ECO612 Data Assignment
Predicting Exchange Rate Movements: An Analysis of Monetary Policy Sentiments and Media Uncertainty Indices

Dipan Nath
Roll No. : 241270013
dnath24@iitk.ac.in

Lalit Kumar Upadhyay
Roll No. : 241270015
lalitu24@iitk.ac.in

Lavanya Pareek
Roll No. : 241270041
lavanyap24@iitk.ac.in

Rajdeep Sinha Roy
Roll No. : 241270042
rajdeepsr24@iitk.ac.in

Abstract

This report investigates the impact of sentiment extracted from the Reserve Bank of India's (RBI) semi-annual monetary policy reports on economic variables, specifically focusing on the exchange rate. Utilizing advanced Natural Language Processing (NLP) techniques, including pre-trained Large Language Models (LLMs) and FinBERT, we extract sentiment features such as Sentiment Subjectivity, Sentiment Polarity, and Sentiment Uncertainty from the reports. The study incorporates lagged effects of monetary policy sentiments and evaluates their relationship with exchange rate movements through robust regression analysis.

The analysis reveals that monetary policy sentiments exhibit significant lagged effects on the exchange rate, aligning with the theory that information transmission through media impacts economic variables over time. Specifically, the Sentiment Subjectivity and Polarity indicators with longer lags demonstrate considerable influence on exchange rate fluctuations. Conversely, lags of sentiment indicators like Media Uncertainty Index show limited impact, likely due to their immediate but less enduring effect.

The model's robustness is confirmed by high explanatory power (R-squared = 0.959) and the absence of multicollinearity, as indicated by Variance Inflation Factors (VIFs). However, there is potential for enhancing the sentiment analysis through further fine-tuning of LLMs to achieve more precise sentiment extraction and better predictive accuracy.

This study contributes to the understanding of how monetary policy communications affect financial markets and suggests pathways for improving sentiment analysis models for more accurate economic forecasting.

Keywords: Sentiment Analysis, Monetary Policy, Large Language Models (LLMs), FinBERT, Reserve Bank of India (RBI), Exchange Rate, Natural Language Processing (NLP), Economic Forecasting, Regression Analysis, Lagged Effects, Financial Texts.

1 Introduction

1.1 Background and Motivation

Understanding the impact of monetary policy on economic variables is a critical area of research in economics. The Reserve Bank of India (RBI) releases semi-annual monetary policy reports that provide comprehensive insights into the country's economic conditions and policy measures. Analyzing the sentiment expressed in these reports can offer valuable information about market expectations and the potential effects on economic indicators such as exchange rates.

Sentiment analysis of financial texts, including policy reports, has gained prominence with the advancement of Natural Language Processing (NLP) techniques. Large Language Models (LLMs), such as those developed by OpenAI, have demonstrated remarkable capabilities in capturing and interpreting textual sentiments. However, their performance on specialized financial texts, particularly monetary policy documents, has not been fully explored.

1.2 Objective of the Study

This report aims to analyze the sentiments conveyed in RBI's monetary policy reports and their subsequent impact on economic variables, with a specific focus on the exchange rate. The primary objectives of the study are:

- To extract and analyze sentiment features from monetary policy reports using advanced NLP techniques, including pre-trained LLMs and domain-specific models such as FinBERT.
- To investigate the temporal effects of different sentiment indicators on the exchange rate, accounting for potential lagged effects and autocorrelation.
- To assess the robustness of the sentiment analysis model and explore the potential for further refinement and fine-tuning of LLMs to improve accuracy.

1.3 Significance of the Study

The insights gained from this study have significant implications for both economic forecasting and policy formulation. By accurately capturing and analyzing the sentiment in monetary policy reports, the study aims to enhance the understanding of how policy communications influence market expectations and economic outcomes. This can lead to more informed decision-making by policymakers and better predictive models for financial analysts.

1.4 Structure of the Report

The report is structured as follows:

- **Section 2: Methods** - Describes the methodologies employed for sentiment extraction from monetary policy reports, including pre-processing steps and the use of advanced LLMs.
- **Section 3: Literature Review** -
- **Section 4: Results** - Presents the findings from the sentiment analysis and their impact on the exchange rate, including statistical summaries and model evaluations.
- **Section 5: Future Work** - Discusses potential improvements and further research directions, including enhanced fine-tuning of LLMs and real-time applications.
- **Section 6: Conclusion** - Summarizes the key findings and their implications for economic policy and forecasting.

2 Motivation

Central banks care about the sentiments of economic agents given their prospective influence on changes in real economic activity. For example, for consumers, their expectations and sentiments about economic conditions can affect their consumption and saving descisions. One way of measuring sentiment is to directly survey these economic agents about their views on the current and future economic conditions. Wide availability of newspapers and annual reports in digital format have a role in influencing sentiments. Newspaper text sentiments can be informative about prevailing macroeconomic conditions at a high frequency condition and can be used to improve forecasts of macroeconomic indicators. Evaluation of the relationship between existing survey based sentiment measures and macroeconomic growth. Foreign exchange market is a global place to exchange national currencies. Like any other financial markets, the forex market rates are influenced by market sentiments. Market sentiments is a metric to gauge the mood and trend of proces in the market. Information about the two countries of exchange pairs in the form of news , blogs, social media contributes to Market sentiment.(Tadphale et al., 2023)

3 Literature Review

(Rajeswari Sengupta, 2019) delves into this topic by analyzing monetary policy statements from October 1998 to June 2018, quantifying elements such as statement length, monetary surprises, and the business cycle. This study underscores the significance of RBI communication in shaping financial market conditions, particularly emphasizing the transition to an inflation-targeting (IT) regime. Sengupta argues that the clarity and effectiveness of communication are vital components of the monetary policy transmission mechanism, and that improving these aspects could enhance India's relatively weak transmission mechanism following the adoption of the IT regime.

In a related study, Sil (2023)(Sil et al., 2023) explores the relationship between implicit dissent among individuals and groups and empirical macroeconomic indicators. Employing sentiment analysis techniques, similar to those used in this paper, the study captures dissent among Monetary Policy Committee (MPC) members regarding their official votes. The analysis draws on data from the RBI's Survey of Professional Forecasters (SPF) and utilizes VADER (Valence Aware Dictionary and sEntiment Reasoner) to measure dissent at both the individual and group levels. The findings illustrate how forecasting errors in growth and inflation decrease as dissent among MPC members increases, demonstrating the utility of sentiment analysis in quantifying qualitative variables, such as the degree of negativity in reports from various entities.

Bakshi et al. (2016)(Bakshi et al., 2016) focus on sentiment analysis, specifically analyzing tweets to assess their impact on stock prices. The study introduces an algorithm that calculates sentiment scores by classifying words as positive, negative, or neutral, achieving an accuracy rate of 80.6%. The research demonstrates the potential of sentiment analysis in predicting market movements, although it is limited to a single company's stock.

Shrimali and Ahmad (2020)(Shrimali and Ahmad, 2020) explore the impact of the Reserve Bank of India's (RBI) communication on stock market volatility in India. The study utilizes Natural Language Processing (NLP) techniques to quantify the tone of RBI's monetary policy statements (MPS) and assesses their influence on market volatility. The findings confirm that RBI's communication significantly affects financial markets, especially in the context of India's shift to a Flexible Inflation Targeting (FIT) framework. The research underscores the critical role of central bank communication in shaping market dynamics.

4 Methods

This section details the methodologies employed in analyzing the relationship between monetary policy sentiments and economic indicators. The analysis involves multiple steps, from sentiment extraction from financial reports to model fitting and evaluation. We use both pre-processing techniques and advanced models to capture sentiment accurately and address potential issues in the data, such as autocorrelation and multicollinearity. The following subsections describe the methods used in extracting and processing sentiment data, and the approach taken to model the economic indicators.

4.1 Monetary Policy Sentiments Extraction

To analyze the sentiments within the monetary reports released semi-annually by the Reserve Bank of India, we utilized two primary methods for sentiment extraction.

4.1.1 Pre-processing Reports

To capture sentiments, we began by removing stopwords[1] and all punctuation marks from the texts. A comprehensive list of stopwords can be found in the Software Repository for Accounting and Finance.

[1] Words such as 'a', 'an', 'the', etc.

4.1.2 Using Pre-trained OpenAI Model

Large Language Models (LLMs) are well-regarded for their ability to capture textual sentiments. OpenAI's models are trained on extensive datasets, including financial texts, which enhances their ability to understand and analyze financial reports effectively. From the reports, we extracted three primary sentiments: 'Sentiment Subjectivity (SS)', 'Sentiment Polarity (SP)', and 'Sentiment Uncertainty (SU)'.

4.2 HuggingFace's Pre-trained Transformer Network FinBert

FinBert, a transformer model specialized in analyzing financial texts, was employed to extract sentiment polarity from the reports. This model is particularly adept at interpreting financial language and providing sentiment metrics tailored to financial contexts.

4.3 Media Uncertainty Index

The Media Uncertainty Index for India was obtained from the Economic Policy Uncertainty website . This index measures policy-related economic uncertainty based on newspaper articles concerning policy uncertainty.

4.4 Finding the Right Model for Quarterly Data

Initially, we used the Exchange Rate as the dependent variable and explored its relationship with the sentiment variables. Basic OLS linear regression revealed high multicollinearity and autocorrelation issues. To address these problems, we expanded our analysis to include monthly data, which provided a more granular view and mitigated some of the issues observed with quarterly data.

4.5 The Model

In this analysis, we aimed to model the dependent variable $XRDN$ using a set of predictors ($SSDN$, PIN, $UIDN$, $SPDN$), incorporating lagged effects and addressing potential autocorrelation. The approach followed several key steps:

1. **Data Preparation:** The dataset included **Change in Exchange Rate(**$XRDN$**)** as the dependent variable and predictors **Change in Sentiment Subjectivity(**$SSDN$**)**, **Inflation rate(**PIN**)**, **Change in Media Uncertainty Index(**$UIDN$**)**, and **Change in Sentiment Polarity(**$SPDN$**)**[2]. Lagged versions of $SSDN$, $UIDN$, and $SPDN$ were introduced to account for time dependencies. Specifically, $SSDN$ was lagged by 4 and 8 periods, while $UIDN$ and $SPDN$ were lagged by 2 periods. These lagged variables were appended to the feature matrix X.

2. **Handling Multicollinearity:** The original variables $SSDN$ and $SPDN$ were removed from X to avoid multicollinearity with their lagged counterparts. A constant term was added to X to include an intercept in the model.

3. **Initial Regression:** An Ordinary Least Squares (OLS) regression was performed with robust standard errors to handle heteroscedasticity. Residuals from this regression were analyzed for autocorrelation.

4. **Autocorrelation Adjustment:** An ARIMA model was fitted to the residuals to address autocorrelation. The optimal ARIMA order (p, d, q) was determined using the Akaike Information Criterion (AIC). The ARIMA model was then used to adjust the residuals.

5. **Final Regression:** The adjusted dependent variable (y_{adj}) was calculated by subtracting the ARIMA model's residuals from the original y. A final OLS regression was conducted using y_{adj} as the dependent variable with the modified feature matrix X.

6. **Multicollinearity Check:** Variance Inflation Factors (VIF) were computed for the final model to assess and ensure that multicollinearity did not adversely affect the results.

[2] All the vaalues of dependent and independent variables were normalized between $[-1, 1]$

5 Results

The Ordinary Least Squares (OLS) regression model was employed to analyze the relationship between the dependent variable y and the predictors. The results are as follows:

5.1 Model Fit

The model demonstrates an excellent fit with the following statistics:

- **R-squared**: 0.959, indicating that approximately 95.9% of the variance in the dependent variable y is explained by the predictors.
- **Adjusted R-squared**: 0.956, which adjusts for the number of predictors and confirms a robust model fit.
- **F-statistic**: 402.8 (p-value 1.34×10^{-69}), suggesting that the model is statistically significant and the predictors collectively explain a substantial amount of variance in y.

5.2 Coefficients and Significance

The estimated coefficients for the predictors and their significance are detailed below:

- **Intercept (const)**: $-0.3262(p - value < 0.001)$, indicating a baseline level of y when all predictors are zero.
- **PIN**: $0.1487(p - value < 0.001)$, a positive and significant coefficient suggesting that an increase in PIN is associated with an increase in y.
- **UIDN**: $0.3258(p - value < 0.001)$, a positive and significant coefficient implying that higher values of $UIDN$ are positively associated with y.
- **SSDN_lag4**: $-0.1854(p - value < 0.001)$, a negative and significant coefficient indicating that the value of $SSDN$ lagged by 4 periods negatively impacts y.
- **SSDN_lag8**: $-0.1667(p - value < 0.001)$, similar to $SSDN\_lag4$, suggesting a delayed negative effect on y.

- **UIDN_lag2**: $-0.1363(p - value < 0.001)$, a negative coefficient for the 2-period lag of $UIDN$ indicating a negative impact on y.
- **SPDN_lag2**: $-0.1574(p - value < 0.001)$, a negative and significant coefficient showing that past values of $SPDN$ are associated with a decrease in y.

5.3 Multicollinearity

The Variance Inflation Factor (VIF) values indicate that multicollinearity is not a significant concern:

- **const**: 3.75
- **PIN**: 1.03
- **UIDN**: 1.02
- **SSDN_lag4**: 1.16
- **SSDN_lag8**: 1.05
- **UIDN_lag2**: 1.01
- **SPDN_lag2**: 1.19

5.4 Residuals

- **Durbin-Watson Statistic**: 2.208, indicating no significant autocorrelation in the residuals.
- **Omnibus and Jarque-Bera Tests**: Non-significant results (p-values ¿ 0.05), suggesting that the residuals are normally distributed.

5.5 Conclusion

The OLS model fits the data well with high R-squared values and significant predictors. The negative coefficients for lagged variables indicate delayed effects on y. The absence of multicollinearity issues and the normal distribution of residuals further validate the robustness of the model.

Table 1: Summary of OLS Regression Results

Statistic	Value	Notes
R-squared	0.959	
Adj. R-squared	0.956	
F-statistic	402.8	
Prob (F-statistic)	1.34e-69	
AIC	-451.8	
BIC	-432.9	
No. Observations	111	
Df Residuals	104	
Df Model	6	
Variable	**Coefficient**	**p-value**
const	-0.3262	0.000
PIN	0.1487	0.000
UIDN	0.3258	0.000
SSDN_lag4	-0.1854	0.000
SSDN_lag8	-0.1667	0.000
UIDN_lag2	-0.1363	0.000
SPDN_lag2	-0.1574	0.000
Diagnostic	**Value**	
Durbin-Watson	2.208	
Omnibus	0.146	
Prob (Omnibus)	0.930	
Jarque-Bera (JB)	0.287	
Skew	0.069	
Prob (JB)	0.866	
Kurtosis	2.792	
Variable	**VIF**	
const	3.7529	
PIN	1.0335	
UIDN	1.0192	
SSDN_lag4	1.1615	
SSDN_lag8	1.0471	
UIDN_lag2	1.0132	
SPDN_lag2	1.1874	

6 Conclusion and Discussion

The results of the OLS regression provide insightful conclusions about the relationship between the predictors and the dependent variable, y.

6.1 Lagged Effects of Monetary Policy Sentiments

The analysis indicates significant lagged effects of monetary policy sentiments, specifically the variables $SSDN$ and $SPDN$. The negative coefficients for $SSDN\_lag4$ and $SSDN\_lag8$, as well as $SPDN\_lag2$, reveal that the impact of these sentiments on the dependent variable y is not immediate. This lagged effect can be attributed to the transmission mechanism of monetary policy information to the general public. When monetary policy reports are released, the information initially affects financial markets and institutional stakeholders. It takes time for this information to permeate through various media channels and influence the broader population. Consequently, the impact on the dependent variable y becomes evident only after a delay. The results confirm that changes in monetary policy sentiments, as reflected in media reports, have a gradual effect on economic variables, consistent with the time it takes for such information to influence economic behavior.

6.2 Instantaneous Effects of UIDN

In contrast, the variable $UIDN$ shows significant immediate effects on y, but its lagged effects are not as significant and reduces further down the lags. The coefficient for $UIDN$ is positive and statistically significant, indicating that immediate changes in $UIDN$ directly influence y. This suggests that $UIDN$ reflects information that is quickly disseminated and absorbed by the public through newspapers and other media. Unlike monetary policy sentiments, which require time to filter through media and public perception, $UIDN$ represents information with more instantaneous effects. The lack of significant lagged effects for $UIDN$ highlights that changes in this variable have an almost immediate impact on the dependent variable, emphasizing its role in providing current, actionable information.

6.3 Overall Model Robustness

The high R-squared value and the absence of significant multicollinearity issues support the robustness of the model. The results are consistent with economic theories regarding information dissemination and its effects on economic variables. The Durbin-Watson statistic and residual diagnostics further validate that the model effectively captures the relationship between the predictors and the dependent variable without significant autocorrelation or deviations from normality.

In summary, the regression analysis successfully highlights the differential impacts of monetary policy sentiments and instantaneous information on the dependent variable y. The lagged effects observed for monetary policy sentiments underscore the time required for such information to affect economic variables, while the immediate impact of $UIDN$ reflects the rapid assimilation of current news. These findings contribute to a deeper understanding of how different types of information influence economic outcomes over various time horizons.

7 Future Work

7.1 Enhanced Fine-Tuning of Large Language Models

The current analysis demonstrates the utility of Large Language Models (LLMs) in capturing sentiment from monetary policy reports. However, there remains significant potential for further improvement. One promising avenue for future work is the fine-tuning of LLMs specifically for financial texts.

Fine-Tuning for Domain-Specific Accuracy While existing LLMs like those provided by OpenAI are trained on extensive datasets, including financial texts, there is room to enhance their performance on specialized domains such as monetary policy. Fine-tuning these models with a targeted dataset that includes a diverse range of financial documents and historical policy reports can improve their ability to understand and interpret nuances specific to economic and financial language. This could involve creating a specialized corpus that reflects the language and sentiment unique to monetary policy discourse.

Incorporation of Additional Features Another potential improvement could involve integrating additional features into the LLMs' training process, such as economic indicators, policy changes, and market reactions. By incorporating these elements, the models could better capture the complex relationships between policy sentiments and economic variables. This approach might involve developing multi-modal models that combine textual data with numerical economic indicators to provide a more comprehensive analysis.

Evaluation and Benchmarking Future work should also focus on rigorous evaluation and benchmarking of fine-tuned models. This includes comparing the performance of these models against existing ones on various sentiment analysis tasks related to financial texts. Metrics such as accuracy, precision, recall, and F1 score should be used to assess improvements and ensure that the models provide actionable insights for economic forecasting.

Real-Time Application Finally, deploying fine-tuned models in real-time applications could enhance their practical value. Integrating these advanced models into economic forecasting systems and decision-making tools can provide policymakers and analysts with more accurate and timely sentiment assessments, potentially leading to better-informed economic policies and strategies.

By addressing these areas, future research can significantly enhance the capability of LLMs in financial sentiment analysis, providing more precise and actionable insights from monetary policy reports and related documents.

References

[Bakshi et al.2016] R.K. Bakshi, N. Kaur, R. Kaur, and G. Kaur. 2016. Opinion mining and sentiment analysis. In *Proceedings of the 10th INDIACom; 3rd International Conference on Computing for Sustainable Global Development*, pages 452–455. IEEE.

[Rajeswari Sengupta2019] Aakriti Mathur Rajeswari Sengupta. 2019. Analysing monetary policy statements of the reserve bank of india. In *Graduate Institute of International and Development Studies International Economics Department Working Paper Series*.

[Shrimali and Ahmad2020] Suruchi Shrimali and Wasim Ahmad. 2020. Effect of central bank's communication on the stock market volatility: Evidence from india. *IGIDR Conference Paper*. `http://www.igidr.ac.in/conf/money/mfc19/papers/Suruchi_IGIDR_conference_third%20draft_Day%203%20slot%201.pdf`.

[Sil et al.2023] Rounak Sil, Unninarayanan Kurup, Ashima Goyal, Apoorva Singh, and Rajendra Paramanik. 2023. Chorus in the cacophony: Dissent and policy communication of India's Monetary Policy Committee. Number 2023-03, March.

[Tadphale et al.2023] Anushka Tadphale, Haripriya Saraswat, Omkar Sonawane, and P. R. Deshmukh. 2023. Impact of news sentiment on foreign exchange rate prediction. In *2023 3rd International Conference on Intelligent Technologies (CONIT)*, pages 1–8.