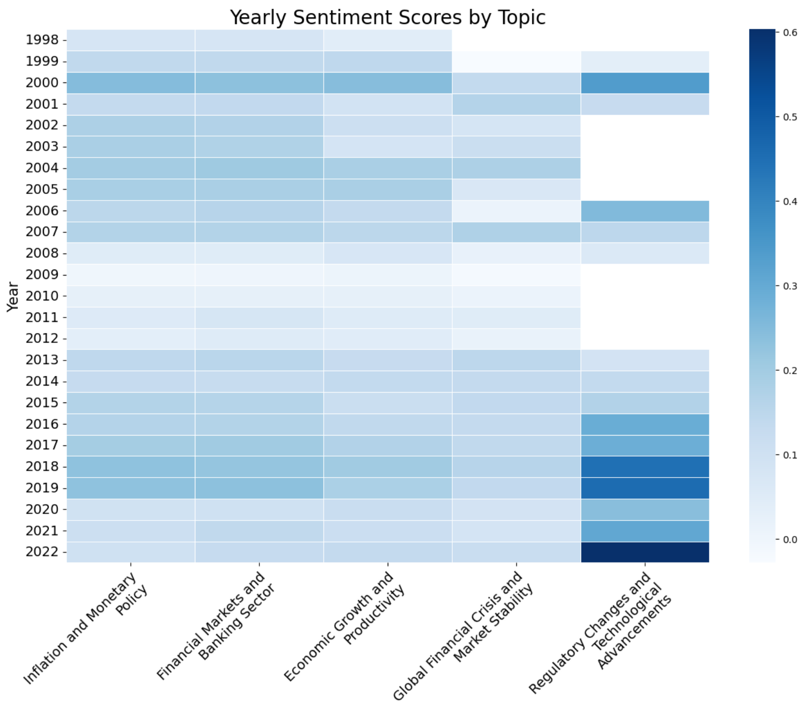

Figure 6: Heatmap of the BOE's thematic sentiment across five overarching topics.

We utilised LDA to uncover thematic structures within the text, opting for it over Dynamic Topic Modeling (DTM) due to its computational efficiency, despite DTM's advantages in

[4] Cabinet Office. (2022). The benefits of Brexit: How the UK is taking advantage of leaving the EU. GOV.UK. Published January 31, 2022.

tracking topic evolution over time.[5] By annually grouping speeches and creating a dictionary and corpus, the LDA model identified key topics, which we aggregated into overarching themes. Topic-specific text extraction involved identifying speeches containing predefined keywords, and categorising these texts under relevant topics for sentiment analysis. Figure 6 exhibits the BOE's shifting focus and sentiment over time, which includes a marked increase in positive sentiment towards technology and regulation.

Technology and Regulation

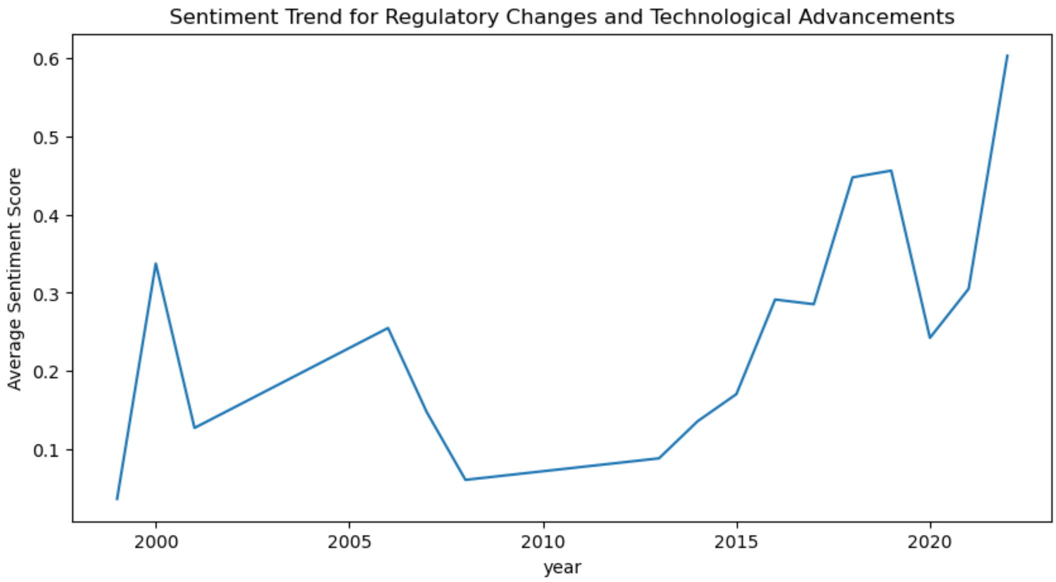

Figure 7: Plot illustrating the Bank's strategic focus on technological innovation and regulatory changes.

Figure 7 reveals an uptrend in positive sentiment since 2013, underscoring the BOE’s proactive stance towards technological progress and regulatory reform. This likely signifies its strategic initiative to ready the public for imminent policy transformations, driven by fintech and the adaptation of regulatory frameworks. Many central banks are investigating the introduction of a central bank digital currency (CBDC) and building bank-operated payment infrastructures.[6]

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[5] Hansson, M. (2021). Evolution of topics in central bank speech communication. arXiv:2109.10058v1 [econ.GN], Sep 21.
[6] Auer, R., Cornelli, G., & Frost, J. (2020). Covid-19, cash, and the future of payments. BIS Bulletin, No 3, April 3.

5. Correlation Analysis

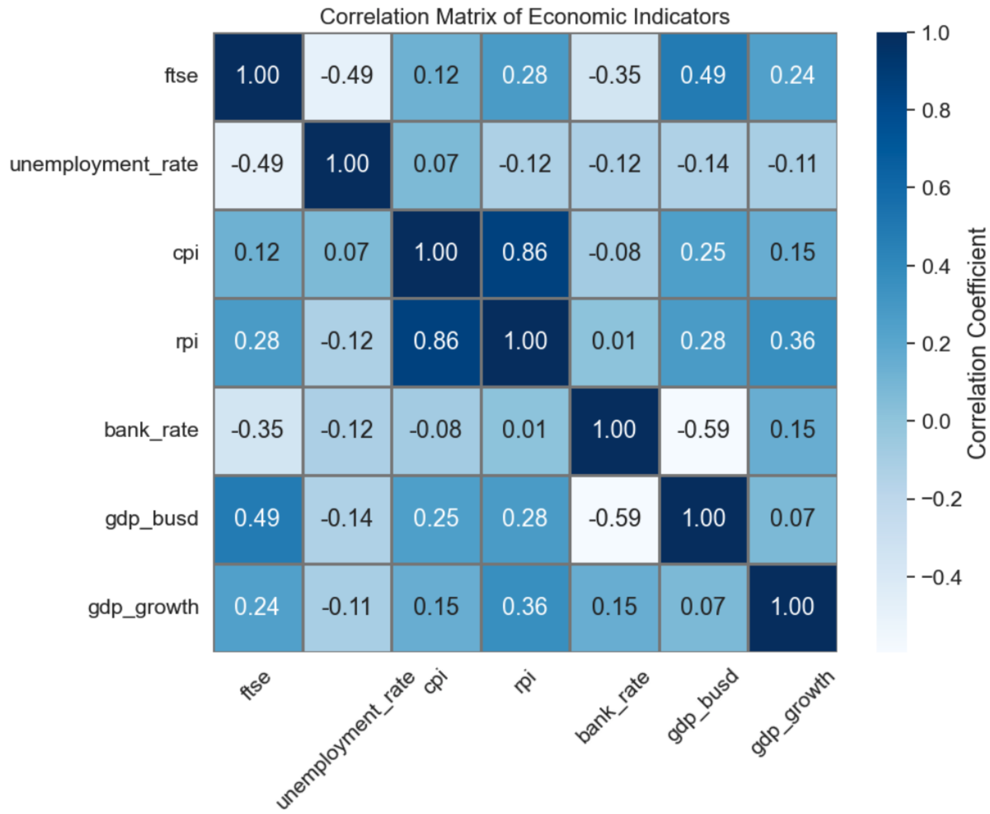

Figure 9: Correlation matrix of selected economic indicators.

Figure 9 shows high correlation between indicators such as CPI and RPI, which can affect the overall reliability of regression models as there is the possibility of collinearity. Identifying high positive or negative correlations like that between the bank rate and GDP (in Billions USD) may indicate an inverse relationship where periods of high interest rates are associated with a weaker GDP. However, correlation may not necessarily mean causation, as such an assumption always requires more rigorous statistical analysis and consideration of domain specific knowledge.

Correlation with Sentiment

	GDP	GDP Growth	CPI	RPI	Bank Rate	Unemployment	FTSE
Pearson Coefficient	-0.1	0.11	-0.09	-0.1	0.05	-0.25	0.2

Pearson P-value	0.82	0.001	0.002	0.73	0.067	0.0	0.0
Spearman Coefficient	0.04	0.11	-0.13	-0.4	0.07	-0.23	0.21
Spearman P-Value	0.14	0.0002	0.0	0.14	0.011	0	0.0

Figure 10: Correlation coefficients between sentiment and economic indicators.

Figure 10 exhibits the Pearson and Spearman's coefficient of the sentiment correlated with economic indicators. Evidently, most of the economic indicators have a very weak or non-existent correlation, with correlation coefficients close to zero, with many being statistically significant with p-values below 0.05.

Inflation: CPI

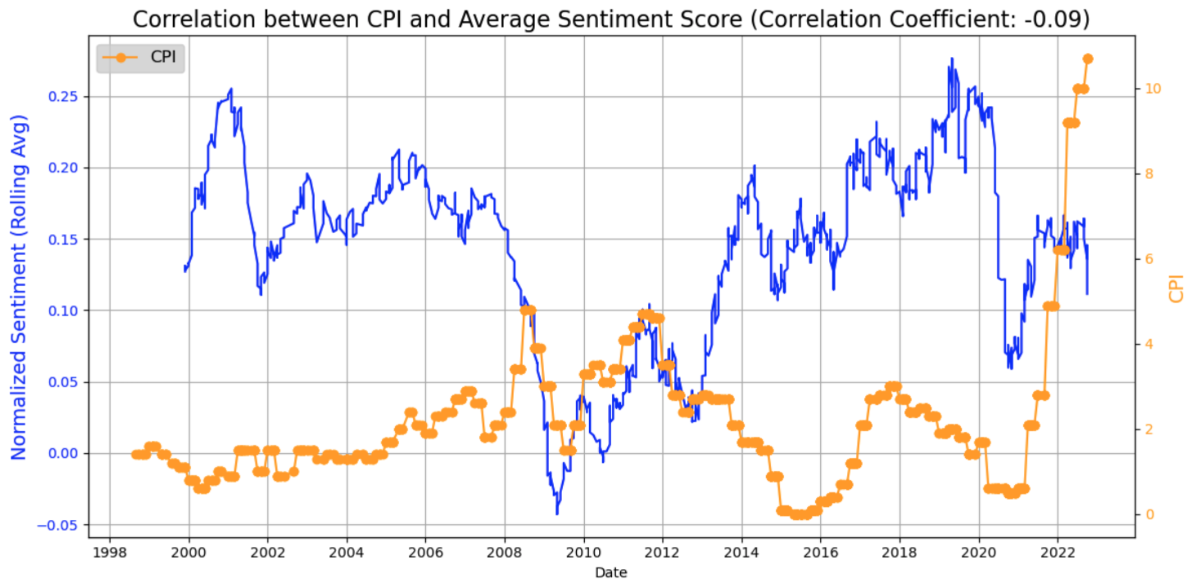

Figure 11: Time series analysis displays a weak inverse relationship between CPI and average sentiment score.

When examining CPI, we noticed that the correlation of sentiment with inflation indices (including RPI) were statistically insignificant. The correlation coefficient of -0.09 above indicates a relatively weak inverse relationship between the two variables. By running a linear regression model, both indicators had low R-squared values of 0.008, suggesting that such a model only explains a small portion of the variance with a very weak effect. More rigorous investigation is required to determine whether CPI is likely to decrease as sentiment increases.

GDP

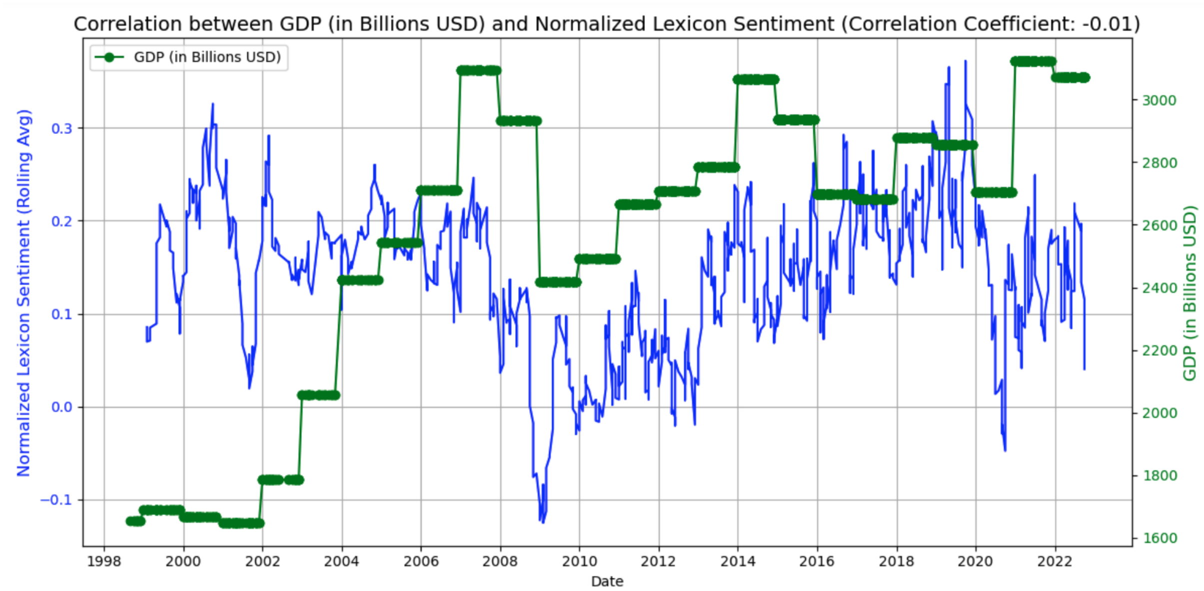

Figure 12: Time-series plot shows a negligible correlation coefficient between UK GDP and sentiment.

Figure 12 depicts UK GDP's correlation with sentiment. Initially, the hypothesis would posit that GDP precedes changes in sentiment. However, additional statistical tests found that sentiment did not have a significant impact on GDP. From our linear regression results, we notice a non-linear relationship between the two indicators where residuals are not normally distributed, indicating the assumptions of linear regression are not met.

GDP Growth

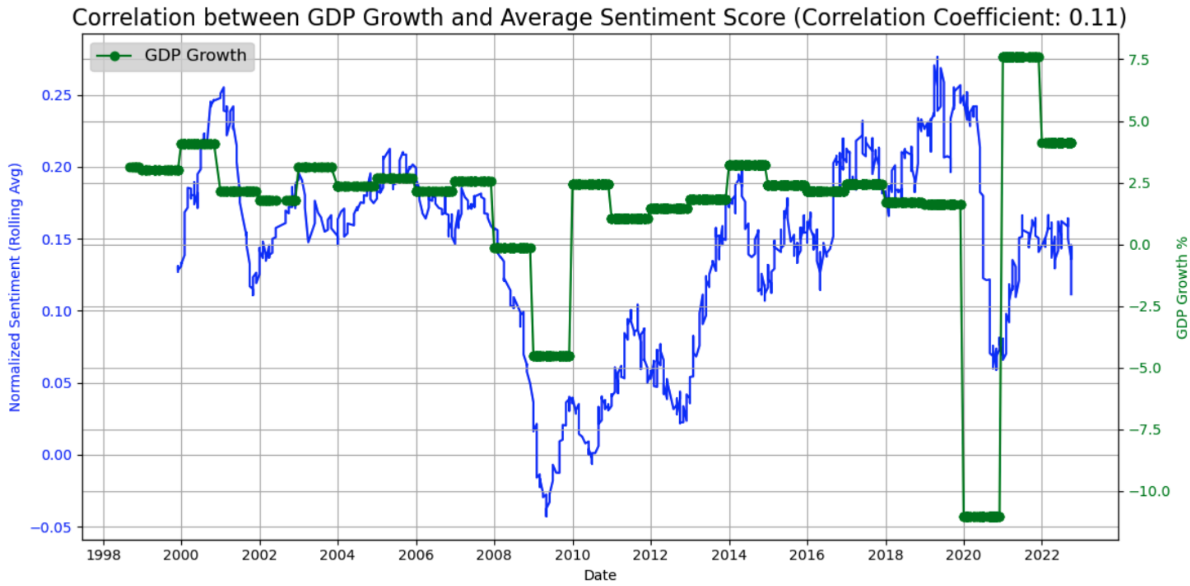

Figure 13: Time-series plot shows a weak correlation coefficient between UK GDP growth and sentiment.

Upon reflection, GDP growth was used as it may have been a better economic indicator to see whether a relationship exists with sentiment. The correlation coefficient is relatively weak and statistically accurate, as seen in Figure 13, GDP growth does positively correlate with a decrease in sentiment, as seen in both 2008 financial crash as well as at the end of COVID-19.

Time-lag analysis revealed a significant correlation with a 15 month lag. Granger causality testing resulted in non-significant P values, indicating the changes in sentiment do not cause changes in GDP growth and vice versa. In our regression models, low are squared and adjusted or squared values, as well as non-normally distributed residuals suggest the model assumptions do not hold on further investigation of alternative modelling approaches need to be considered.

Unemployment

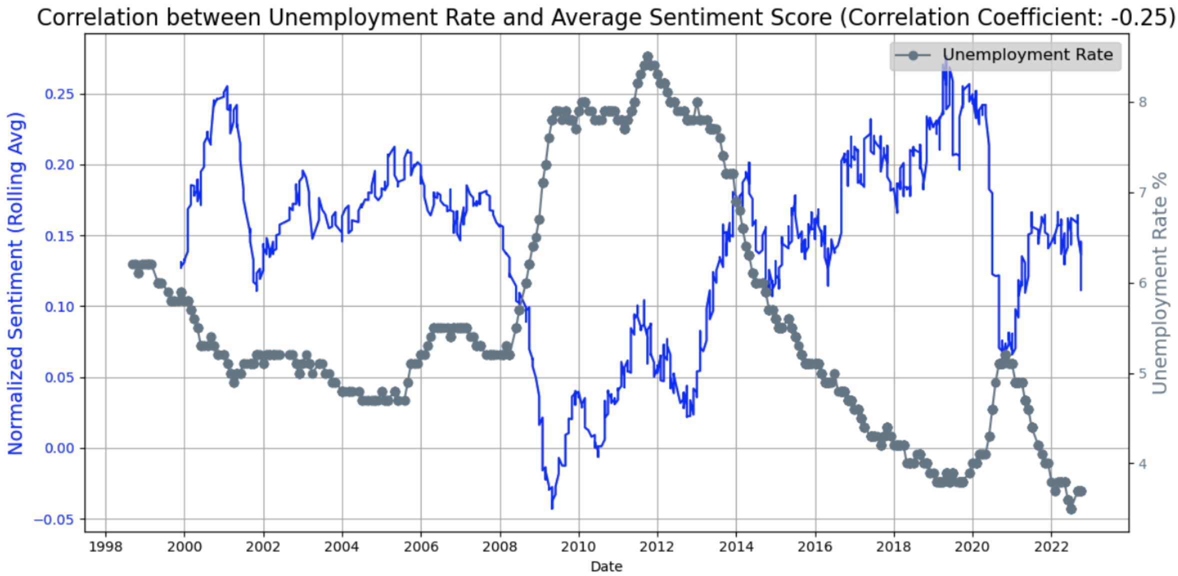

Figure 14: Time-series plot shows an almost inverse relationship between unemployment and sentiment.

Unemployment's coefficient of -0.25 is a bit higher than the aforementioned indicators. However, as illustrated in Figure 14 illustrates unemployment rates have an almost inverse relationship with sentiment.

Such a trend can be explained by factors such as the increased expenditure in consumer confidence, where increasing spending is most likely to boost overall economic activity, thus creating more opportunities in the labour market and reducing overall unemployment rates.

Additional analysis revealed a significant negative correlation with a 15 month lag, as well as an indication that sentiment could be a useful predictor of an appointment (Granger causality). Linear regression models presented significant negative predictors on unemployment, reinforcing that as sentiment increases, unemployment tends to decrease. However, autocorrelation heteroscedasticity and non-normality of residuals continue to remain a concern.

FTSE

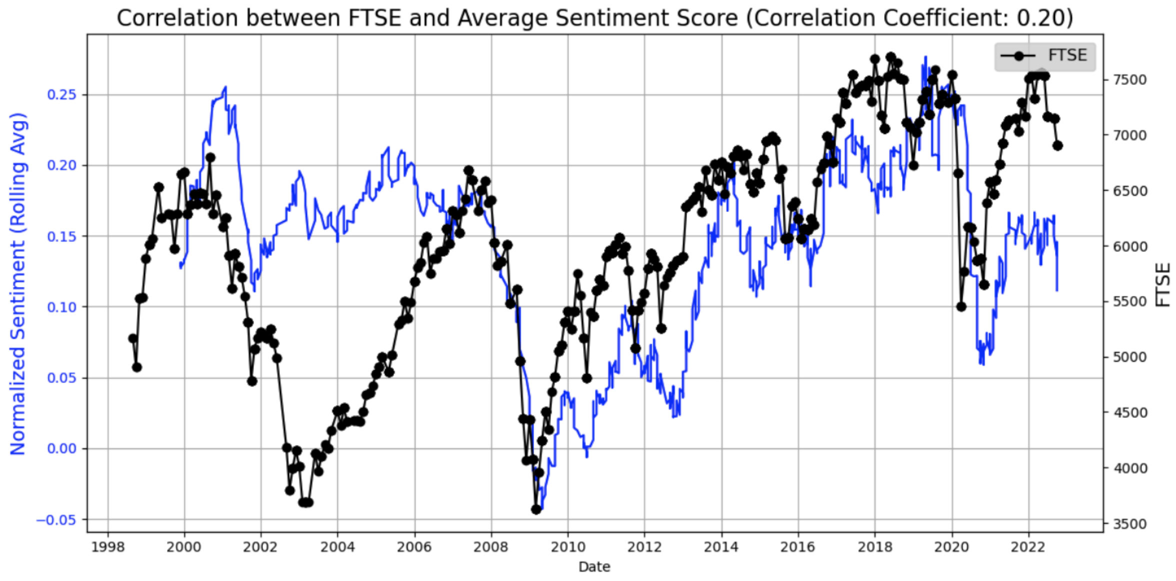

Figure 15: Time-series plot shows a positive relationship between the FTSE and sentiment.

As Figure 15 suggests there is some type of correlation, which can be seen from 2008 onwards, with both indicators tending to move with one another. With a coefficient of 0.20, it is the only indicator that has a positive relationship with sentiment, albeit not strong. Stock market indices such as FTSE should vary with overall sentiment because they reflect an investor's expectations on future financial performances of the market, thus currently highlighting some correlation between the two.

Cross-correlation analysis indicates a significant time lag of -7 months, demonstrating that sentiment can act as a leading indicator for the FTSE to predict future movements with a lead time of seven months. However seasonal decomposition revealed that the relationship may not be statistically significant based on the current data in chosen significance level. As previously mentioned, high degrees of multicollinearity and overfitting suggest alternative modelling techniques or transformations are required.

Limitations and Recommendations

The analysis of BOE speeches revealed significant patterns and insights. However, challenges in the regression models were encountered, such as autocorrelation, heteroscedasticity, and non-normality of residuals. These are crucial aspects of linear regression assumptions, and their negativity can significantly impact the overall model's validity and predictive accuracy.

Addressing multicollinearity through variable transformation could enhance the models' performance. Regularisation techniques such as ridge regression or lasso regression are also valuable, as they introduce a penalty component to the regression, reducing the risk of overfitting and helping with multicollinearity.

The exploration of alternative ML techniques warrants further exploration. Techniques like random forests and gradient boosting (XGBoost) could offer more sophisticated and nuanced insights than simple linear regression models in this project. Benchmarking these models against complementary algorithms like support vector machines could also provide a more comprehensive understanding of their performance.

Considering DTM for future studies could improve our topic analysis, as DTM offers superior temporal analysis. Also, our analysis relied exclusively on speeches, which may not encompass the full spectrum of the Bank's communications. Thus, including reports and written disclosures of meeting minutes[7] is recommended, which could provide a more exhaustive view and indication of the predictive ability of sentiment on financial events and changes in economic indicators. However, challenges exist in creating deep learning models to use textual data for predicting economic indicators. Previous research has shown limitations in text-based prediction performance using neural networks, primarily due to the small number of training datasets and the extensive length of each text.[8]

This initial analysis provided insightful results yet should only be used as a reference point to explore further options in the future. Such analysis should be used as a stepping stone to offering a more dynamic and comprehensive perspective on how BOE can influence financial markets. The proposed options, such as DTM, and optimised wordlists can be used to elevate the sentiment analysis from its current state to a more sophisticated and predictive level, opening new options for exploration and yielding more concrete, actionable insights. This sentiment analysis, if improved, can provide a lot of insight into the relationship between central bank communications and economic outcomes.

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[7] Sardelich, M., & Kazakov, D. Extending the Loughran and McDonald Financial Sentiment Words List from 10-K Corporate Filings using Social Media Texts. University of York, Heslington, York YO10 5GH, UK.

[8] Altayeb, M., Elamin, A. M., Ahmed, H., Ibrahim, E. E. E., Haydar, O., Abdulaziz, S., & Mohamed, N. H. M. (2021). Confidence-Nets: Enhancing Prediction Intervals for Regression Neural Networks on Small Datasets. Department of Electrical and Electronic Engineering, University of Khartoum, Sudan.

References

Nakamura, E. & Steinsson, J. (2018). *High-Frequency Identification of Monetary Non-Neutrality*. The Quarterly Journal of Economics, 133(3), 1283–1330.

Ter Ellen, S., Larsen, V. H., & Thorsrud, L. A. (2020). *How Central Banks Reach the General Public*. BI Norwegian Business School.

Al-Shabi, M. A. (2020). *Evaluating the performance of the most important Lexicons used to Sentiment analysis and opinions Mining*. International Journal of Computer Science and Network Security, 20(1), 51.

Priola, M. P., Molino, A., Tizzanini, G., & Zicchino, L. (2022). *The informative value of central banks talks: a topic model application to sentiment analysis*. Data Science in Finance and Economics, 2(3), 181-204. doi: 10.3934/DSFE.2022009.

Al-Shabi, M. A. (2020). *Evaluating the performance of the most important Lexicons used to Sentiment analysis and opinions Mining*. International Journal of Computer Science and Network Security, 20(1), 51.

Cabinet Office. (2022). *The benefits of Brexit: How the UK is taking advantage of leaving the EU*. GOV.UK. Published January 31, 2022.

Hansson, M. (2021). *Evolution of topics in central bank speech communication*. arXiv:2109.10058v1 [econ.GN] Sep 21.

Auer, R., Cornelli, G., & Frost, J. (2020). *Covid-19, cash, and the future of payments*. BIS Bulletin, No. 3, April 3.

Sardelich, M., & Kazakov, D. *Extending the Loughran and McDonald Financial Sentiment Words List from 10-K Corporate Filings using Social Media Texts*. University of York Heslington York YO10 5GH UK.

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