The Federal Open Market Committee (FOMC) Interest Rate Decision:

Dec 17-18, 2024

"Don't fight the Fed" - Marty Zweig

Yunus Gümüşsoy
yunusgumussoy@icloud.com
Ankara, Turkey

2024

Disclaimer: This report is provided solely for informational and educational purposes. It does not constitute personalized financial advice or recommendations.

Introduction

I developed a multiclass classification model to predict the Federal Open Market Committee's (FOMC) interest rate decisions, integrating confidence scores to assess the probabilities of various potential outcomes. The model is designed to serve as a tool for analyzing and forecasting interest rate adjustments by leveraging key economic, market, and communication-based factors that influence Federal Reserve decisions. Central to the model's performance is the construction of a robust dataset that combines diverse sources of information, ensuring a comprehensive approach to prediction.

1. Data Gathering

Accurate prediction of the Federal Reserve's interest rate decisions requires a well-rounded dataset that extends beyond traditional macroeconomic indicators. To address this, the data gathering process was structured into three key components: (1) Economic Data, which includes a wide range of market and financial indicators that provide insights into the broader economic environment, (2) FOMC Meeting and Decision Data, which is historical data on FOMC meetings and their corresponding decisions form the backbone of the dataset, and (3) FOMC Communication Data. Statements, minutes, and other FOMC communications were analyzed using Natural Language Processing (NLP) techniques to extract engineered features, such as sentiment scores and keyword trends, which add an additional layer of predictive power.

1.1. Economic Data

The economic data used in this analysis was sourced from the Federal Reserve Economic Data (FRED) API, which provides a comprehensive repository of economic time series data. Key variables included in the dataset are the Federal Funds Rate, Consumer Price Index (CPI), Gross Domestic Product (GDP), employment metrics (such as non-farm payrolls and unemployment rates), and Treasury yields. These variables are essential for capturing macroeconomic trends and understanding their influence on monetary policy decisions (for a complete list of variables, see Appendix 1).

The earliest available data point corresponds to the FOMC decision date of October 15, 1998. To maintain consistency and comprehensiveness, this date was selected as the starting point for collecting economic data. Since some variables are reported monthly or quarterly, the dataset was resampled to a daily frequency using forward-fill interpolation to ensure no gaps in daily values. This approach allows for seamless integration with other time-sensitive data components.

1.2. FOMC Meeting and Decision Data

Historical data on FOMC meetings was collected to provide a foundation for understanding the Federal Reserve's decision-making process. This dataset includes details such as FOMC meeting dates, historical interest rate changes, and corresponding decision outcomes. The data was sourced from Investing.com[1], a reliable platform for financial and economic information. This component of the dataset is essential for capturing the timing and context of past policy decisions, which serve as a benchmark for forecasting future rate adjustments.

Figure 1. FOMC Meeting and Decision Data.

	Release Date	Time	Actual	Forecast	Previous
0	Dec 18, 2024	14:00:00	NaN	NaN	4.75%
1	Nov 07, 2024	14:00:00	4.75%	4.75%	5.00%
2	Sep 18, 2024	13:00:00	5.00%	5.25%	5.50%
3	Jul 31, 2024	13:00:00	5.50%	5.50%	5.50%
4	Jun 12, 2024	13:00:00	5.50%	5.50%	5.50%

To ensure compatibility with the economic data fetched from the FRED API, I standardized the date format to YYYY-MM-DD, a crucial step for maintaining consistency in time-series data. This format is also consistent across all three datasets, enabling a seamless merge process.

Next, the "Actual" and "Previous" columns were converted to numeric values to facilitate accurate calculations. A new column, "Decision", was created by computing the difference between "Actual" and "Previous" interest rates (Decision = Actual - Previous). This column represents the FOMC's decision on interest rate changes and serves as a target variable for the final model.

As the final preparation step, I set the "Release Date" column as the index and sorted the dataset in ascending order by this index. This ensures proper chronological alignment for further analysis and modeling. Figure 2 illustrates the final processed version of the FOMC meeting and decision dataset, ready for integration into subsequent analysis and modeling workflows.

[1] https://www.investing.com/economic-calendar/interest-rate-decision-168

Figure 2. Final Version of FOMC Meeting and Decision Data.

Release Date	Time	Actual	Forecast	Previous	Decision
1998-10-15	13:00:00	5.00	NaN	5.25	-0.25%
1998-11-17	13:00:00	4.75	NaN	5.00	-0.25%
1999-06-30	13:00:00	5.00	NaN	4.75	+0.25%
1999-08-24	13:00:00	5.25	NaN	5.00	+0.25%
1999-11-16	13:00:00	5.50	NaN	5.25	+0.25%
...	...	...	...	...	...
2024-06-12	13:00:00	5.50	5.50%	5.50	+0.00%
2024-07-31	13:00:00	5.50	5.50%	5.50	+0.00%
2024-09-18	13:00:00	5.00	5.25%	5.50	-0.50%
2024-11-07	14:00:00	4.75	4.75%	5.00	-0.25%
2024-12-18	14:00:00	NaN	NaN	4.75	+0.00%

1.3. FOMC Communication Data

I collected FOMC communications, including statements and meeting minutes, by scraping data directly from the Federal Reserve's official website. This dataset captures the textual content of FOMC communications, which often provides valuable insight into monetary policy sentiment and forward guidance.

To analyze and visualize this data, I applied several Natural Language Processing (NLP) techniques. Sentiment analysis was used to measure the tone and sentiment conveyed in the communications, providing insights into the FOMC's outlook. Keyword extraction helped identify significant terms and phrases that emphasize key policy areas. Topic modeling was employed to uncover underlying themes or discussion topics present in the texts. Additionally, I utilized Term Frequency-Inverse Document Frequency (TF-IDF) to quantify the relative importance of specific words across the dataset, facilitating a deeper understanding of language patterns and priorities in FOMC communications.

These methods allow for the extraction of engineered features that reflect the FOMC's sentiment and guidance. Figure 3 presents the first few lines of the scraped FOMC communication dataset, illustrating the raw data format before processing.

Figure 3. Scraped FOMC Communication Data.

Date	Release Date	Type	Text
2000-02-02	2000-02-02	Statement	The Federal Open Market Committee voted today ...
2000-02-02	2000-03-23	Minute	Minutes of the Federal Open Market Committee\n...
2000-03-21	2000-05-18	Minute	Minutes of the Federal Open Market Committee\n...
2000-03-21	2000-03-21	Statement	The Federal Open Market Committee voted today ...
2000-05-16	2000-06-29	Minute	Minutes of the Federal Open Market Committee\n...

2. Exploratory Data Analysis (EDA)

To understand the underlying mechanisms behind interest rate decisions, I conducted Exploratory Data Analysis (EDA) by extracting insights through trends and visualizations. I began with an analysis of the economic data to explore relationships among various economic indicators, key events, and monetary policies. Particular attention was given to changes in the Federal Funds Rate, examining its patterns during specific periods and its correlations with other economic variables.

Subsequently, I analyzed FOMC communications, including statements and minutes, to uncover potential clues about interest rate decisions. By visualizing trends and patterns in this textual data, I aimed to capture the relationship between communication content and monetary policy actions.

Figure 4. Fed Funds Rate Over Time.

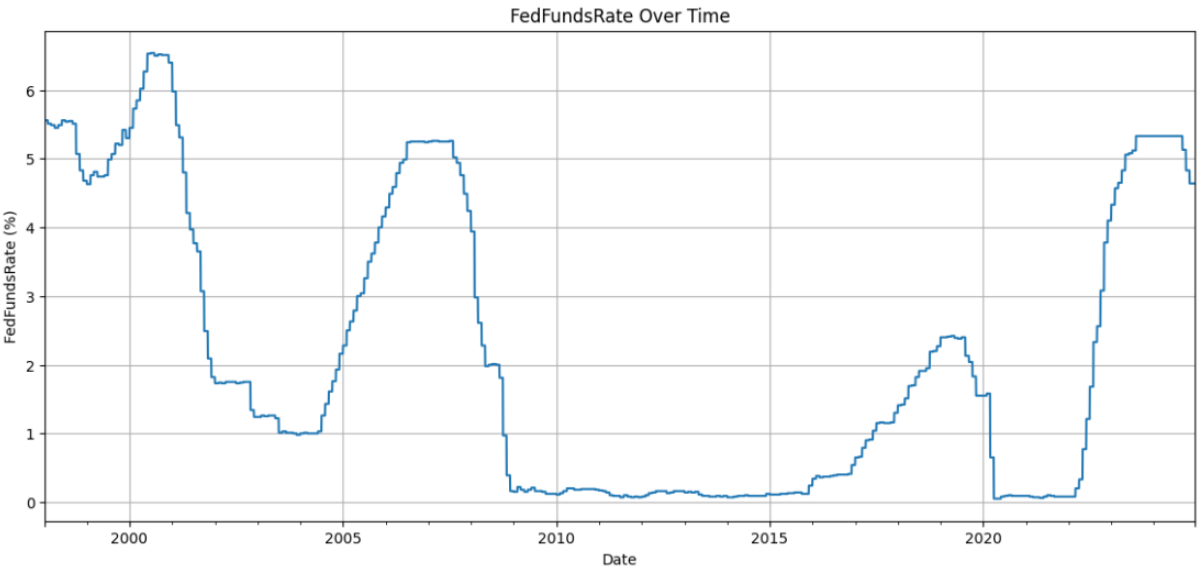


Figure 4 illustrates the historical values of the Federal Funds Rate (in percent) from 1999 to 2024. The Fed Funds Rate follows a cyclical pattern, with periods of both increases and decreases. In the early 2000s, the rate starts at a high level, experiences a sharp decline, and then rises again, peaking around 2006. To enhance understanding of these fluctuations, I overlaid key economic events on the plot (Figure 5).

More specifically, my initial analysis revealed clear cyclical trends in the Federal Funds Rate over the past two decades, reflecting the broader economic cycles and the Federal Reserve's monetary policy responses. From 2004 to 2006, I observed a steady increase in the rate, reaching a peak of approximately 5.25% in 2006–2007. This period of rising rates was likely a response to a growing economy and mounting inflationary pressures.

The rate then drops sharply starting in 2007, with an accelerated decline in 2008, coinciding with the Global Financial Crisis. In response, the Fed rapidly slashed rates to near zero in an attempt to stimulate economic activity. From 2009 to 2015, I observed an unprecedented period of near-zero rates, known as the “zero lower bound” era, reflecting the Fed’s aggressive monetary policy aimed at supporting the economy during the recovery.

Beginning in late 2015, the Fed gradually raised rates as part of the normalization of monetary policy, in response to improving economic conditions. In early 2020, another sharp decline to near-zero rates occurred, mirroring the Fed’s emergency response to the economic shock caused by the COVID-19 pandemic. From 2022 to 2023, I noted a steep and rapid increase in rates, reaching levels not seen since before the 2008 crisis. This reflected the Fed's aggressive tightening measures to combat high inflation. These observations set the stage for a deeper analysis of how Federal Funds Rate changes interact with other key economic indicators and influence credit risk.

Figure 5. Fed Funds Rate Over Time (Highlighting Economic Events).

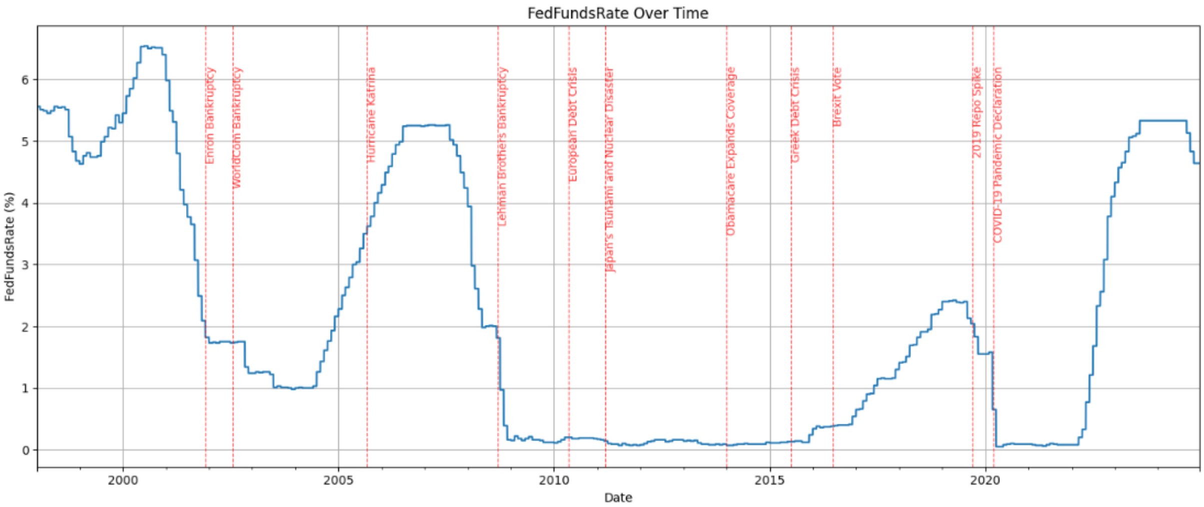


Figure 5 illustrates how significant economic events have influenced the Federal Funds Rate over time. Notably, a dramatic drop in the rate around 2008-2009 coincided with the global financial crisis. In the post-crisis period, the rate remained near zero for an extended period, from 2009 to 2016. In more recent years, a gradual upward trend is observed from 2016 to 2019, followed by a sharp drop in 2020, likely in response to the COVID-19 pandemic, and a steep increase beginning in 2022.

To better visualize the relationship between key economic events and the Federal Funds Rate, I added vertical lines to the plot marking notable events between 2001 and 2023. These events include: the Enron Bankruptcy (2001-12-02), the WorldCom Bankruptcy (2002-07-21), Hurricane Katrina (2005-08-29), the Lehman Brothers Bankruptcy (2008-09-15), the European

Debt Crisis (2010-05-01), Japan's Tsunami and Nuclear Disaster (2011-03-11), the Affordable Care Act Expansion (2014-01-01), the Greek Debt Crisis (2015-07-01), the Brexit Vote (2016-06-23), the 2019 Repo Spike (2019-09-17), the COVID-19 Pandemic Declaration (2020-03-11), and the End of the COVID-19 Pandemic (2023-05-11). These vertical lines provide a clear visual representation of the timing and potential impact of these events on the Fed Funds Rate.

Figure 6. Economic Indicators Over Time (Fed Funds Rate, CPI, Unemployment Rate).

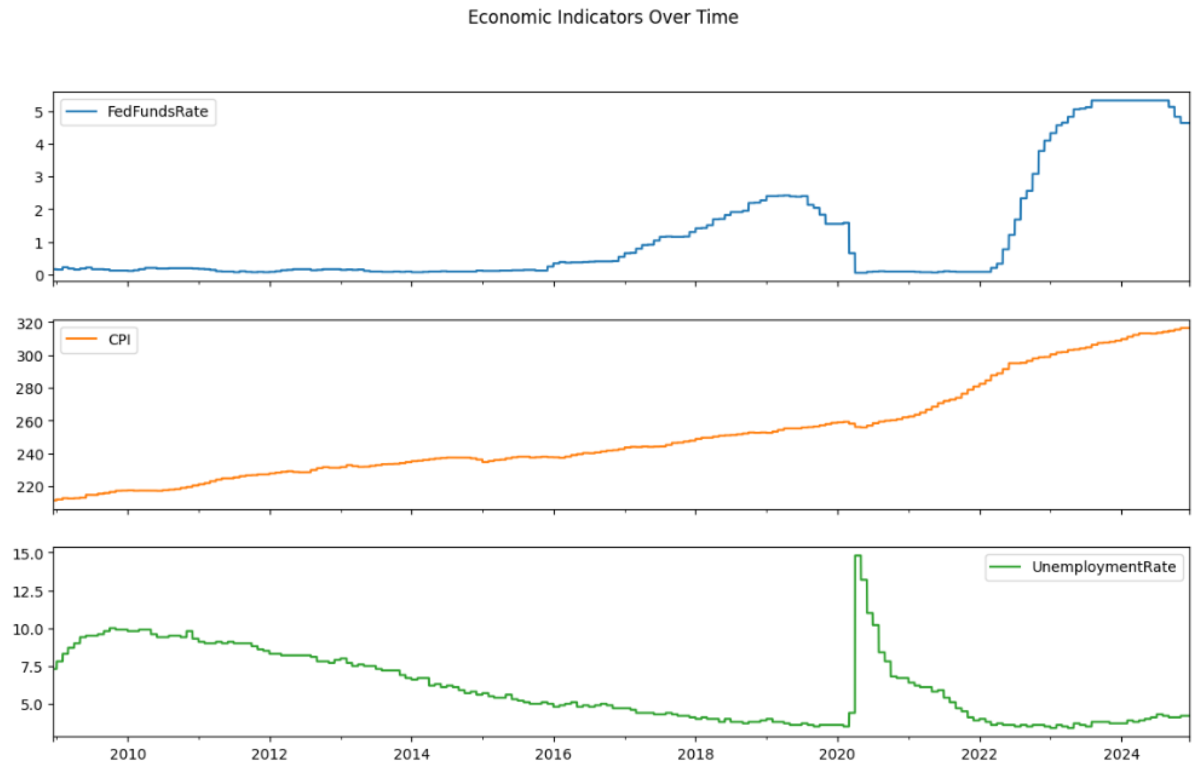


Figure 6 presents the trends of several key economic indicators over time, including the Federal Funds Rate (Fed Funds Rate), Consumer Price Index (CPI), and Unemployment Rate. To facilitate comparison, I overlaid these indicators with the Fed Funds Rate in a combined plot, shown in Figure 7. This stacked visualization offers a clearer understanding of how these indicators evolve in relation to changes in the Fed Funds Rate. For space and readability purposes, I have included only a selection of the plots here; for the full set, please refer to the provided link[2].

[2] https://github.com/yunusgumussoy/FOMC-Interest-Rate-Decision-Prediction

Figure 7. Economic Indicators compared to Fed Funds Rate.

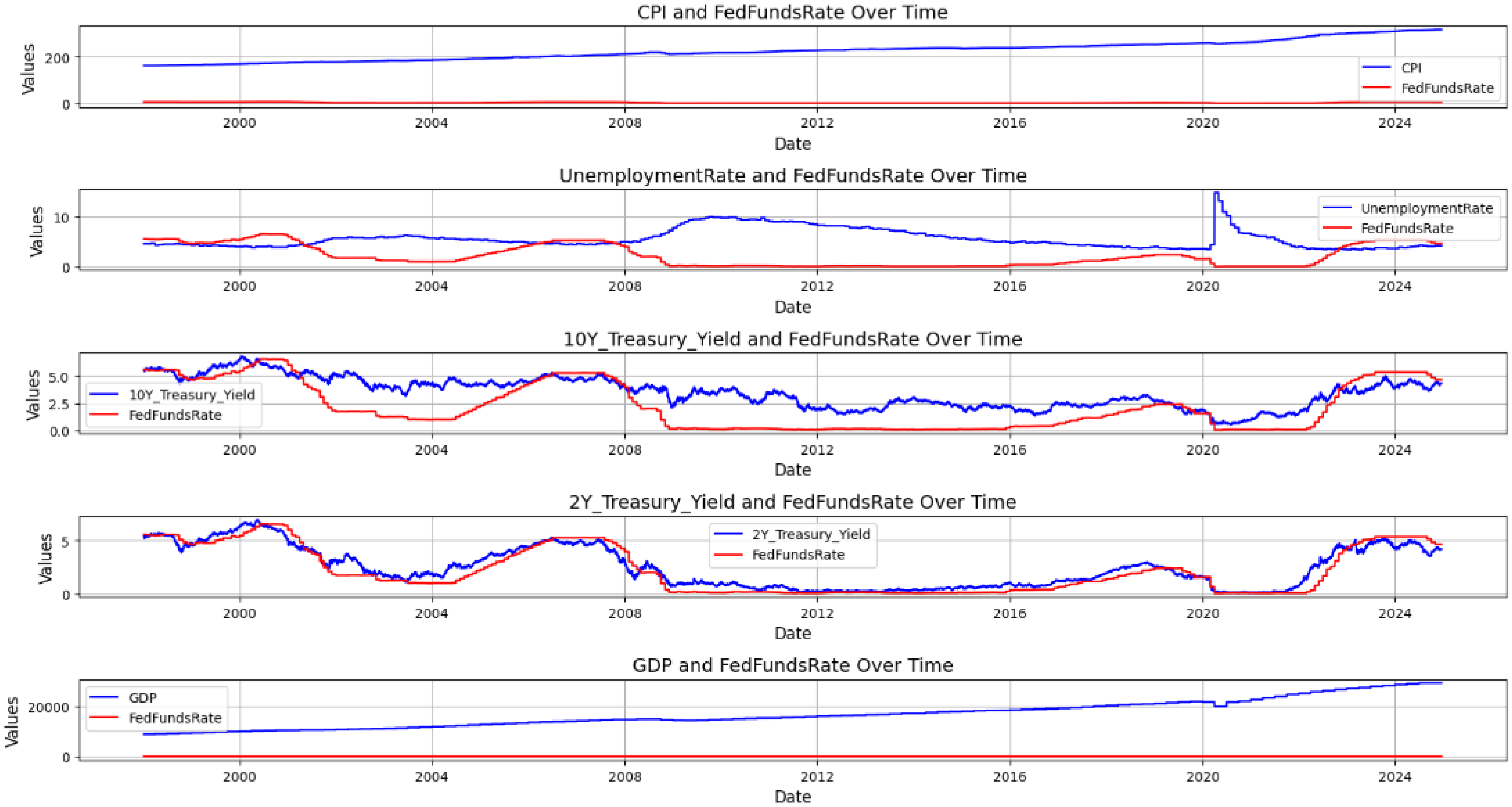


Figure 8. Correlation Heatmap.

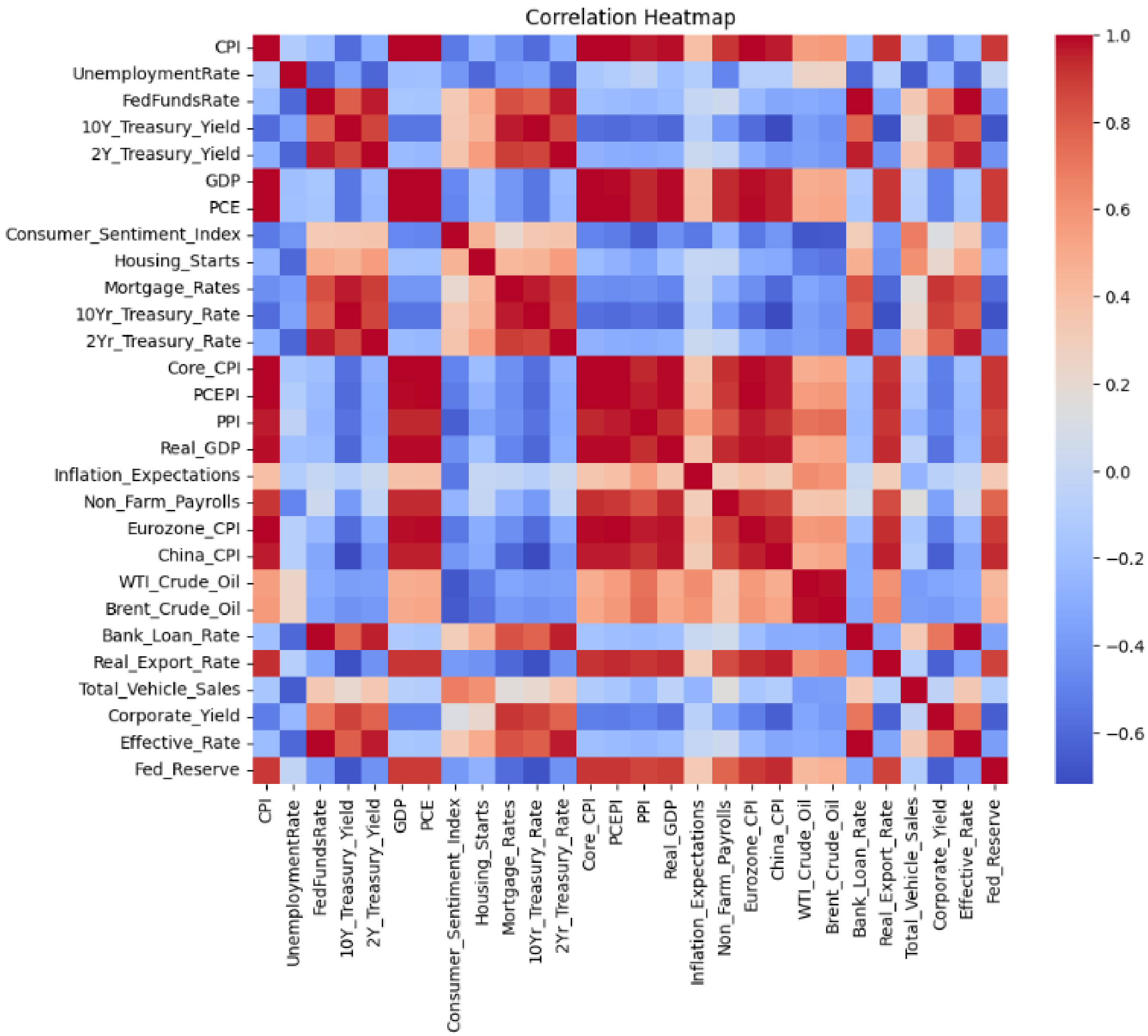


Figure 8 illustrates the strong influence of the Federal Funds Rate on other interest rates in the economy. Changes in the Fed Funds Rate are often reflected in other interest rates, directly affecting borrowing costs for businesses and consumers. However, the relationship between the Fed Funds Rate and housing starts appears weaker, suggesting that factors beyond interest rates may play a more significant role in driving housing market activity.

Figure 9. Top Correlations with Fed Funds Rate.

```
Top Correlations with FedFundsRate:
FedFundsRate          1.000000
Effective_Rate        0.998505
Bank_Loan_Rate        0.998422
2Yr_Treasury_Rate     0.962625
2Y_Treasury_Yield     0.961548
Mortgage_Rates        0.832862
10Yr_Treasury_Rate    0.789964
10Y_Treasury_Yield    0.787799
Corporate_Yield       0.710443
Housing_Starts        0.484668
```

Figures 8 and 9 display the correlation coefficients between the Federal Funds Rate and various other economic indicators. A correlation coefficient quantifies the strength and direction of the linear relationship between two variables. Both figures emphasize that the Fed Funds Rate exhibits a very strong positive correlation with several key interest rates, including the Effective Rate (the average interest rate that banks charge each other for overnight loans), the Bank Loan Rate (the interest rate banks charge their customers for loans), and the interest rate and return on two-year U.S. Treasury bonds.

Additionally, the Fed Funds Rate shows a moderate positive correlation with Mortgage Rates (the interest rate charged on home loans), the interest rate and return on ten-year U.S. Treasury bonds, and Corporate Yield (the average interest rate companies pay on their bonds). However, the Fed Funds Rate has only a weak positive correlation with Housing Starts, suggesting a less direct relationship between the two.

Figure 10. Correlation of Variables with Fed Funds Rate.

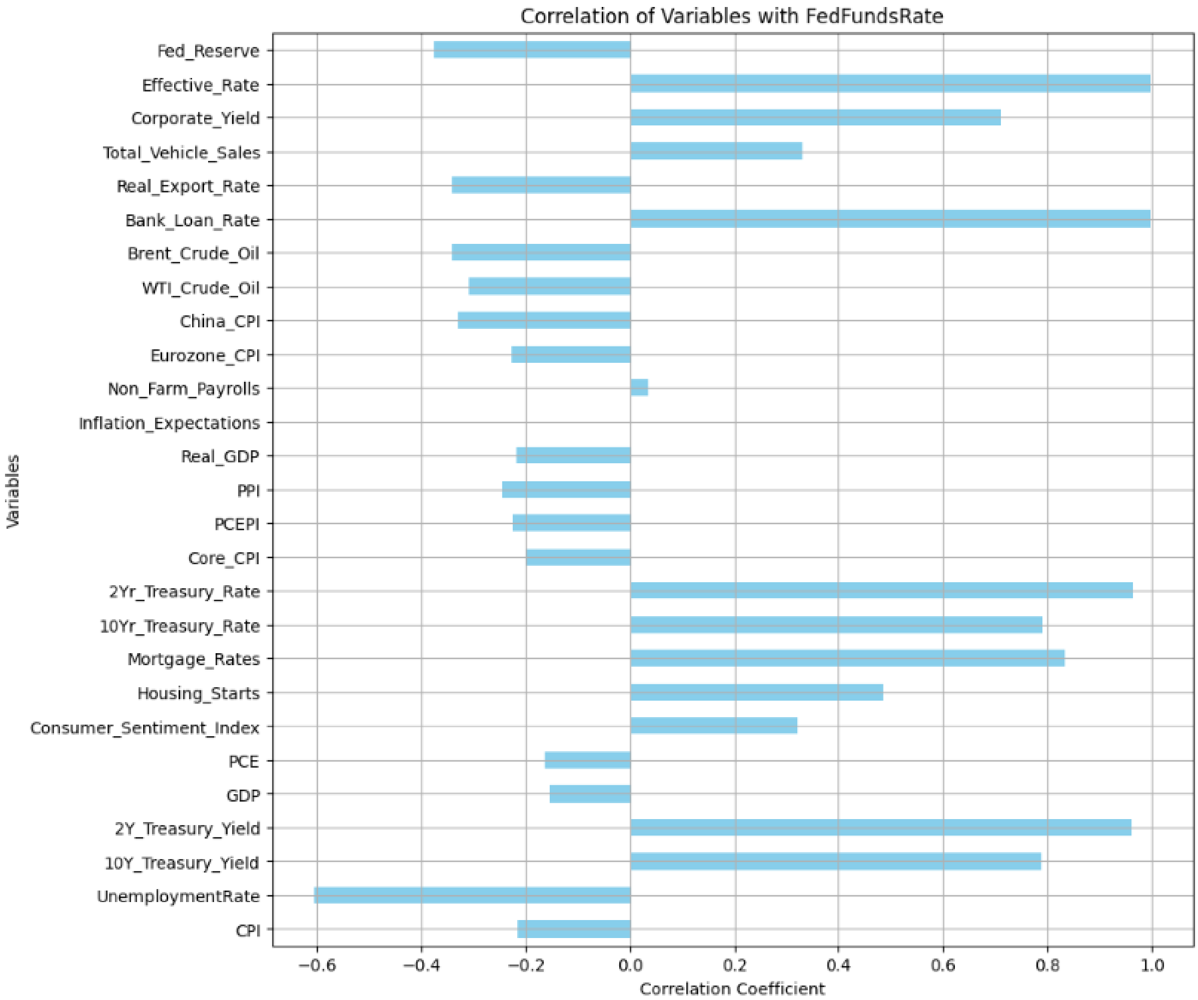


Figure 11. The Relationship between the Fed Funds Rate (%) and CPI.

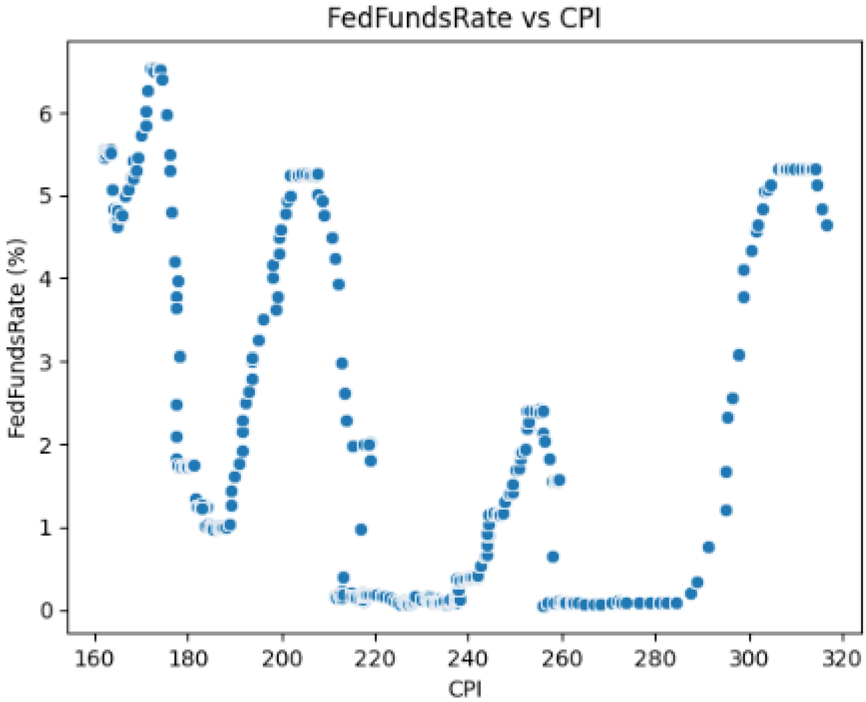


Figure 11 illustrates the relationship between the Federal Funds Rate (%) and the Consumer Price Index (CPI). A non-linear relationship between the two variables is evident, prompting the use of a Generalized Additive Model (GAM) to capture this potentially complex association. GAMs are particularly effective in modeling situations where the response variable (Fed Funds Rate) does not change linearly with the predictor (CPI), allowing for more flexibility in understanding the relationship between these economic indicators.

Figure 12. Non-linear Relationship between the Fed Funds Rate (%) and the CPI.

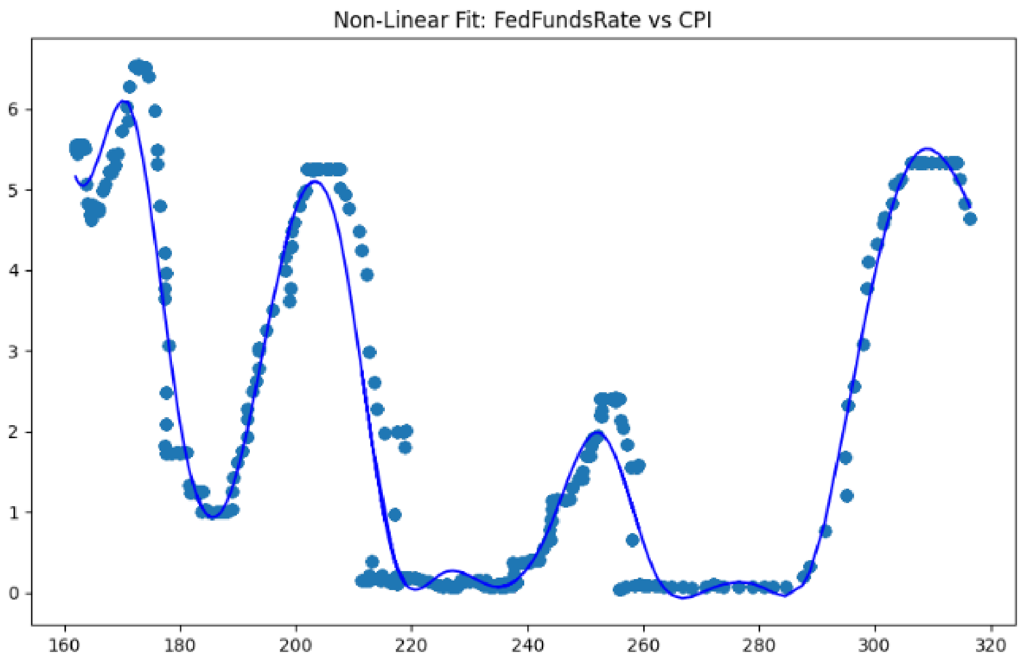


Figure 12 illustrates that changes in the Consumer Price Index (CPI) may not have a linear impact on the Federal Funds Rate, as evidenced by the flat sections of the line. However, during certain periods, even small changes in CPI can lead to significant adjustments in the Fed Funds Rate, as seen in the steep sections of the curve. This plot was instrumental in understanding monetary policy behavior. For instance, the sharp rise in the blue line at higher CPI values may indicate aggressive rate hikes implemented during periods of high inflation.

Figure 13. The Relationship between the Fed Funds Rate (%) and Unemployment Rate.

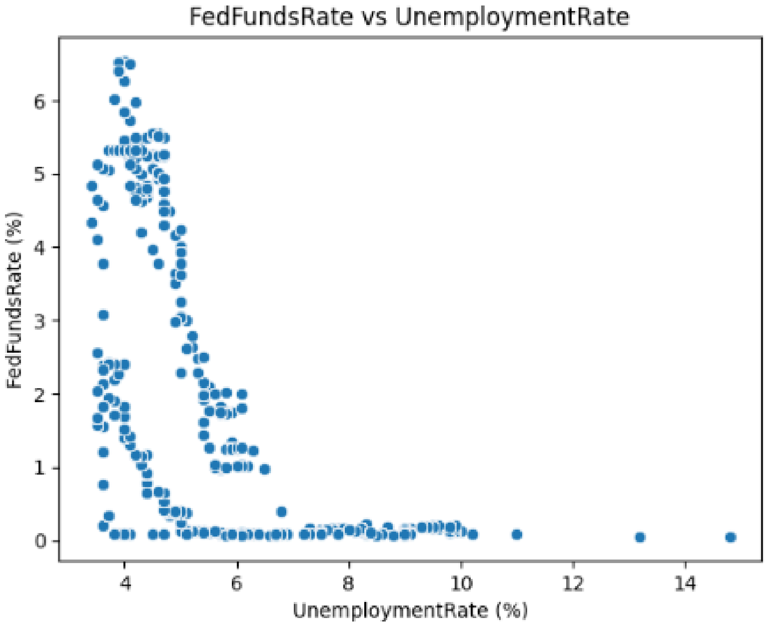


Figure 13 visualizes the relationship between the Federal Funds Rate and the Unemployment Rate. A negative correlation is apparent between the two variables, especially within the range of unemployment rates from approximately 3% to 7%.

Figure 14. Average Fed Funds Rate by Decade.

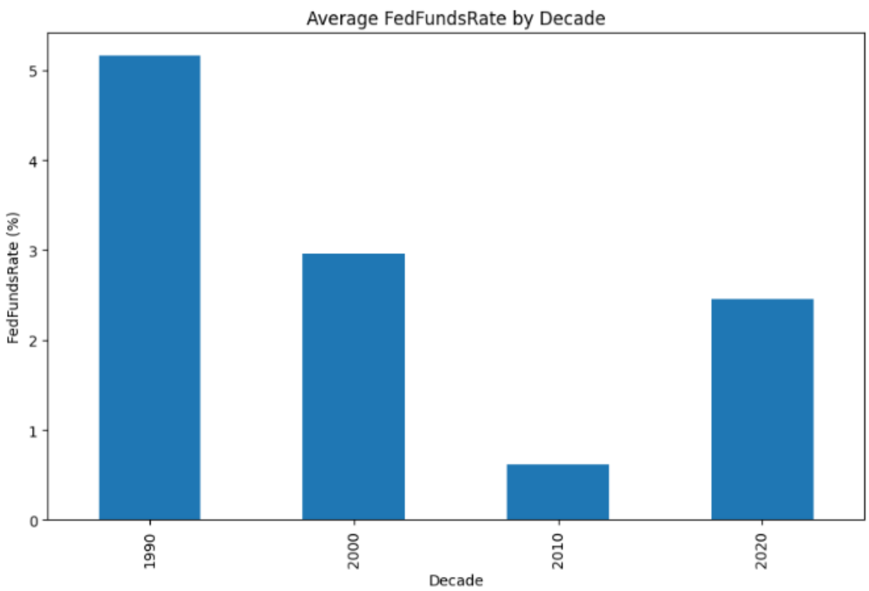


Figure 14 illustrates the average Federal Funds Rate for each decade, spanning from 1990 to 2020. The 1990s stand out with the highest average Fed Funds Rate, exceeding 5%, indicating a period of tighter monetary policy aimed at controlling inflation and preventing economic overheating. In contrast, the 2000s saw a moderate average rate of around 3%, suggesting a period of balanced economic growth and stable inflation. The 2010s experienced the lowest average Fed Funds Rate, barely reaching 0.5%, reflecting an era of exceptionally loose monetary policy following the 2008 financial crisis, designed to stimulate economic recovery. Finally, the 2020s show a resurgence in the average rate, reaching approximately 2.5%, signaling a shift toward tightening monetary policy in response to inflationary pressures and the economic recovery from the COVID-19 pandemic.

Figure 15. Fed Funds Rate and Volatility (Rolling 12-Month Window)

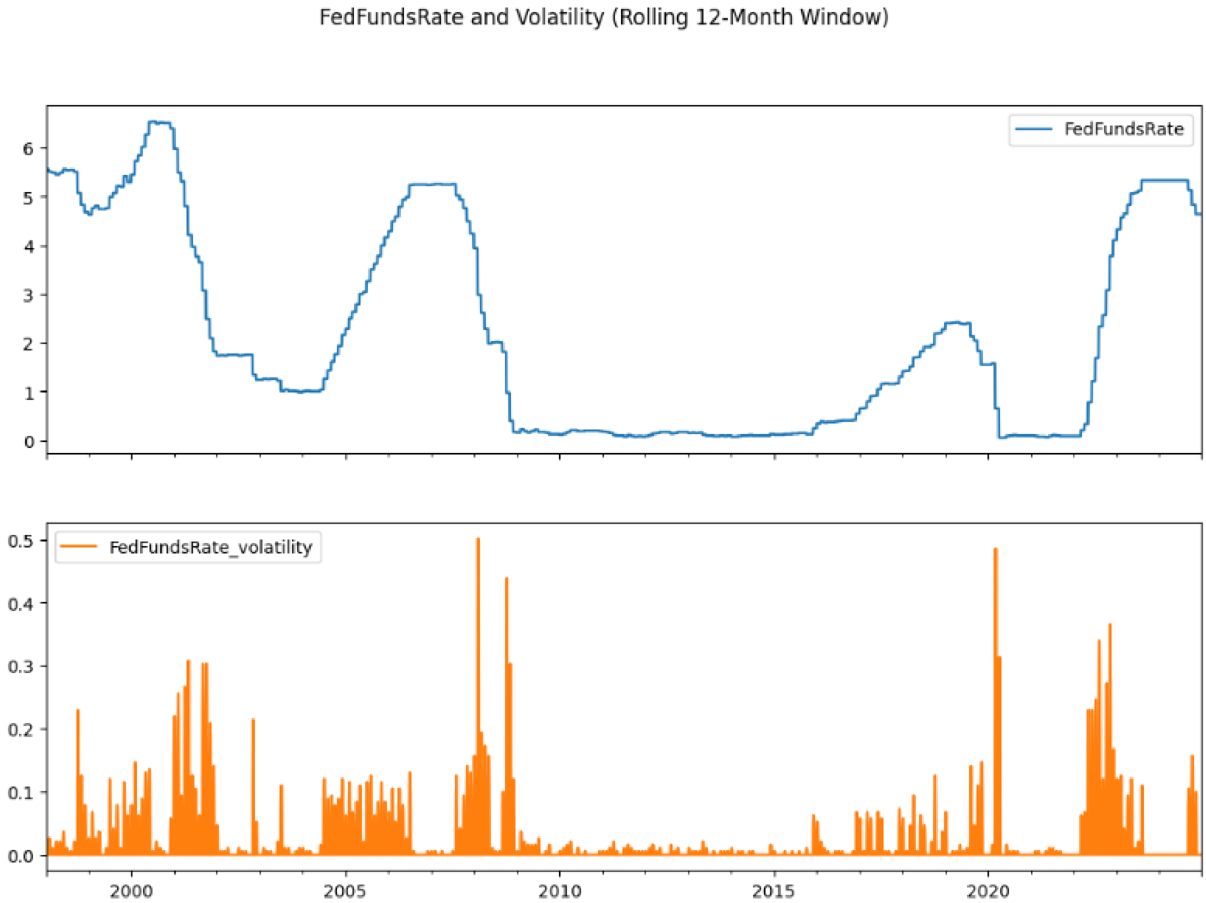


Figure 15 displays the rolling standard deviation (volatility) of the Federal Funds Rate as a measure of economic uncertainty over time. This measure reflects periods of economic instability or rapid policy adjustments. The visualization offers a clear view of how the Fed's monetary policy evolves and how it correlates with periods of economic stability or turmoil. During times of economic distress, such as recessions or financial crises, policymakers may adjust rates more frequently or significantly, resulting in increased volatility. Conversely, during periods of economic stability, rates may remain steady or change incrementally, reflecting low uncertainty.

To further explore seasonal patterns in the Fed Funds Rate, I calculated the average rate for each month across all years. These averages were then plotted to highlight any recurring trends on a monthly basis (Figure 16).

Figure 16. Seasonal Trends in Fed Funds Rate.

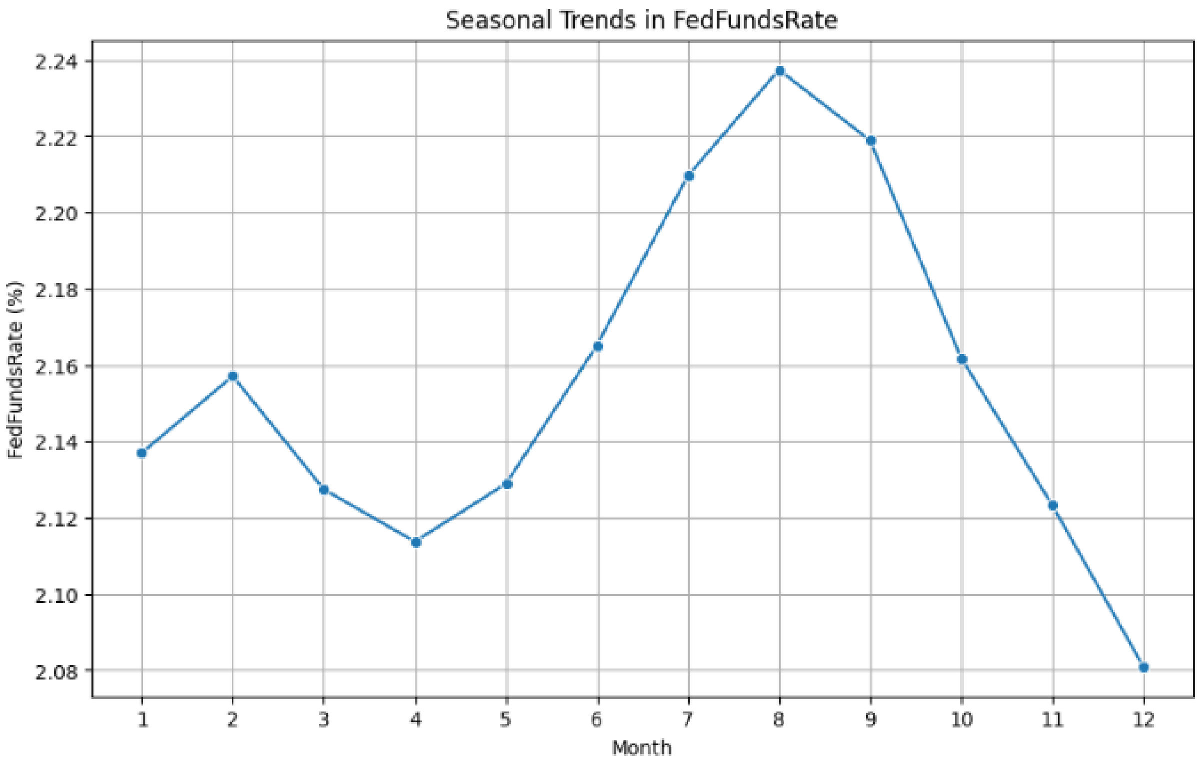
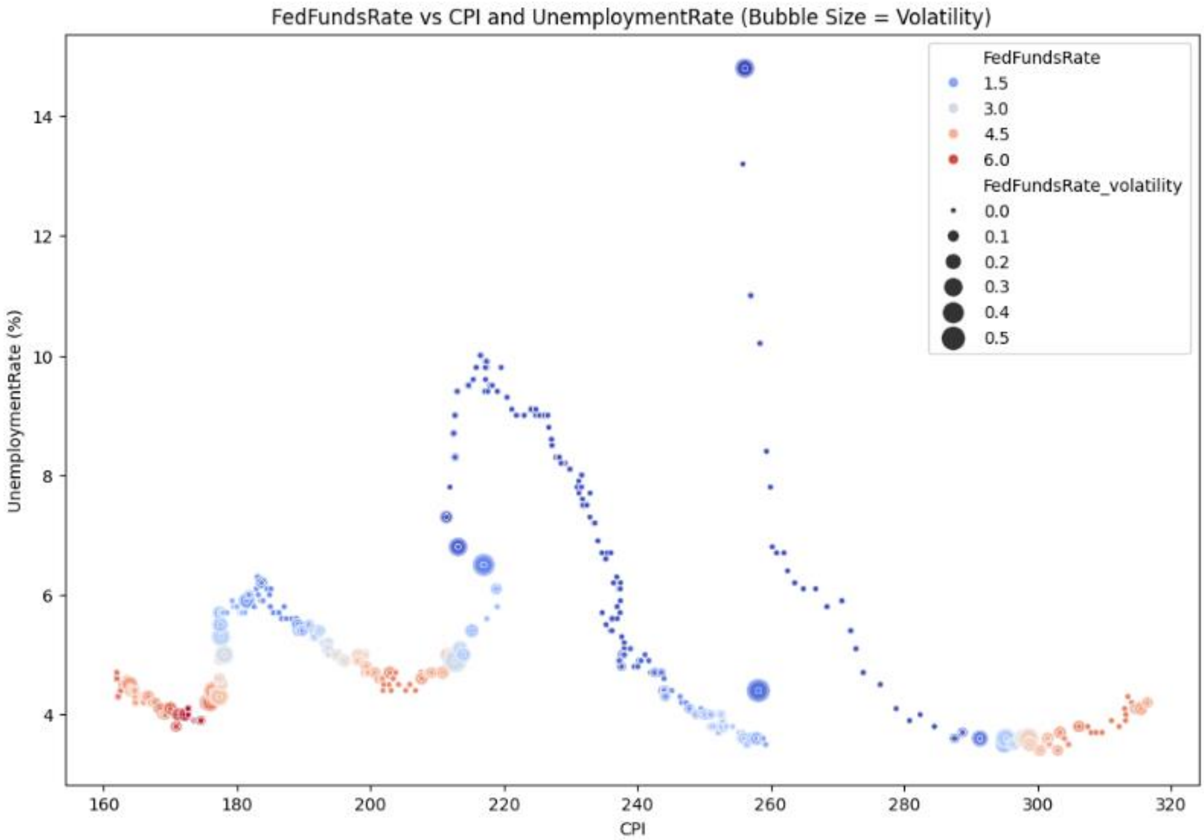


Figure 16 illustrates the seasonal trends in the Federal Funds Rate over the course of a year. A clear pattern emerges, with the rate generally increasing at the start of the year, peaking around August, and then declining toward the end of the year. This cyclical behavior suggests a potential correlation between the Fed Funds Rate and certain economic factors that tend to fluctuate seasonally.

Next, I created a scatterplot (Figure 17) to visualize the relationships between the Consumer Price Index (CPI), the Unemployment Rate, and the Fed Funds Rate, while also incorporating additional dimensions such as volatility and rate magnitude. This plot provides a comprehensive visual summary of how key economic indicators interact with the Fed Funds Rate and its volatility.

Figure 17. The Relationship between the Consumer Price Index (CPI), the Unemployment Rate, and the Fed Funds Rate.

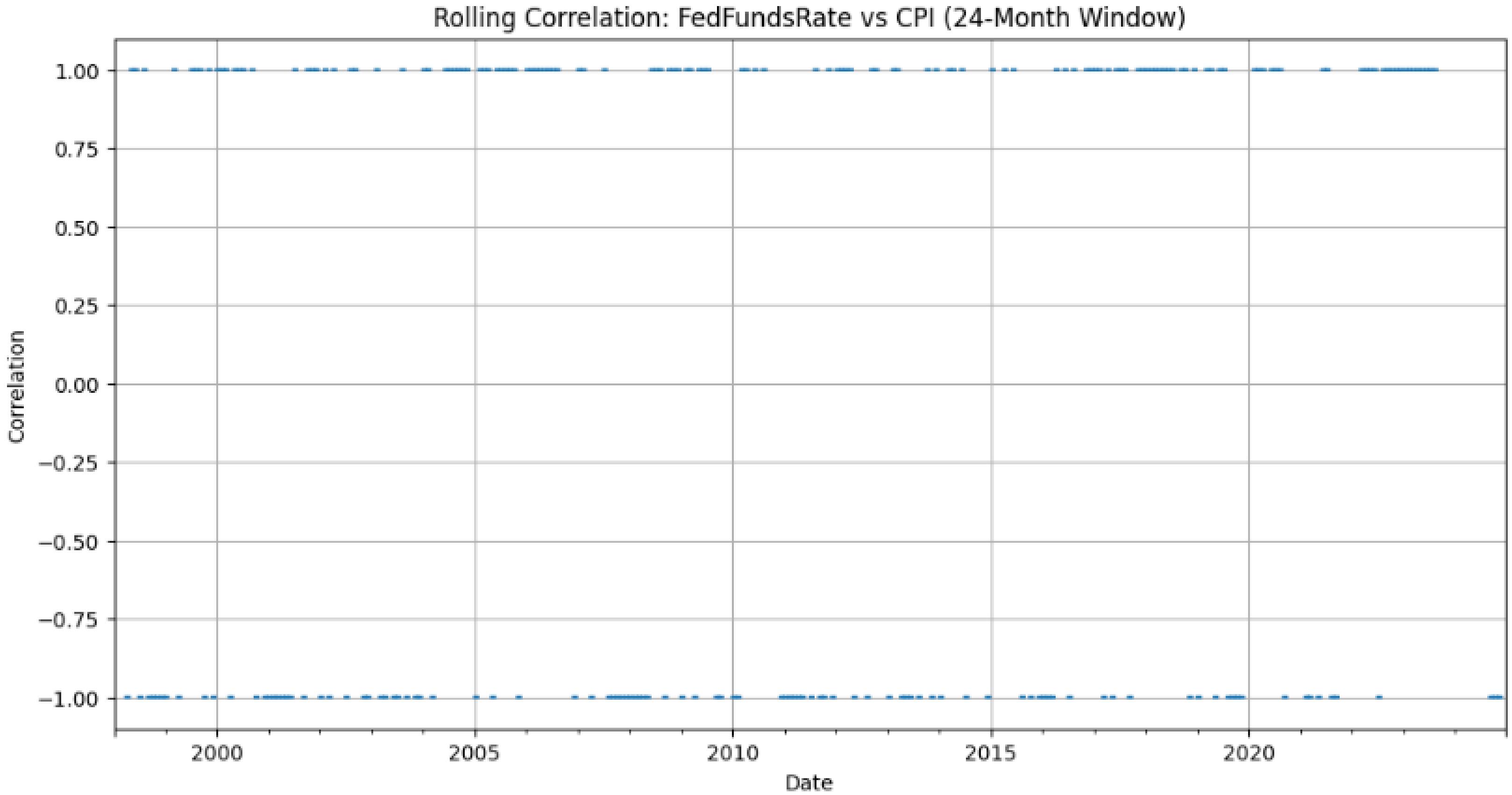


In Figure 17, the blue-colored points represent periods of low interest rates, typically during economic recessions or expansions, while the red-colored points indicate periods of high interest rates, often implemented to combat inflation. Additionally, larger bubbles correspond to periods of higher volatility in the Federal Funds Rate, which may coincide with economic uncertainty or rapid policy changes.

I observed that periods of high CPI and low unemployment tend to align with high interest rates (red points) and occasionally higher volatility (larger bubbles). When high CPI values are associated with high Fed Funds Rates (red bubbles), it suggests that monetary policy is responding to inflationary pressures. Conversely, periods of low unemployment are often accompanied by smaller bubbles (low volatility), indicating more stable economic conditions. Notably, larger bubbles tend to cluster around significant economic events, such as financial crises or major policy shifts.

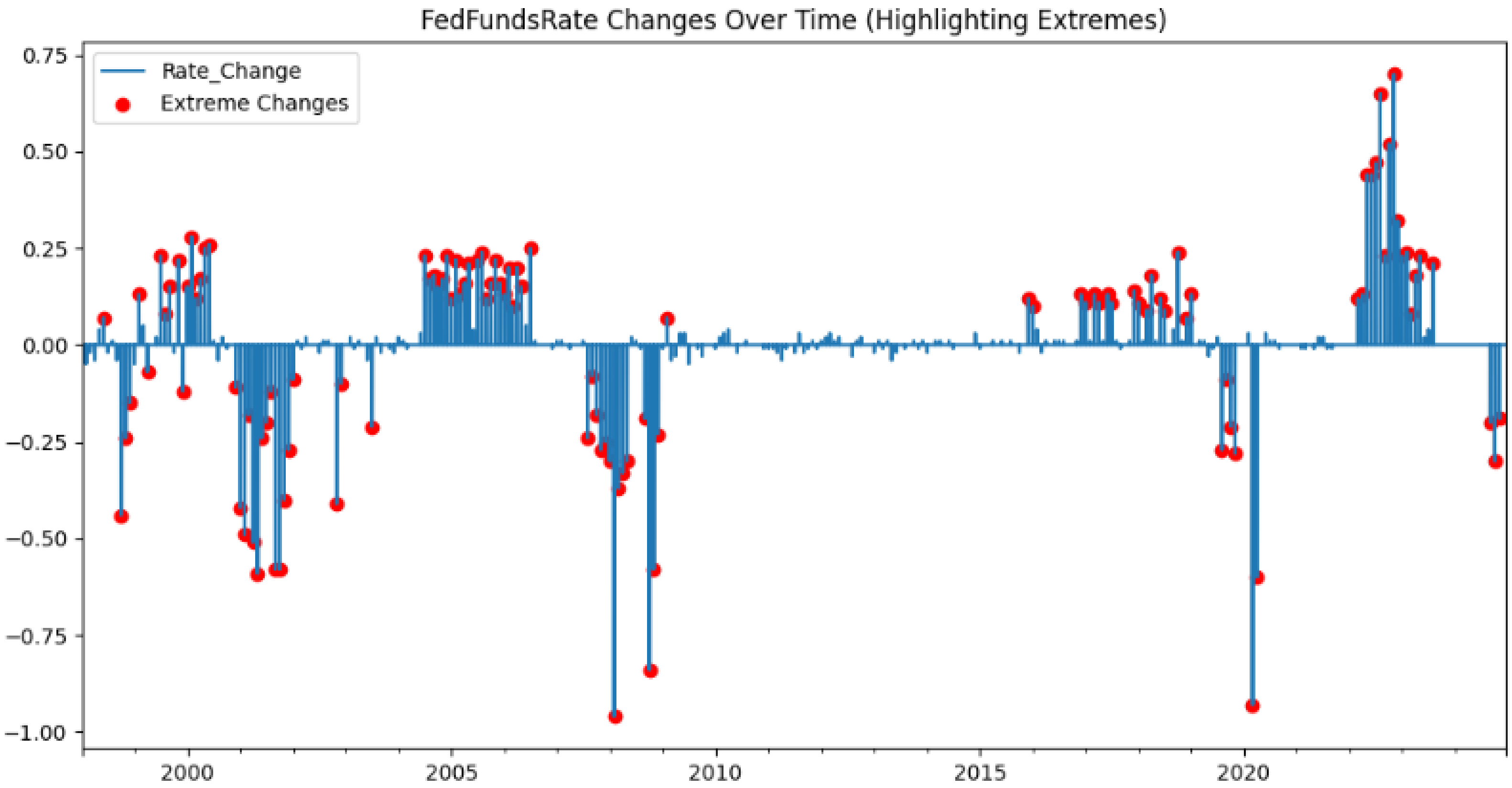
Furthermore, I calculated and visualized the rolling correlation between the Fed Funds Rate and the Consumer Price Index (CPI) over a 24-month rolling window, as shown in Figure 18.

Figure 18. The Rolling Correlation between the Fed Funds Rate and the Consumer Price Index (CPI) over A 24-Month Rolling Window.



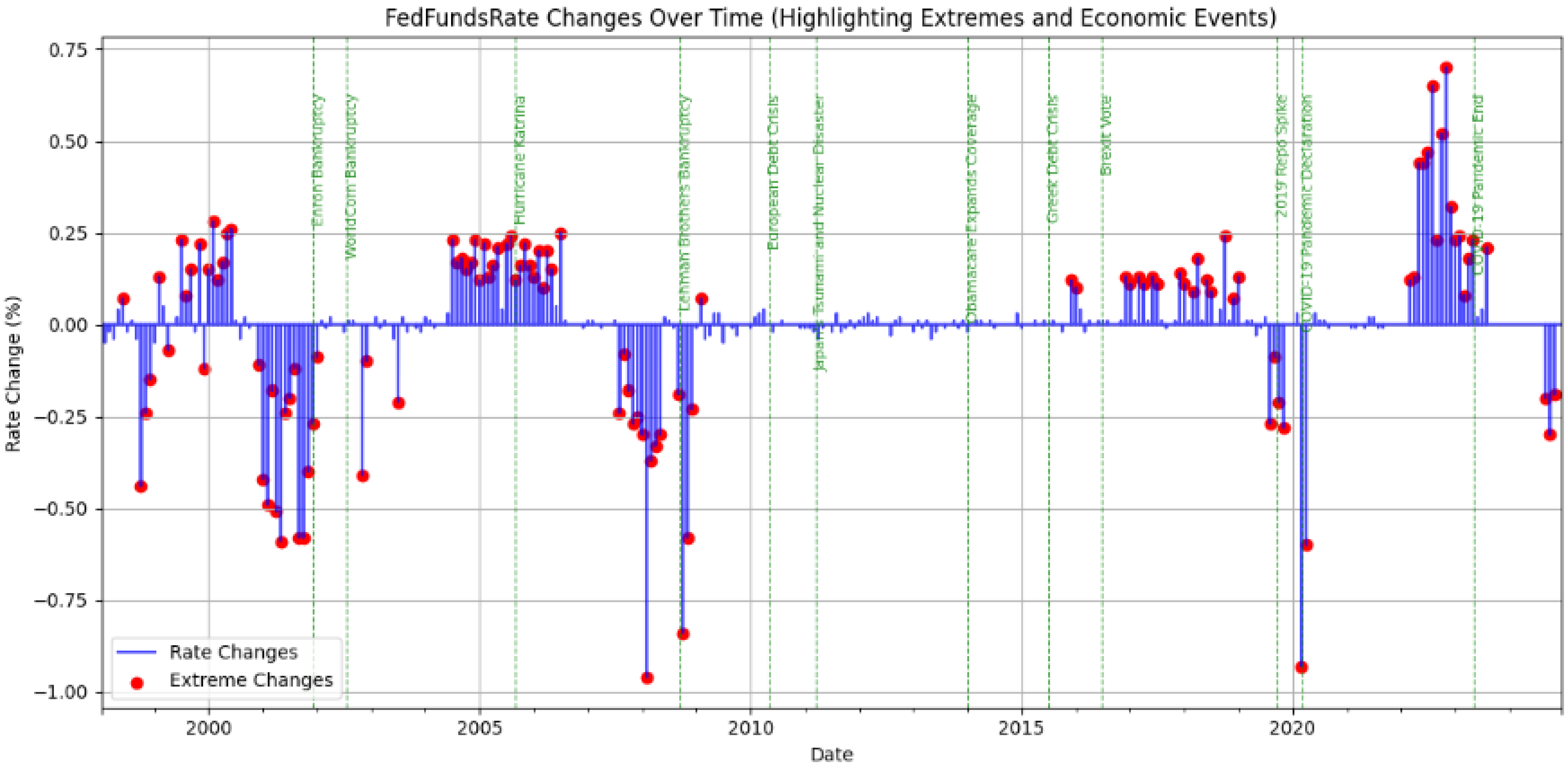
Throughout my exploratory data analysis, I observed that the relationship between the Federal Funds Rate and the Consumer Price Index (CPI) is not constant over time. To capture this evolving relationship, I visualized the rolling correlation between the two variables. In Figure 18, a value of +1 indicates a perfect positive correlation, meaning the Fed Funds Rate and CPI move in the same direction. Conversely, a value of -1 represents a perfect negative correlation, where the Fed Funds Rate and CPI move in opposite directions.

Figure 19. Fed Funds Rate Changes Over Time (Highlighting Extremes).



To better understand how the Federal Reserve has adjusted interest rates in response to economic conditions and major events over the past two decades, I plotted Figures 19 and 20.

Figure 20. FedFundsRate Changes Over Time (Highlighting Extremes and Economic Events).



Figures 19 and 20 illustrate the historical changes in the Federal Funds Rate, highlighting periods of significant fluctuations and key economic events. The blue bars represent the percentage change in the Federal Funds Rate over time. Positive values indicate rate increases, while negative values indicate rate decreases.

Red dots highlight periods of particularly large rate changes, indicating significant shifts in monetary policy. Green vertical lines and text annotations mark major economic events that likely influenced the Federal Reserve's interest rate decisions. Examples include the dot-com bubble burst, the 2008 financial crisis, and the COVID-19 pandemic.

Figure 20 reveals a strong correlation between extreme rate changes and these economic events. For example, the sharp rate cuts in the early 2000s and late 2000s coincide with the dot-com bubble burst and the 2008 financial crisis, respectively. Similarly, the steep decline in rates in 2020 reflects the Federal Reserve's response to the economic shock caused by the COVID-19 pandemic.

2.1. FOMC Communication Data Sentiment Analysis

I performed sentiment analysis on the "Text" column using the VADER sentiment analysis tool, calculating the compound score for each statement, which is stored as the Sentiment Score. Additionally, I created sentiment categories (Positive, Neutral, Negative) based on the score to determine the tone of the communications. These sentiment scores and categories offer a clear breakdown of sentiment trends over time. To further enhance the analysis, I also employed FinBERT, a transformer-based model designed for financial text sentiment analysis, to assess the sentiment of FOMC statements. I compared the sentiment scores and categories from both VADER and FinBERT to evaluate how well they align.

Figure 21. Distribution of FinBERT Sentiment Categories across all Statements.

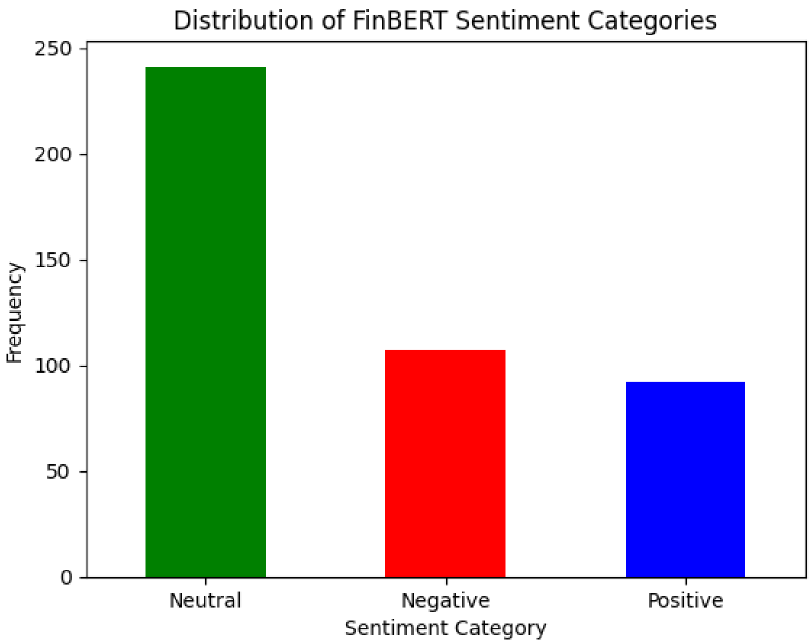
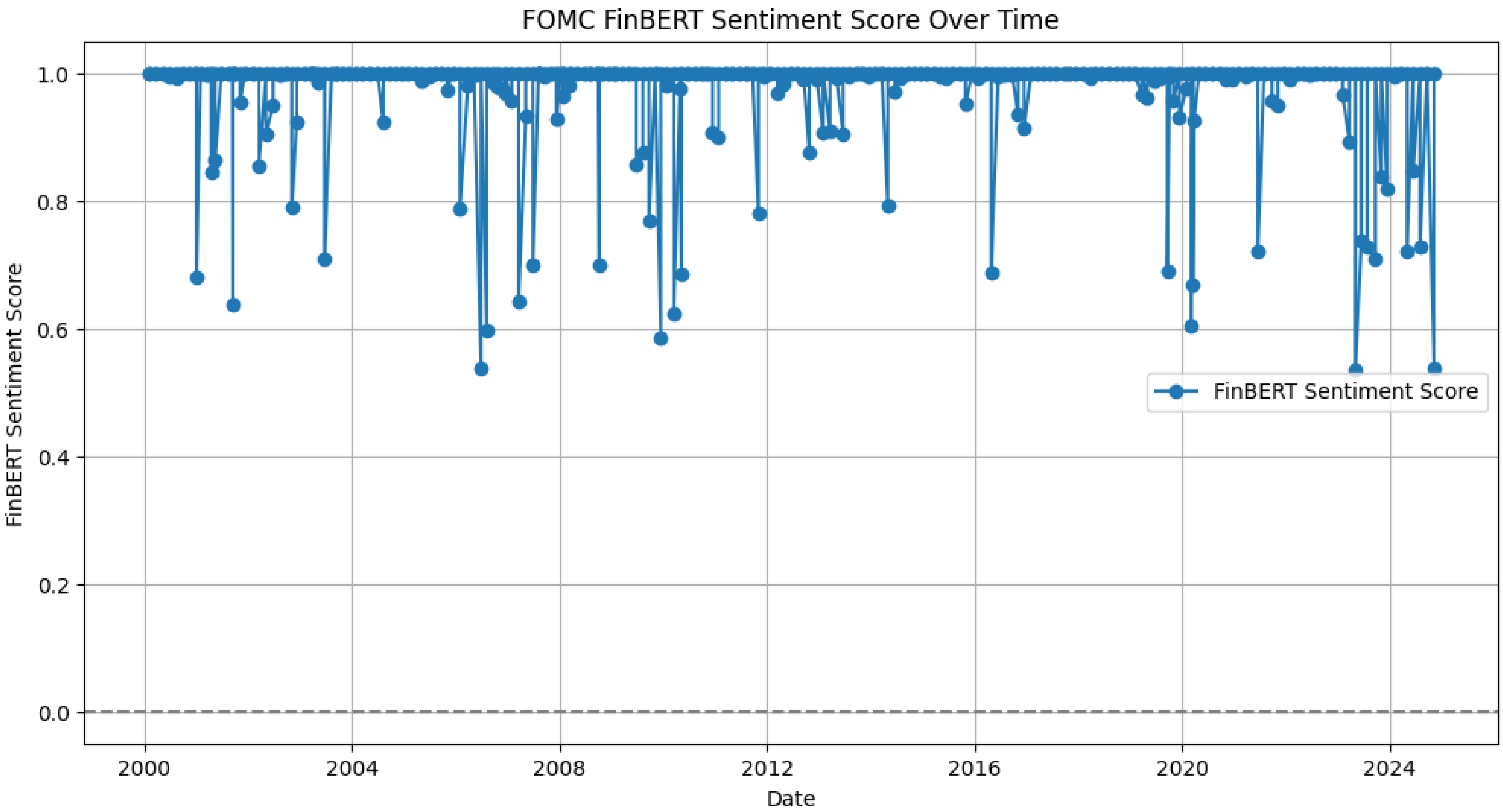


Figure 21 illustrates the distribution of FinBERT sentiment categories across all FOMC statements. Additionally, I resampled the data by month and counted the occurrences of each sentiment category over time.

Figure 22. FOMC FinBERT Sentiment Score Over Time.



Figures 22 and 23 display the trends of the FOMC FinBERT sentiment scores and categories over time. Specifically, Figure 22 shows the sentiment expressed in FOMC statements over the analyzed period using the FinBERT model. The sentiment score generally remains around 1, indicating that the majority of FOMC communications were either positive or neutral. However, noticeable dips in sentiment suggest periods when FOMC statements reflected more negative or uncertain economic outlooks. These dips often coincide with significant economic events and crises, including the 2008 financial crisis and the COVID-19 pandemic.

Figure 23. FOMC FinBERT Sentiment Categories Over Time.

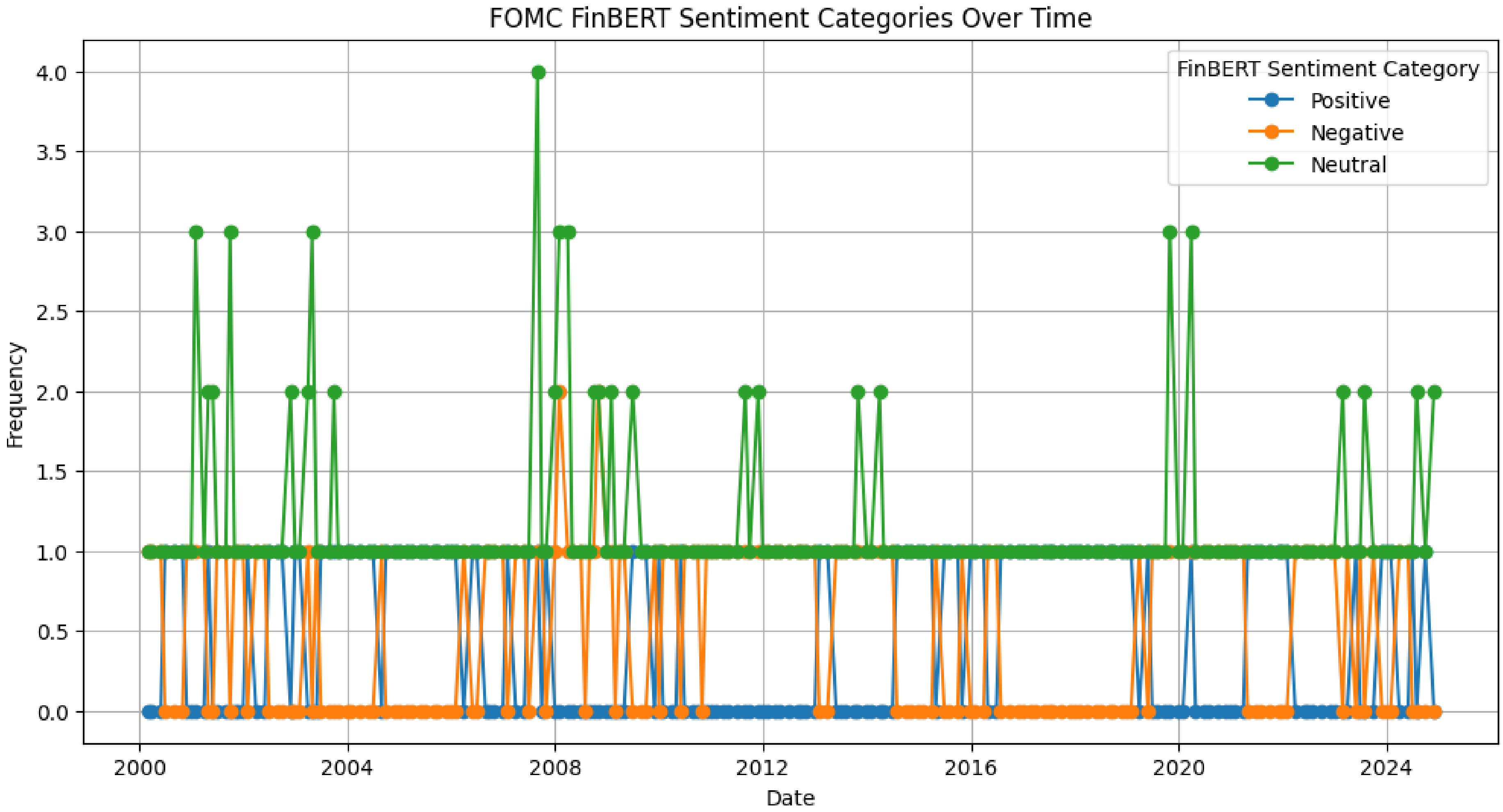


Figure 24. Keyword Extraction.

```
# Keyword Extraction
# Keyword Frequency - Define lists of hawkish and dovish keywords

hawkish_keywords = [
    'tightening', 'inflation', 'rate hike', 'restrictive', 'interest rate increase',
    'monetary policy tightening', 'overheating', 'constraining', 'hawkish', 'discipline'
]

dovish_keywords = [
    'easing', 'accommodative', 'supportive', 'stimulation', 'interest rate cut',
    'monetary policy easing', 'softening', 'expansionary', 'stimulus', 'dovish'
]

# Keyword frequency function
def count_keywords(text, keywords):
    return sum(text.lower().count(word) for word in keywords)

# Add keyword frequency columns
df['Hawkish_Count'] = df['Text'].apply(lambda x: count_keywords(x, hawkish_keywords))
df['Dovish_Count'] = df['Text'].apply(lambda x: count_keywords(x, dovish_keywords))
df['Hawkish_to_Dovish_Ratio'] = df['Hawkish_Count'] / (df['Dovish_Count'] + 1)  # Prevent division by zero
```

Identification and counting of hawkish and dovish keywords, along with weighted analysis, are effective methods for gauging the tone of FOMC policy. As shown in Figure 24, I compiled lists of hawkish and dovish keywords and analyzed the sentiment of FOMC statements by counting the occurrences of these keywords. The Hawkish_to_Dovish_Ratio serves as a metric to assess the overall sentiment, indicating whether the policy stance leans more hawkish or dovish.

Figure 25. The Prevalence of Hawkish and Dovish Language Used Over Time.

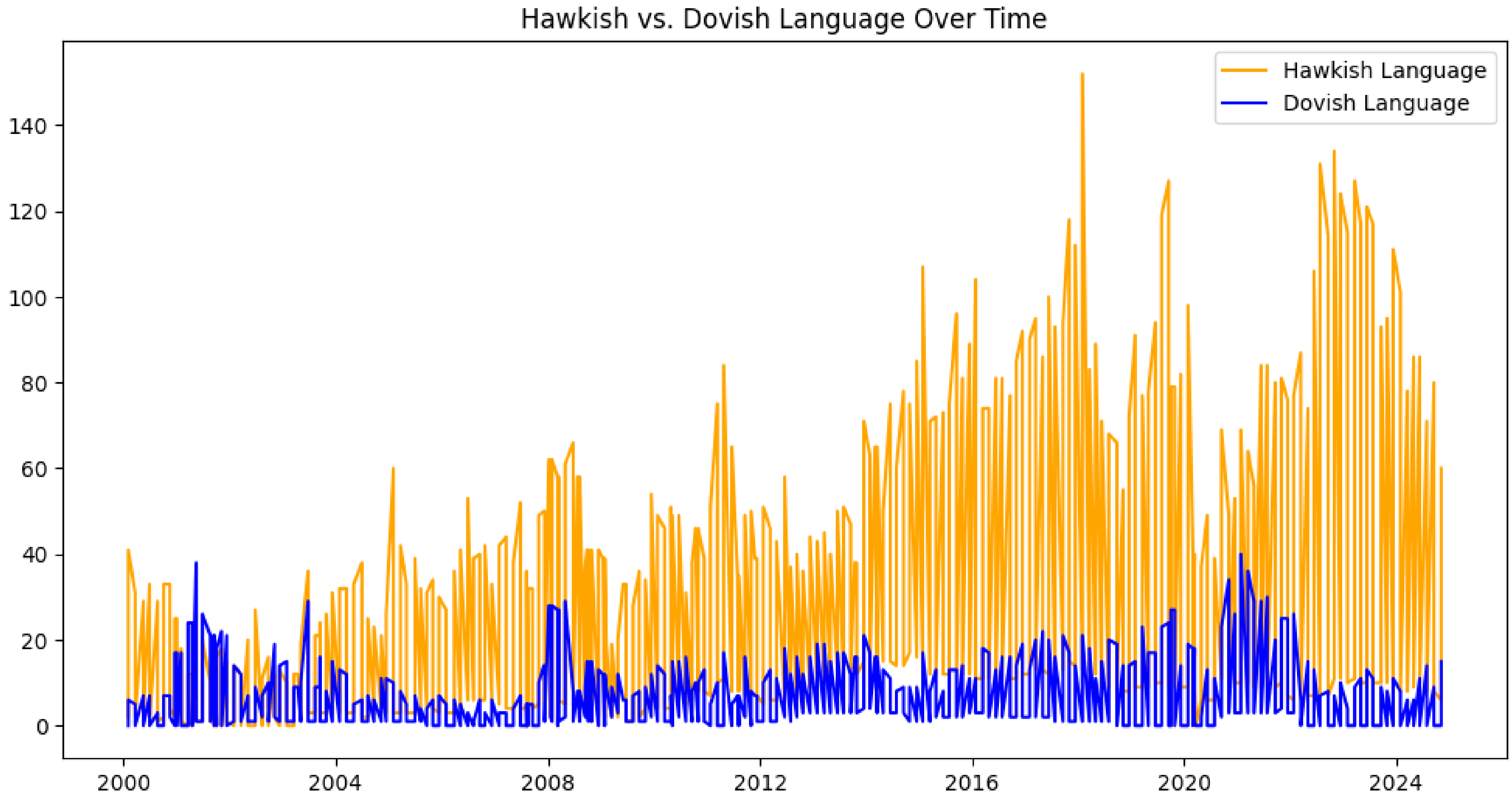


Figure 25 illustrates the prevalence of hawkish and dovish language used over time, with each type distinguished by color. The orange line, representing hawkish language, consistently remains higher than the blue line, which represents dovish language. This indicates that hawkish language was more prevalent overall during the period captured by the data.

Additionally, I used BERTopic to identify underlying topics in the FOMC statements. Based on this, I created two new features: 'Topic' and 'Topic_Probabilities'. Each statement was assigned a topic, and the model also generated probabilities for each identified topic. Furthermore, I calculated the length of each statement in terms of characters (Text_Length) and words (Word_Count). These features, along with the identified keywords, were then used as inputs in the predictive models (Figure 26 and 27).

Figure 26. Statement Text Length Trends Over Time.

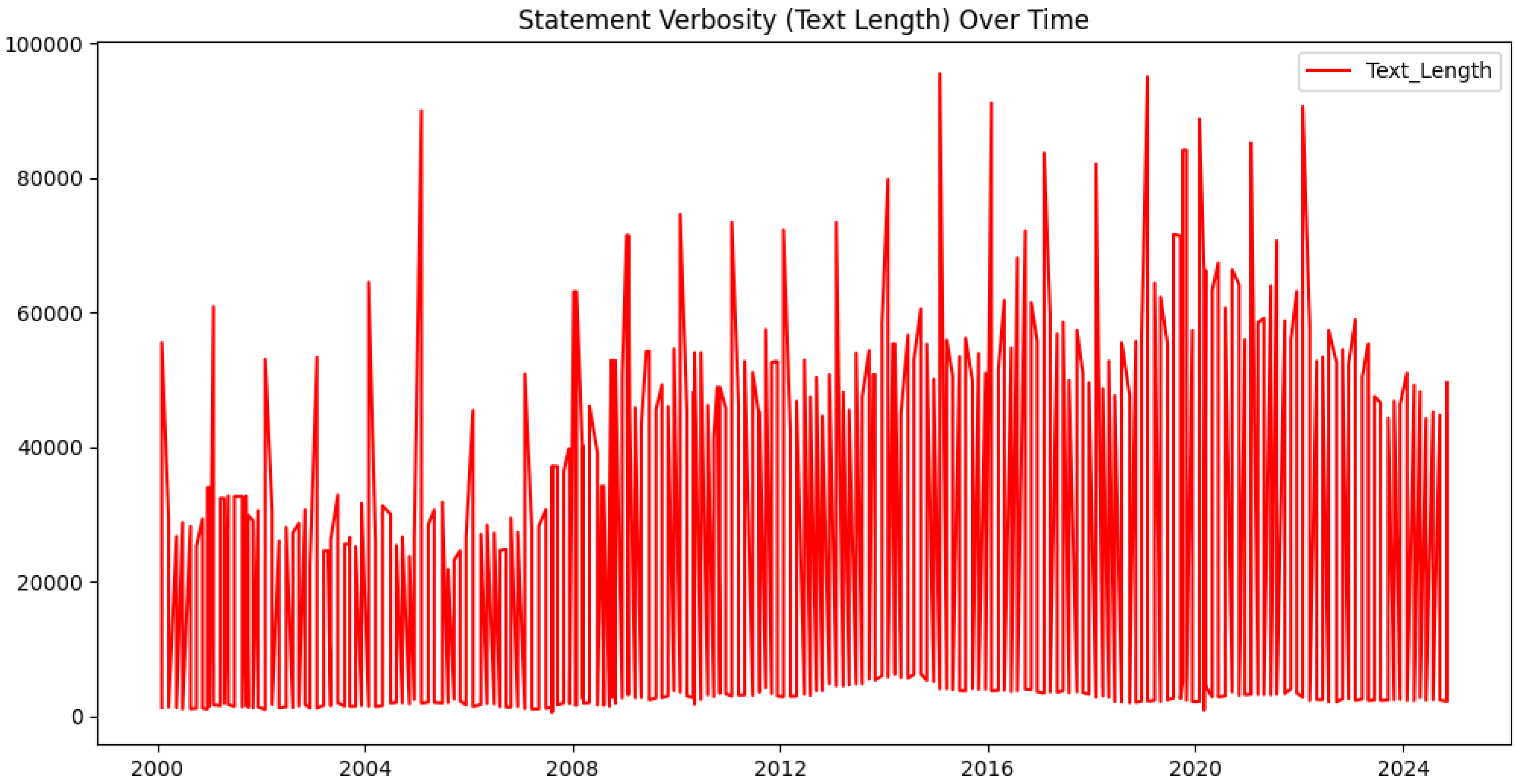
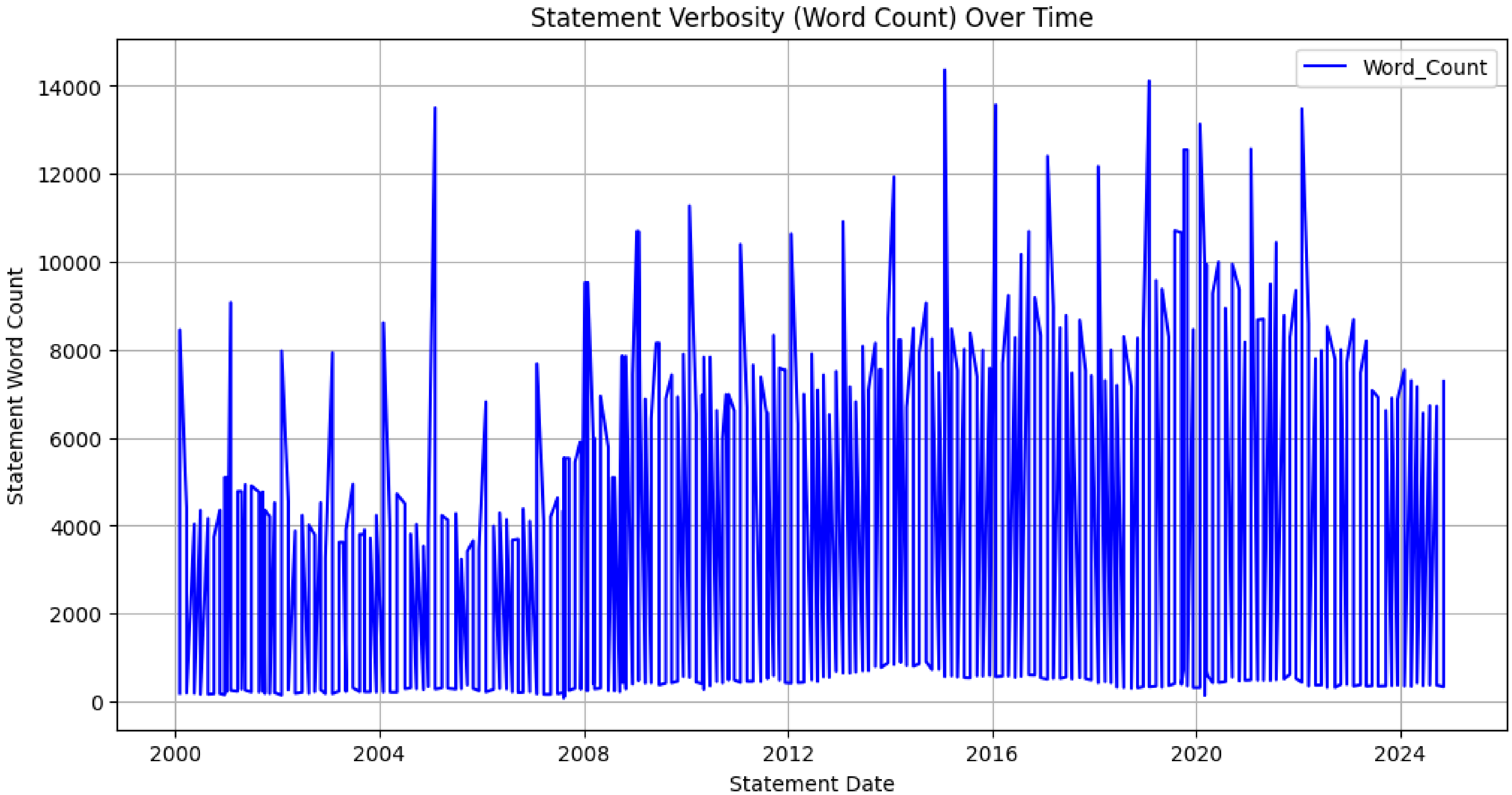


Figure 27. Statement Word Count Trends Over Time.



Figures 26 and 27 showcase the length of FOMC statements over time, specifically focusing on text length and word count. I observed that FOMC statements have become longer in the past decade, suggesting an increase in the level of detail and information provided in these communications.

Additionally, I used TF-IDF (Term Frequency-Inverse Document Frequency) to analyze the importance of specific terms, such as hawkish and dovish keywords, within the FOMC statements. To do this, I created a custom vocabulary consisting of hawkish and dovish terms, and the resulting TF-IDF scores highlight the most significant terms. Figure 28 illustrates the TF-IDF scores for hawkish and dovish language over time, allowing for a comparison of how the tone of the documents has evolved.

Figure 28. Hawkish vs. Dovish language over time.

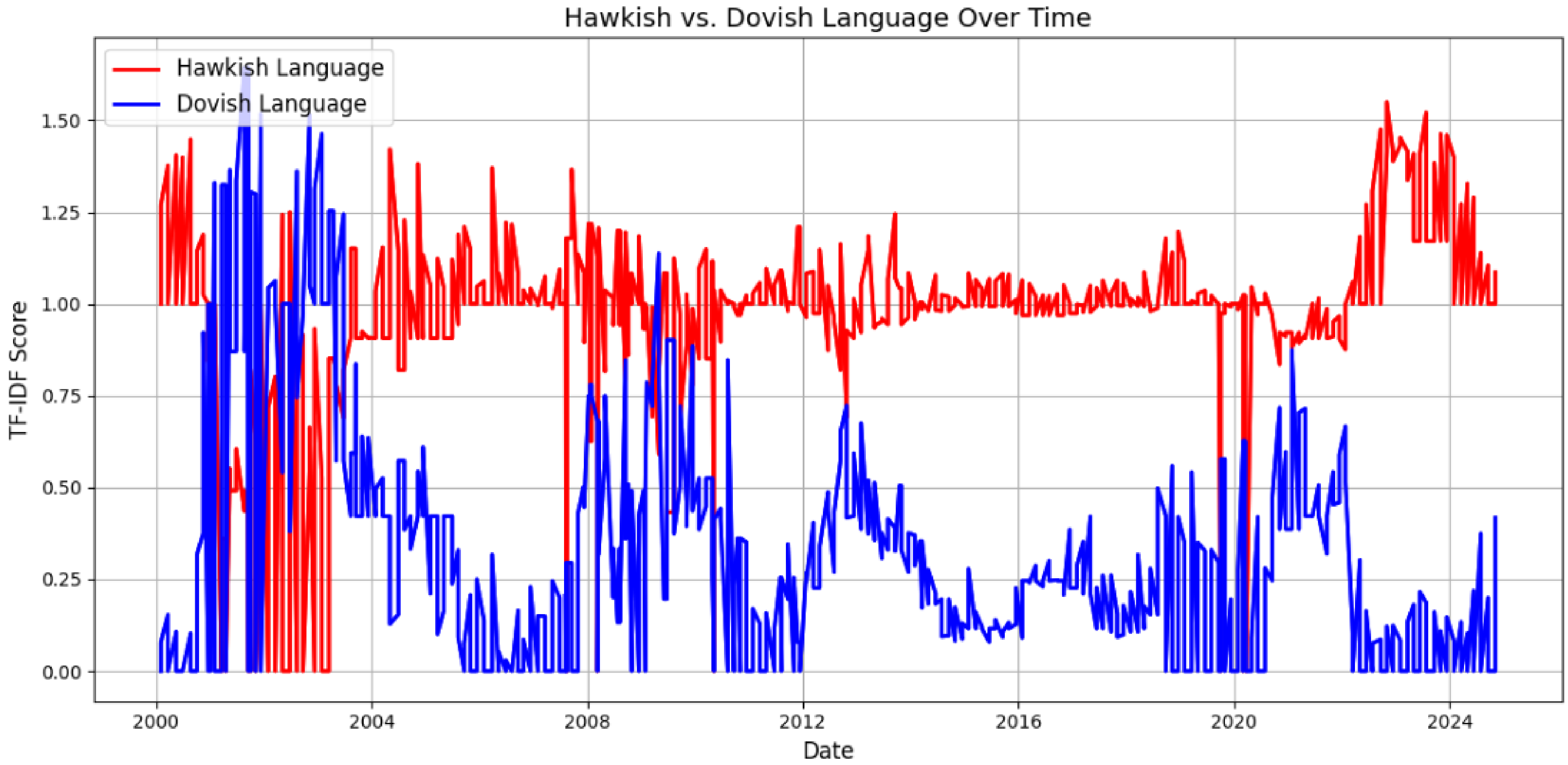


Figure 29. Average TF-IDF Scores for Hawkish and Dovish Keywords.

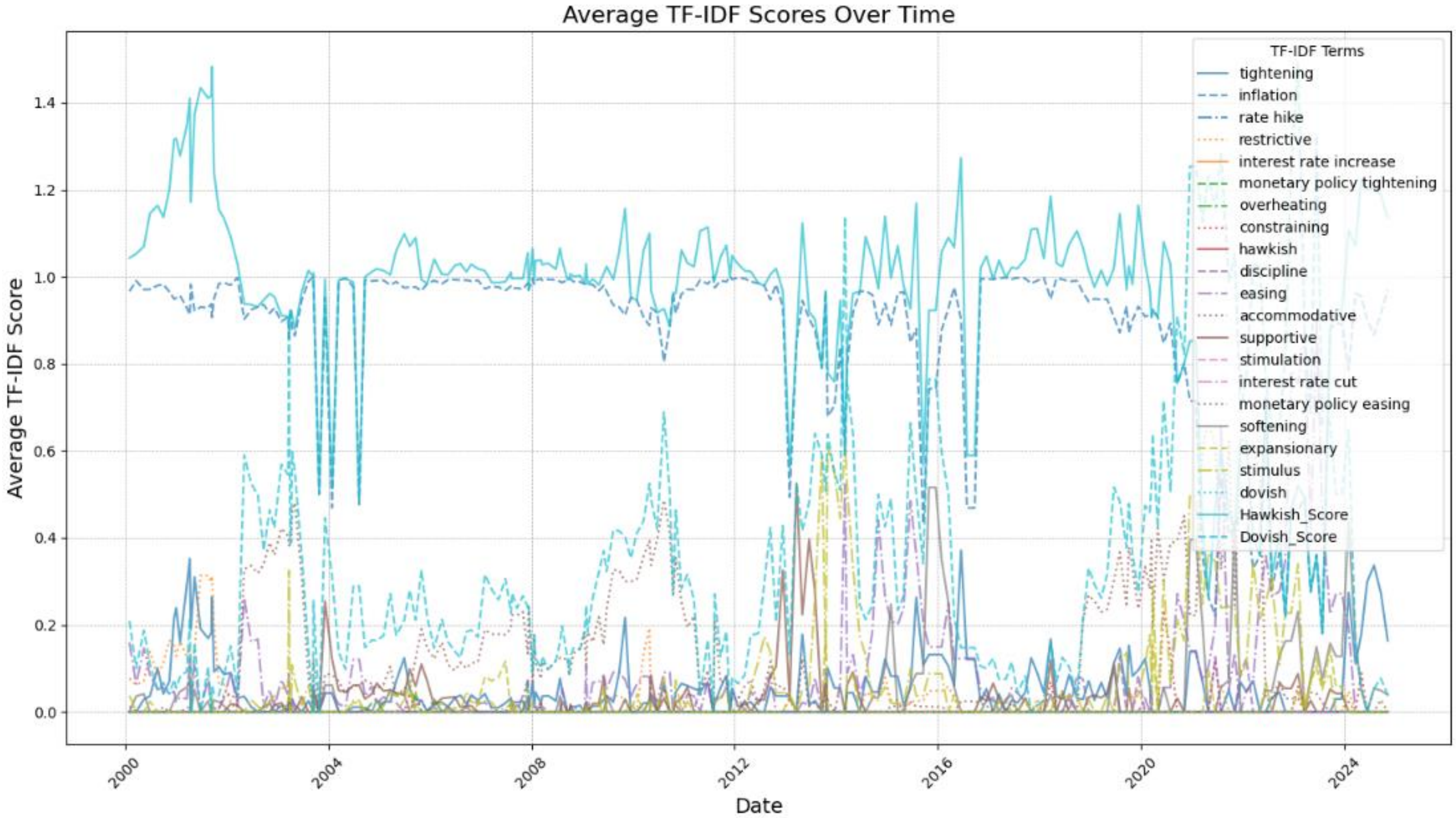


Figure 29 tracks the evolution of the importance of specific keywords over time, aiding in trend analysis.

Figure 30. Statement Verbosity Over Time with Economic Events and High Points.

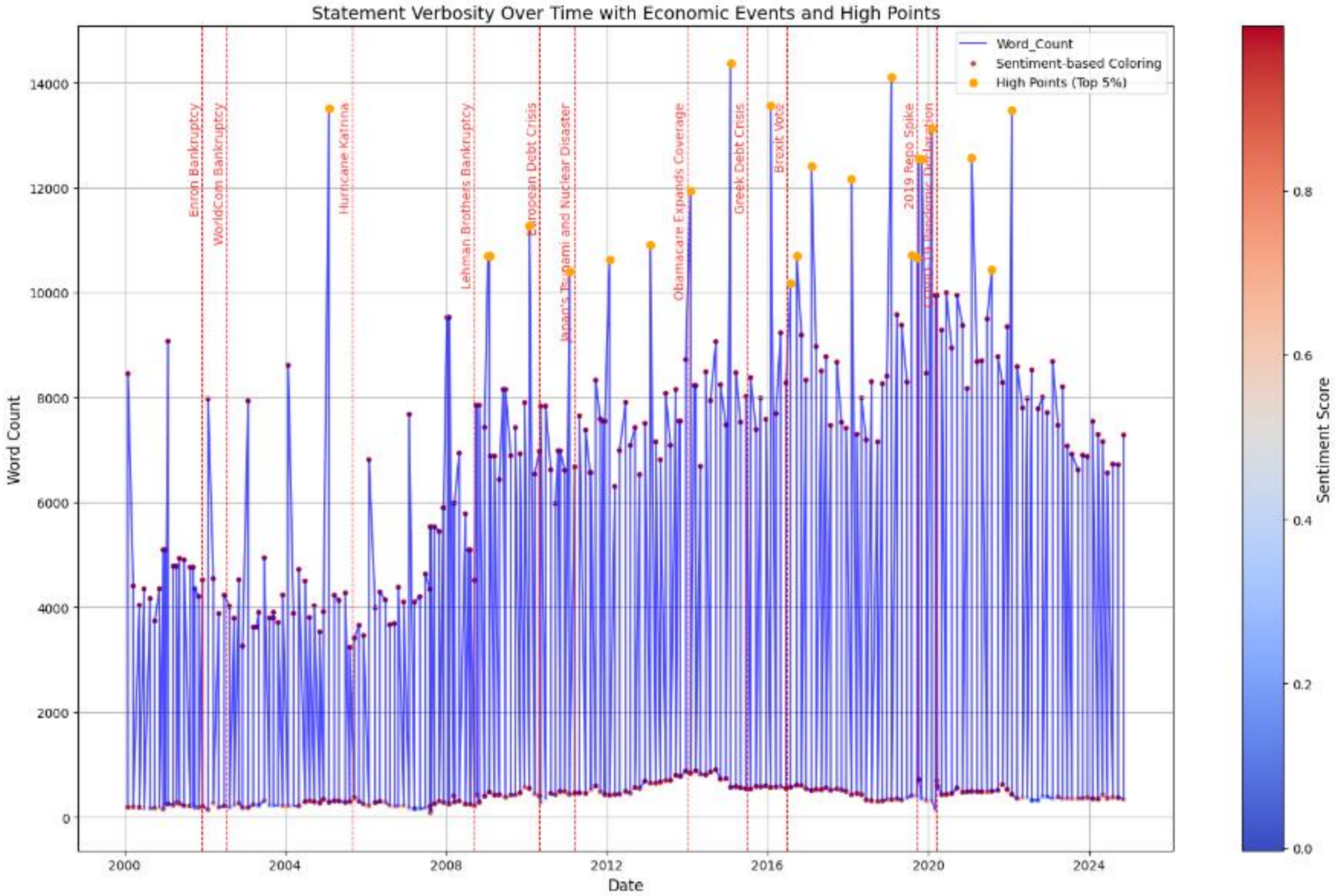


Figure 30 combines word count trends (verbosity), significant economic events, and sentiment scores to provide a rich contextual analysis of the FOMC statements. The top 5% of high points highlight statements that are more verbose, often occurring during times of heightened economic uncertainty or policy shifts. Similar to previous plots, key economic events (e.g., financial crises, pandemics) are annotated to provide context for the changes in verbosity and sentiment. For instance, a verbose statement or sharp sentiment shift during events like the "Lehman Brothers Bankruptcy" and the "COVID-19 Pandemic Declaration" aligns with intuitive expectations. Additionally, I used a sentiment gradient (e.g., coolwarm) to visually complement the plot, showing how the tone shifts over time without overcrowding the visualization.

3. Feature Engineering

During the exploratory data analysis and natural language processing stages, I engineered several features to enrich the model and better capture patterns in the FOMC communications. Key features included both VADER and FinBERT sentiment scores and categories, which were used to evaluate the tone of the statements. I also derived hawkish and dovish keyword counts and their corresponding hawkish-to-dovish ratio, as these indicators help assess the policy stance reflected in the statements.

Additionally, I used topic modeling to extract relevant topics from the statements and created features such as Topic labels and Topic Probabilities, which capture the likelihood of each statement belonging to a particular topic. For analyzing verbosity, I calculated features related to text length and word count to identify whether the level of detail in FOMC communications changed over time.

Beyond the textual features, I carefully revised and dropped certain non-contributory or redundant features, such as Release Date, Announcement Date, and Decision column. I also dealt with numeric features, ensuring they were appropriately processed (e.g., as percentages) and rebalanced where necessary to maintain consistency across the dataset.

This feature engineering process was crucial in transforming raw communication data into structured inputs that could be leveraged for predictive modeling.

3.1. Imbalanced Class

Given the highly imbalanced nature of the original dataset, I found it necessary to rebalance the "Decision" column to simplify the prediction task. The original class distribution had a significant imbalance, with certain rate changes (such as +0.75%, -0.75%, and -1.00%) being underrepresented. To address this, I merged these infrequent classes into more common ones, such as +0.50% and -0.50%. This rebalancing step reduces the risk of the model overfitting to rare classes, making the prediction task more tractable.

While the rebalanced distribution is more manageable, it's important to note that an imbalance still exists, particularly with the +0.00% category, which dominates the dataset. This is reflective of how the FOMC tends to make decisions in smaller increments, typically around +0.25%. Grouping extreme rate changes into larger, more common categories ensures that the analysis aligns with central bank decision-making practices.

Despite these adjustments, the distribution of values in the Decision column remains imbalanced. Therefore, I employed more advanced techniques to handle the imbalanced classes during model selection, training, and evaluation. These techniques, including resampling and cost-sensitive learning, were crucial in ensuring that the models would not be biased towards the majority class.

4. Model Selection

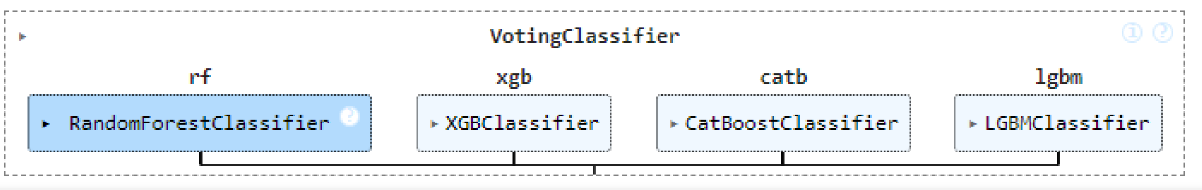
To finalize the dataset for use with machine learning models, I developed a pipeline that processed the data, transforming it into a suitable format for model training. I then trained and evaluated several machine learning models, including Random Forest, XGBoost, LightGBM, and CatBoost, to compare their performance in predicting FOMC rate decisions. The table below presents the accuracy scores for each of the models.

Table 1. Model Comparison.

	Accuracy Score
Random Forest	**0.881**
XGBoost	0.821
LightGBM	0.831
CatBoost	0.831

As shown in the table, Random Forest outperformed the other models with an accuracy score of 0.881, indicating the best generalization on the data. XGBoost, LightGBM, and CatBoost followed with comparable performance, each achieving an accuracy of around 0.83.

Figure 31. Ensembled Model.



After comparing the models' accuracy scores and confusion matrices, I chose the Random Forest Classifier due to its superior performance in handling the task. To enhance the model's ability to handle imbalanced data, I implemented a machine learning pipeline that incorporated SMOTE (Synthetic Minority Oversampling Technique) to oversample the minority classes. Additionally, I used "stratify=target" during data splitting to ensure that the class distribution was preserved in both the training and testing sets. To further address the imbalance, I set the class_weight='balanced' parameter in the model to assign weights that are inversely proportional to the class frequencies, thereby improving the model's ability to learn from underrepresented classes.

Figure 32. Original and Resampled Training Class Distribution.

```
Original training class distribution:
Decision
+0.00%    138
+0.25%     46
-0.50%     25
-0.25%     15
+0.50%     10
Name: count, dtype: int64

Resampled training class distribution:
Decision
-0.50%    138
+0.00%    138
+0.50%    138
+0.25%    138
-0.25%    138
Name: count, dtype: int64
Accuracy Score: 0.8811881188118812
```

To optimize the performance of the Random Forest Classifier, I utilized Grid Search Cross-Validation (Grid Search CV) to tune key hyperparameters. Specifically, I optimized parameters such as n_estimators (the number of trees in the forest), max_depth (the maximum depth of the trees), min_samples_split (the minimum number of samples required to split an internal node), min_samples_leaf (the minimum number of samples required to be at a leaf node), and max_features (the number of features to consider when looking for the best split). This hyperparameter tuning was aimed at finding the optimal model configuration to improve prediction accuracy and prevent overfitting. Additionally, I applied Cross-Validation to evaluate the model's robustness and ensure that the results were consistent and reliable across different subsets of the data.

Figure 33. Confusion Matrix.

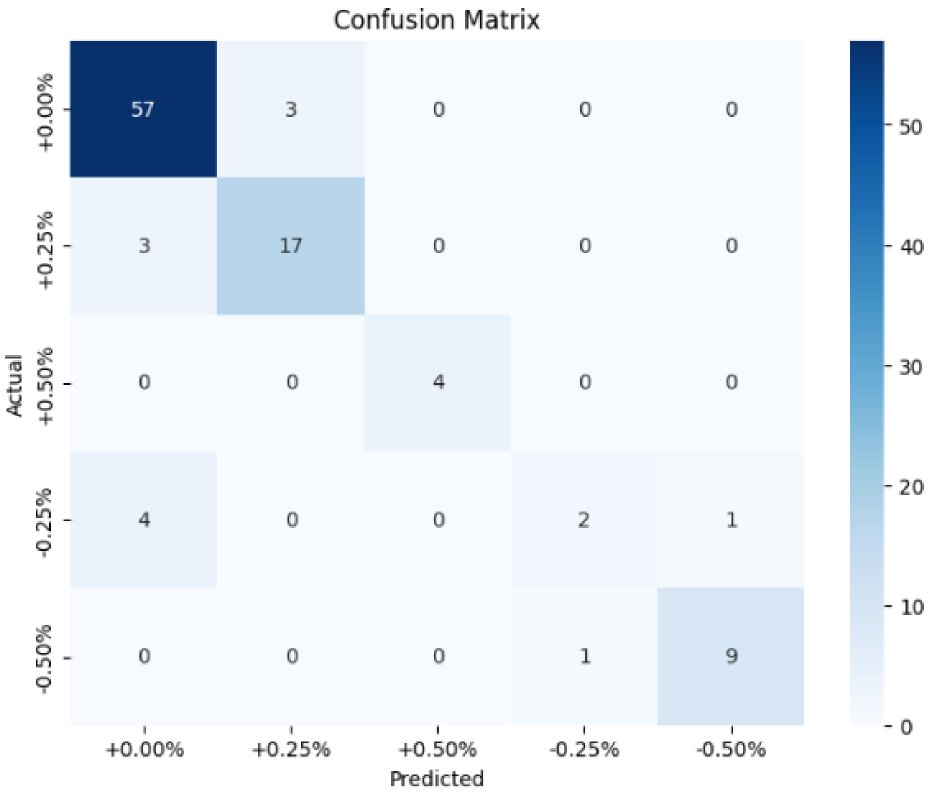


Figure 33 displays the confusion matrix, which illustrates the performance of the classification model in predicting the "Decision" values across five categories: +0.00%, +0.25%, +0.50%, -0.25%, and -0.50%. The model correctly predicted 57 instances of +0.00%, 17 instances of +0.25%, 4 instances of +0.50%, 2 instances of -0.25%, and 9 instances of -0.50%. The off-diagonal values represent misclassifications. For example, 3 instances of +0.00% were incorrectly classified as +0.25%, and 4 instances of -0.25% were misclassified as +0.50%. This confusion matrix provides a clear view of the model's strengths and areas for improvement in predicting rate decisions.

Figure 34. Feature Importance.

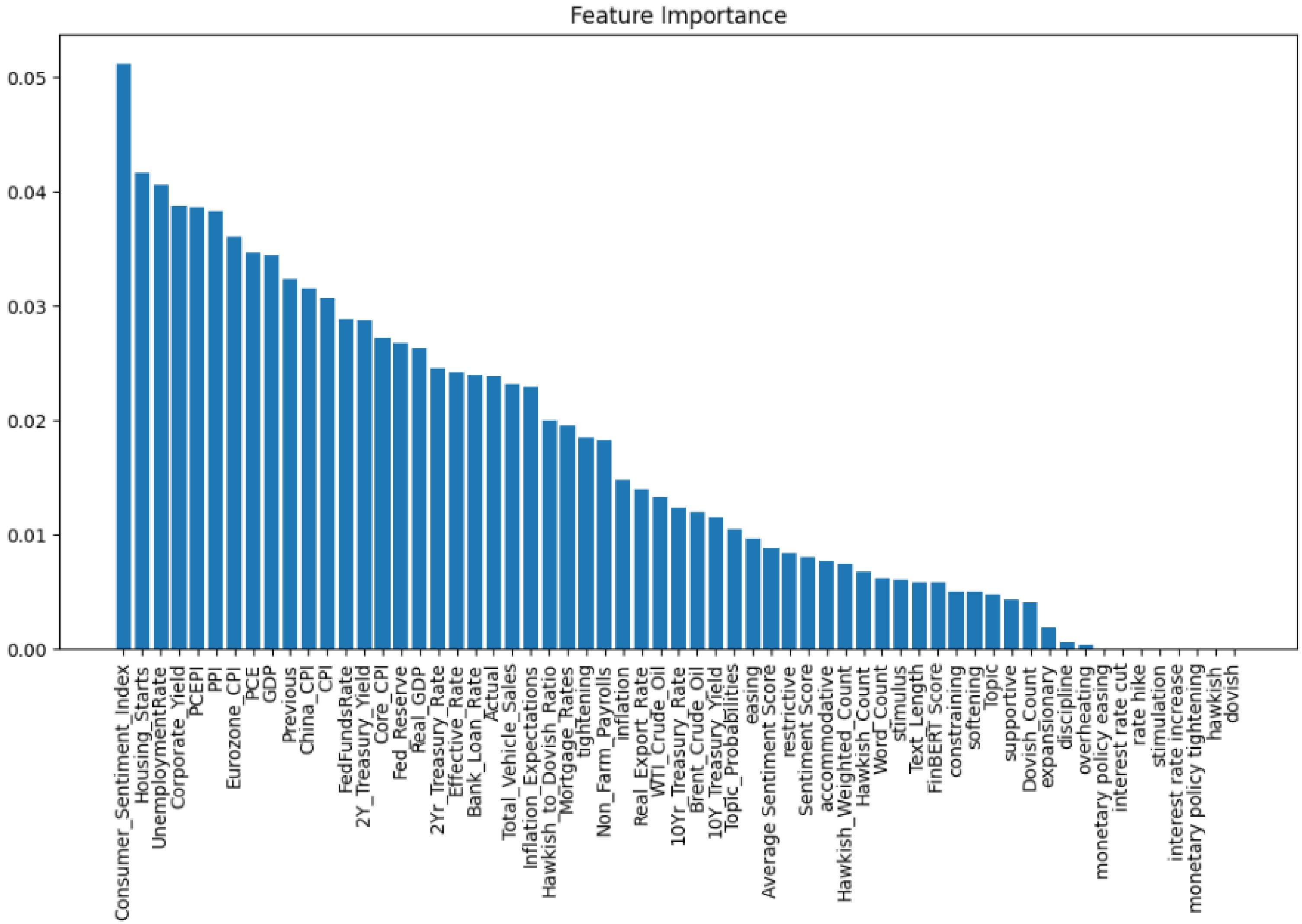


Figure 34 illustrates the feature importance of various economic indicators in my model. The height of each bar reflects the relative importance of the corresponding feature, with higher bars indicating greater influence on the model's predictions. The Consumer Sentiment Index stands out as the most influential feature, followed by Housing Starts and the Fed Funds Rate. The bars are arranged in descending order, visually emphasizing the significance of each indicator in determining the outcome.

Figure 35. Model Prediction Probabilities.

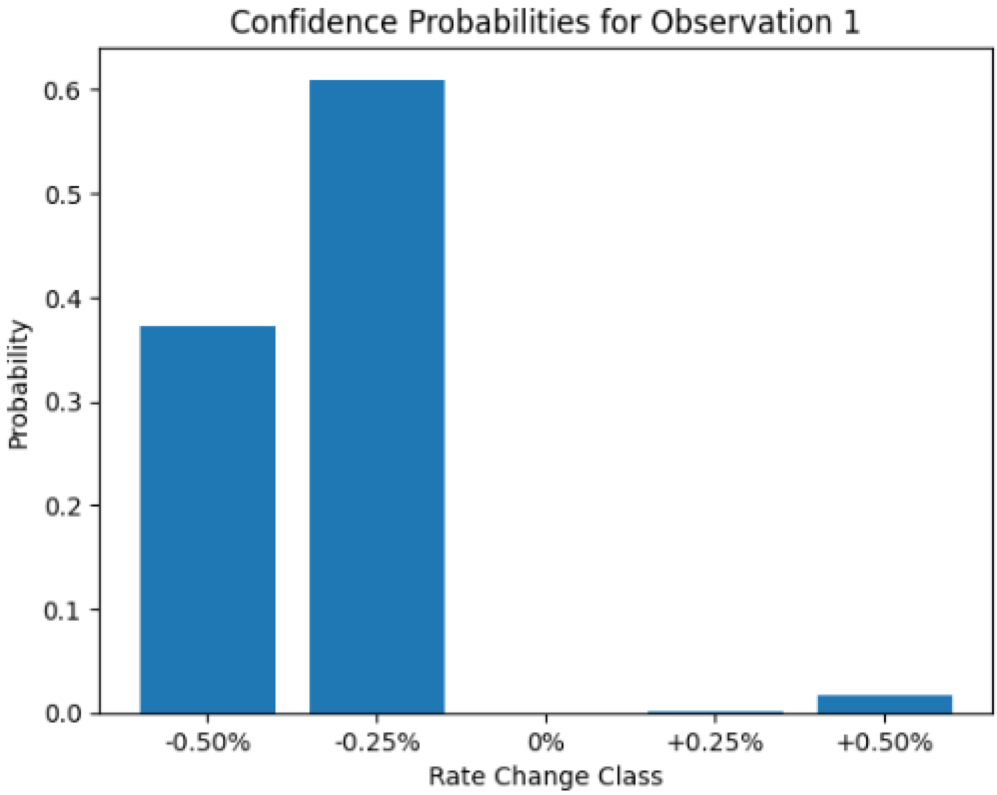


Figure 35 displays the confidence probabilities for the five rate change classes: -0.50%, -0.25%, 0%, +0.25%, and +0.50%. The y-axis represents the probability associated with each class. From the bar chart, it is evident that the model predicts the -0.25% rate change class with the highest probability, approximately 61%. The second most likely class is -0.50%, with a probability around 38%. The remaining classes, including +0.50%, show significantly lower probabilities, with the classes 0% and +0.25% having near-zero probabilities. Figure 36 shows final predictions and probabilities.

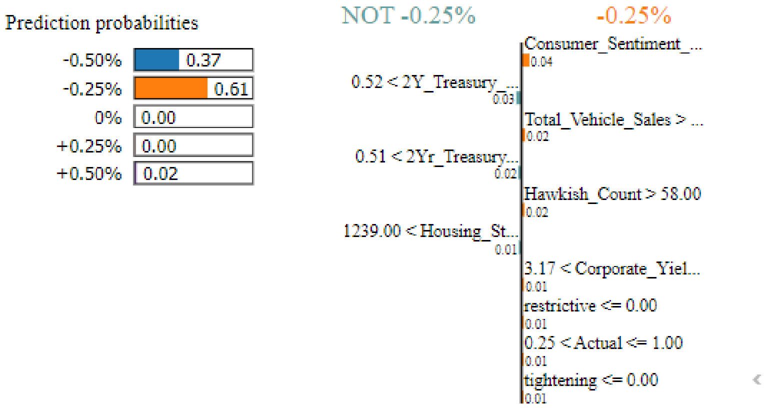
Figure 36. Predictions.

	Desights_ID	Predicted_Class	Probability_-0.50%	Probability_-0.25%	Probability_0%	Probability_+0.25%	Probability_+0.50%
0	0xE599300a2342D69E38B62D9283F4a25E7025992d	-0.25%	0.372	0.61	0.0	0.002	0.016

5. Interpretability

I used both SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) interpretability techniques to explain my model's predictions.

Figure 37. LIME output.



Feature	Value
Consumer_Sentiment_Index	96.30
2Y_Treasury_Yield	1.22
Total_Vehicle_Sales	17.70
2Yr_Treasury_Rate	1.20
Hawkish_Count	90.00
Housing_Starts	1271.00
Corporate_Yield	3.39
restrictive	0.00
Actual	0.75

Figure 37 illustrates the LIME output, which provides a localized explanation of how different features contribute to the prediction of a specific instance. LIME approximates the behavior of the complex model around a specific data point, making the model's decisions more interpretable.

In this case, the probabilities for different interest rate decisions are as follows:

-0.50%: 0.37

-0.25%: 0.61

+0.00%, +0.25%, +0.50%: Almost 0 (zero probability)

The "Feature" and "Value" table in the LIME output shows the importance of each feature for the prediction:

Consumer Sentiment Index (96.30): The feature value of 0.04 indicates a significant contribution. A higher consumer sentiment might suggest a positive economic outlook, influencing the model toward a more dovish or neutral decision.

2Y Treasury Yield (1.22): With a feature value of 0.52, this is another important factor. A higher yield suggests a hawkish monetary policy stance, possibly influencing the model toward a more restrictive decision.

Total Vehicle Sales (17.70): Although it has a lower contribution (0.03), this feature remains relevant. A higher sales figure might indicate economic growth or stability, which could favor a neutral or positive decision.

Corporate Yield (3.39): With a value of 0.02, this feature has a minor effect. Higher corporate yields may indicate increased risk in the market, pushing the model toward a more cautious approach.

2Yr Treasury Rate (1.20): Also, with a value of 0.02, similar to the 2Y Treasury Yield, this feature suggests the stance of monetary policy, potentially influencing the decision toward a more hawkish rate change.

Restrictive (0.00) and Overheating (0.00): These features contribute minimally (0.01 each) in this specific instance, showing little to no impact on the prediction.

Figure 38. SHAP output for "Decision" feature.

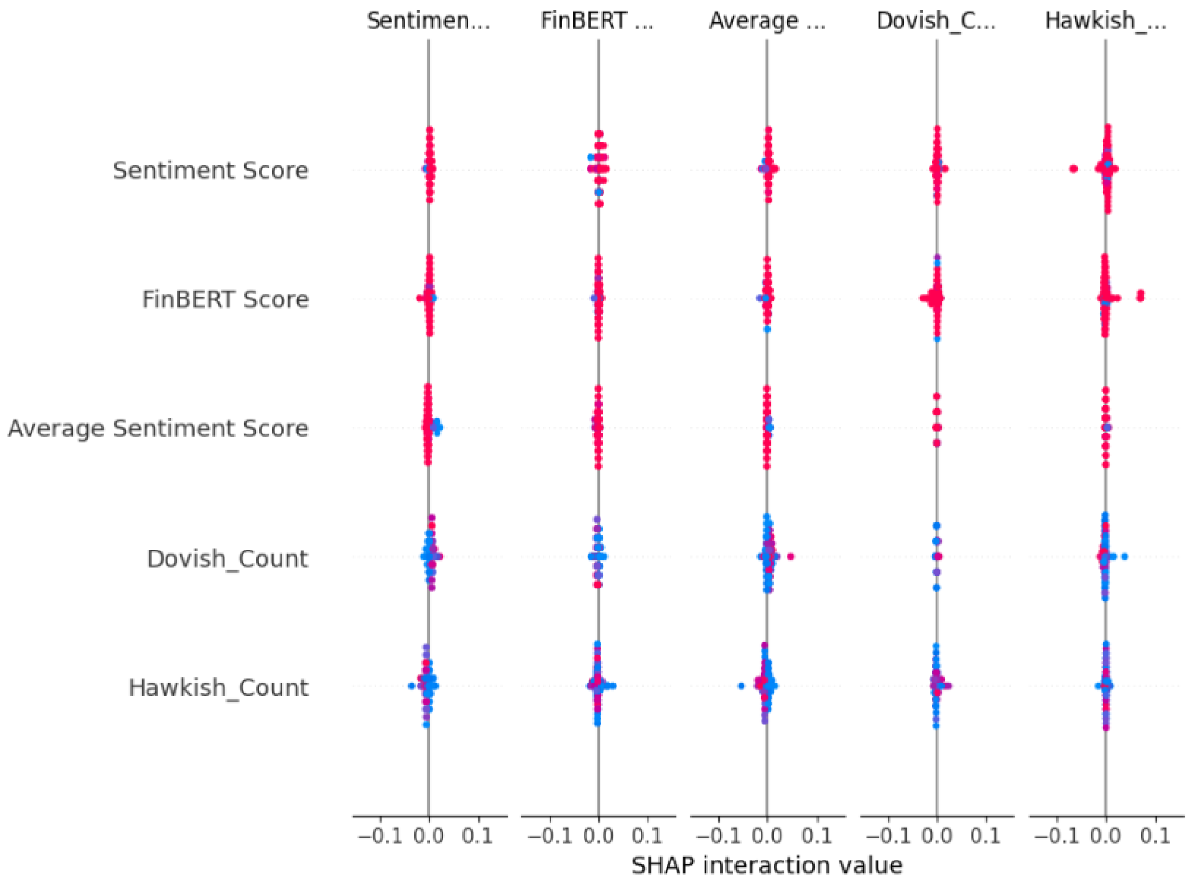
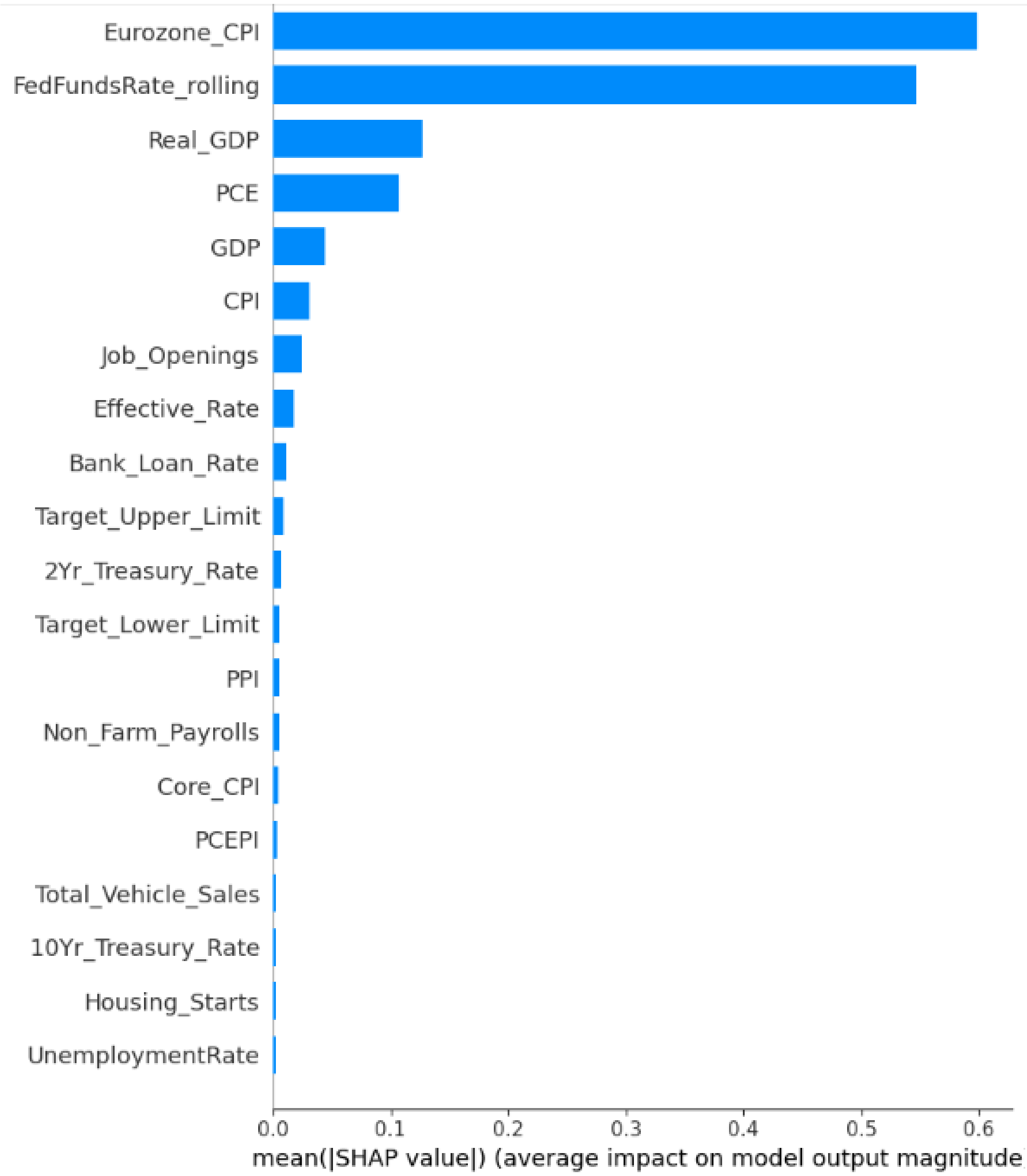


Figure 38 presents the SHAP values for the top features in a model predicting the interest rate "Decision," including NLP-based features. Similarly, Figure 39 illustrates the SHAP values for the top features in a model predicting the Fed Funds Rate. A higher SHAP value indicates a stronger positive influence on the model's output. Notably, Eurozone_CPI exhibits the largest impact on the predictions, suggesting that inflation in the Eurozone plays a significant role in determining the Fed Funds Rate. As anticipated, FedFundsRate_rolling (the rolling average of the Federal Funds Rate) is the second most influential feature, underscoring the importance of historical interest rate trends in forecasting future changes. Real_GDP, PCE (Personal Consumption Expenditures), and GDP are also key features, highlighting that economic growth and consumer spending are critical factors in the determination of interest rates. Other features, such as job openings, the effective rate, and various treasury rates, contribute to the model's predictions, though their impact is comparatively smaller.

Figure 39. SHAP output for "FedFundsRate" feature.



6. Assumptions and Challenges

6.1. Assumptions

I assumed that the FOMC communication data, economic indicators, and sentiment analysis tools (VADER, FinBERT) were accurate, complete, and up-to-date. Missing or incomplete data were addressed through imputation techniques or dropped, assuming that this would not significantly affect the model's performance.

Also, it was assumed that the sentiment extracted from FOMC statements via VADER and FinBERT accurately reflected the tone of the communication and had a meaningful impact on predicting rate decisions. Sentiment and NLP features were treated as important predictive variables, without exploring deeper semantic nuances or possible errors in sentiment classification.

In building the predictive models, it was assumed that the economic indicators (such as CPI, unemployment rates, GDP, etc.) used in the analysis follow a stationary or stable trend, at least for the time periods of interest. This assumption was necessary for ensuring the validity of the relationships between economic conditions and Fed policy decisions.

Most importantly, during model training, it was assumed that rebalancing the data through techniques like SMOTE and merging minor rate change classes would effectively address class imbalance without introducing significant bias or overfitting. This assumption guided the decision to merge small classes (+0.75%, -0.75%, -1.00%) into larger ones, maintaining a more manageable distribution of target classes.

6.2. Challenges

One of the main challenges faced during this analysis was the highly imbalanced nature of the target variable, "Decision." With a dominant class (+0.00%), the model was prone to predicting this class more frequently, leading to inaccurate predictions for less frequent rate changes. While techniques like SMOTE and merging minor classes helped alleviate this issue, some degree of imbalance remained, which impacted the model's ability to predict extreme rate changes.

The decisions made by the FOMC are influenced by a wide range of factors, many of which are not captured directly in the available data, such as geopolitical events, central bank policies in other countries, or market psychology. This added complexity made it difficult to build a model that could reliably predict rate decisions, as external factors were not always accounted for.

Generating meaningful features from text data (such as sentiment scores and topic modeling from FOMC statements) presented challenges in terms of data processing, the consistency of sentiment categorization, and the selection of relevant keywords. Additionally, the interpretation of NLP features, like sentiment and topic probabilities, required careful validation to ensure they were capturing the intended economic signals.

While SHAP and LIME provided valuable insights into the decision-making process of the model, there were still challenges in fully explaining complex interactions between features, especially when considering high-dimensional data with multiple interrelated economic indicators. Some features, like sentiment scores and treasury yields, may have interactions that were not fully captured by these interpretability tools, making the results harder to communicate clearly.

Last but not least, the granularity of the available data posed another challenge. FOMC decisions are made on a quarterly or bi-monthly basis, but economic indicators often fluctuate at finer time scales. This mismatch in time frequency made it challenging to align the data perfectly, and some assumptions had to be made about the relationship between economic data points and the timing of FOMC rate decisions.

Appendices

Appendix 1: Data Sources Overview

1. **CPI** – Consumer Price Index
2. **UnemploymentRate** – Unemployment Rate
3. **FedFundsRate** – Federal Funds Rate
4. **10Y_Treasury_Yield** – 10-Year Treasury Yield
5. **2Y_Treasury_Yield** – 2-Year Treasury Yield
6. **GDP** – Gross Domestic Product
7. **PCE** – Personal Consumption Expenditures
8. **Consumer_Sentiment_Index** – Consumer Sentiment Index
9. **Housing_Starts** – Housing Starts
10. **Mortgage_Rates** – Mortgage Rates
11. **10Yr_Treasury_Rate** – 10-Year Treasury Rate
12. **2Yr_Treasury_Rate** – 2-Year Treasury Rate
13. **Core_CPI** – Core Consumer Price Index
14. **PCEPI** – Personal Consumption Expenditures Price Index
15. **5Yr_Breakeven_Inflation** – 5-Year Breakeven Inflation
16. **10Yr_Breakeven_Inflation** – 10-Year Breakeven Inflation
17. **PPI** – Producer Price Index
18. **Real_GDP** – Real Gross Domestic Product
19. **Inflation_Expectations** – Inflation Expectations
20. **Non_Farm_Payrolls** – Non-Farm Payrolls
21. **Job_Openings** – Job Openings
22. **Eurozone_CPI** – Eurozone Consumer Price Index
23. **China_CPI** – China Consumer Price Index
24. **WTI_Crude_Oil** – West Texas Intermediate Crude Oil Price
25. **Brent_Crude_Oil** – Brent Crude Oil Price
26. **Target_Upper_Limit** – Target Upper Limit (Fed Funds Rate Target)
27. **Target_Lower_Limit** – Target Lower Limit (Fed Funds Rate Target)
28. **Bank_Loan_Rate** – Bank Loan Rate

29. **Real_Export_Rate** – Real Export Rate
30. **USD_Index** – US Dollar Index
31. **Total_Vehicle_Sales** – Total Vehicle Sales
32. **Corporate_Yield** – Corporate Yield
33. **Effective_Rate** – Effective Federal Funds Rate
34. **Fed_Asset** – Federal Reserve Assets
35. **Fed_Reserve** – Federal Reserve Reserve Balances
36. **Inflation_5y_Expectation** – 5-Year Inflation Expectation