FINM 35000: Topics in Economics

Data Project 1 Report

Team Members

Antonio Pineda Acosta

Kaleem Shah Bukhari

Muhammad Raafay Uqaily

Yasmine Ouattara

Submitted To

Professor Rui Zhao

Lisheng Su

Financial Mathematics Department

The University of Chicago

Chicago, IL

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Team Member Contributions:

Antonio: Section 2.1, 3.1, 4.1, Report

Kaleem: Section 2.2, 3.2, 4.1, 4.3, Report

Raafay: Section 2.3, 3.3, 3.4, 4.4, Report

Yasmine: Section 2.4, 2.5, 4.2, Report

Notes for Lisheng:

1. Although rough splits for each section have been listed above, each member contributed equally and reviewed all content.
2. The analysis was based on summaries from the Board of Governors, specifically focusing on the Monetary Policy Beige Book."
3. Section 2.4 and 2.5 are in a separate notebook
4. An API is being used to pull data from fred website

Section 2.1

The project's main objective was to extract and analyze Federal Open Market Committee (FOMC) statements from the Federal Reserve's website during the years 2000 to 2024. The process started by dividing the extraction logic into distinct periods: 2000-2010, 2011-2016, 2017-2018, and 2019-2024. This was necessary because each period had different URL structures and patterns for statement links. The initial step involved constructing functions to dynamically fetch the webpage content and identify the relevant links using BeautifulSoup. Regular expressions were used to filter the links that contained Beige Book statements or press releases, depending on the year range. The resulting URLs for each year were stored in a list for further processing.

After extracting the links, the next step involved creating functions to fetch and extract the textual content from each link. Each web page was accessed via requests, and the response content was parsed using BeautifulSoup. To ensure that only the relevant statement text was retained, markers identifying the start and end of the desired content were defined, and text between these markers was extracted. Additionally, a function was implemented to retrieve and clean the date information from each URL using regex patterns. To avoid redundancy, dates that were flagged for removal were filtered out, and duplicate dates were handled effectively. The extracted statement texts and corresponding dates were organized into pandas DataFrames and formatted with a consistent date structure (YYYY-MM-DD).

Once the text extraction and date cleaning were complete, all DataFrames were merged into a final DataFrame covering the entire period from 2000 to 2024. A column for word count was added to each statement, and summary statistics were calculated to provide insights into the average length and distribution of the statements.

The figure below shows the number of statements extracted by the web scraper along with a non-exhaustive list of dates of each release.

```
Number of Statements Extracted: 170
List of Dates of Release:
2000-01-19
2000-03-08
2000-05-03
2000-06-14
2000-08-09
2000-09-20
2000-12-06
2001-01-17
2001-03-07
2001-05-02
2001-06-13
2001-08-08
2001-09-19
2001-10-24
2001-11-28
2002-01-16
```

Figure 1: Number of Statements Extracted and List of Dates.

The figure below shows results from the summary statistics of the word count for the 170 FOMC statements extracted from the Federal Reserve's website. The mean word count of the statements is approximately 7,124 words. However, there is significant variability in the word counts, as reflected by a standard deviation of approximately 7,892 words. The minimum word count observed is 163 words, while the maximum reaches up to 20,050 words. The median (50th percentile) word count is 2,032, showing that half of the statements are below this length. Additionally, the 25th and 75th percentiles are 526.5 words and 17,232.5 words, respectively, highlighting the wide range and variability in the length of the statements. This indicates that the FOMC releases vary significantly in detail and depth over time.

```
count      170.000000
mean      7124.458824
std       7892.273684
min        163.000000
25%        526.500000
50%       2032.000000
75%      17232.500000
max      20050.000000
Name: Word Count, dtype: float64
```

Figure 2: Summary Statistics of FOMC Statements Word Count.

Section 2.2

In Section 2.2, the focus was on organizing and processing keywords for sentiment analysis of FOMC statements. The initial step involved loading a set of predefined keywords into a DataFrame. These keywords were categorized into five key groups: 'hawkish,' 'dovish,' 'positive,' 'negative,' and 'negation.' Each category contained words relevant to identifying sentiment within the statements. The DataFrame was then converted into a dictionary, where each key represented a sentiment category and each value was a list of associated words. This organized structure allowed for efficient keyword lookups during subsequent text processing.

The next task was to clean and process the FOMC statements. This involved dividing each statement into individual sentences using a function named clean_process_sentences. Each sentence was tokenized and cleaned by removing punctuation and converting words to lowercase. The cleaned sentences were then analyzed to identify any that contained hawkish or dovish keywords. These relevant sentences were stored in a nested dictionary, organized by the date of each statement. This step allowed for the separation of relevant and irrelevant content, focusing the sentiment analysis on sentences that were more likely to convey significant sentiment shifts.

After identifying the relevant sentences, the next step was to assign sentiment scores to each sentence using the function assign_sentence_score. This function utilized the list of keywords to identify whether each sentence had a positive, negative, hawkish, or dovish sentiment. Each relevant sentence was assigned a score of 1, -1, or 0 based on its content and proximity to negation words. These sentence-level scores were then aggregated at the document level using the assign_document_score function. This aggregation resulted in a sentiment index score for each FOMC statement, calculated as a weighted average of the individual sentence scores, and stored in a structured format against each statement's release date.

The final step involved storing the calculated sentiment index scores in an Excel file and visualizing the results. The sentiment index scores for each press release date were saved into a new DataFrame and plotted to observe trends over time.

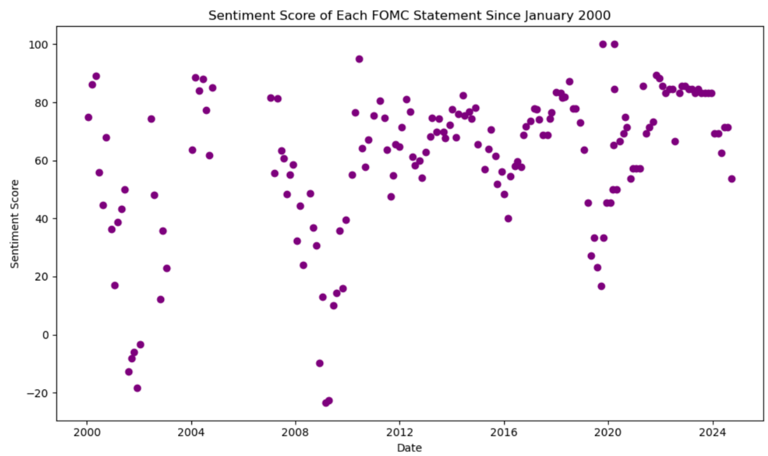

Figure 3: Sentiment Score of Each FOMC Statement.

The scores range from slightly below -20 to around 100, indicating a broad variation in sentiment across different statements. Over the years, there are noticeable periods with clusters of high sentiment scores as well as instances where the scores dipped sharply, reflecting potential market or economic events that prompted more dovish or neutral statements.

Additionally, the sentiment scores were analyzed statistically by calculating mean and median values, followed by creating a histogram to understand the distribution of the scores. The sentiment scores were further classified into three categories—'Dovish,' 'Neutral,' and 'Hawkish'—based on percentile thresholds (25th, 50th, and 75th percentiles). These categories provided a clear segmentation of sentiment intensity across different periods, which was displayed in a summary DataFrame for quick reference. This analysis provided valuable insights into how FOMC sentiment evolved over the years.

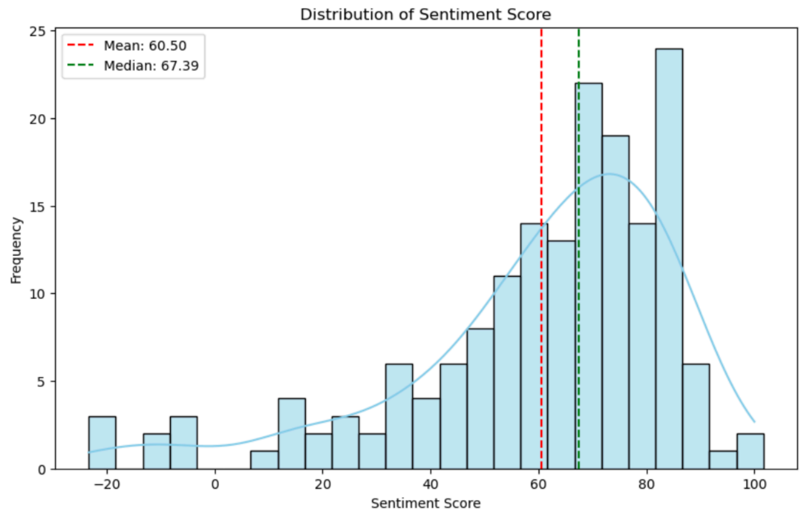

Figure 4: Distribution of Sentiment Score.

The distribution appears to be slightly right-skewed, indicating that most FOMC statements have relatively high sentiment scores. The mean sentiment score, represented by the red dashed line, is approximately 60.5, while the median sentiment score, shown by the green dashed line, is slightly higher at 67.39. This suggests that while there are some statements with lower or even negative sentiment scores, the majority of scores are above average, indicating generally positive or hawkish tones in these statements. Due to these findings, we decided to split dovish, neutral, and hawkish statements based on quartiles as shown in the figure below.

	Category	Range
0	Dovish	Score < 50.00
1	Neutral	67.39 <= Score <= 77.54
2	Hawkish	Score > 77.54

Figure 5: Thresholds for Dovish, Neutral, Hawkish Scores.

We observe a clear pattern in sentiment scores across different time periods. During the dot-com crisis and the 2008 financial crisis, sentiment scores cluster toward more dovish values. This suggests that the government took a more lenient approach to interest rates in an attempt to stimulate the economy. However, from 2010 to 2019, as the economy showed signs of recovery, sentiment scores formed a hawkish cluster, indicating a shift toward tighter monetary policy and an increased likelihood of interest rate hikes.

Around 2020, we see a sharp shift back to dovish sentiment as the COVID-19 pandemic prompted the government to lower interest rates and introduce stimulus packages to support the economy through periods of low output. Post-pandemic, sentiment scores trend upward again, reflecting a return to a more hawkish stance as the economy recovers.

In conclusion, the Taddle methodology effectively captures hawkish and dovish sentiment, showing a positive (though low) correlation with policy actions aligned with economic conditions over various time periods. This point will be further explored in the sections below.

Section 2.3

In this section, we pulled external economic data from the Federal Reserve Economic Data (FRED) using an API to analyze the relationship between changes in monetary policy and FOMC sentiment scores. The fetch_fred_data made an API request to fetch data in XML format, parsed the XML response, and stored the extracted values as pandas Series. We fetched two series: DFEDTAR (lower bound of the target federal funds rate) and DFEDTARU (upper bound), which were combined into a single DataFrame. We then created a new column, Target_Rate, based on a cutoff date, which utilized the DFEDTAR values before December 2008 and the DFEDTARU values afterward, reflecting changes in how the federal funds rate was reported.

Once the target rate data was organized, it was merged with the sentiment index DataFrame on the basis of matching dates. A new column, MPOL (monetary policy change), was introduced to measure the difference in target rates between consecutive FOMC meetings. Then, the final step involved examining the relationship between changes in the target rate (MPOL) and sentiment index scores. We plotted a scatter plot to visualize this relationship, with the change in target rate on the x-axis and sentiment index scores on the y-axis. To understand the strength and direction of this relationship, we also implemented a linear regression analysis, fitting a model between the two variables.

Based on the figure below, we can observe a clustering of data points around zero on the x-axis, indicating that in most cases, the changes in the target rate are zero. Despite this concentration, there are a few instances with larger changes in the target rate, which correspond to higher sentiment index scores. The spread of points along the y-axis suggests variability in sentiment scores even when the target rate remains unchanged, indicating other factors may also influence the sentiment index. Overall though, there seems to be a weak positive correlation between both variables.

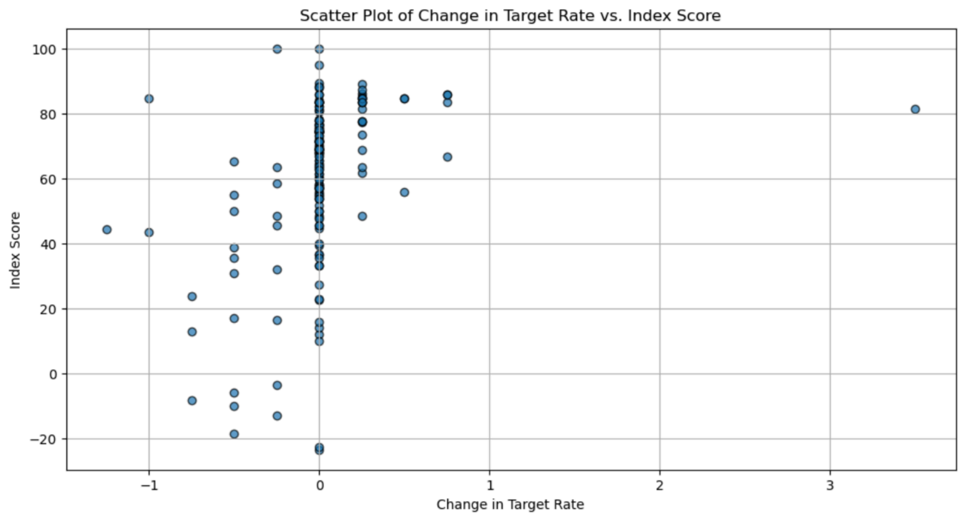

Figure 6: Scatterplot of Change in Target Rate vs Index Score.

The regression analysis indicates a positive slope, implying that an increase in the target rate change is generally associated with an increase in the sentiment index score. However, the R-squared value is relatively low (0.131). This indicates that while there is a positive relationship between changes in the target rate and sentiment, the effect is not strongly linear, and there are likely other variables influencing the sentiment index. The correlation coefficient (0.36) also supports this conclusion, indicating a weak to moderate positive association between the two variables.

Section 2.4

Tadle's Method

Tadle (2022) employs a sentiment analysis framework specifically designed to evaluate the hawkish or dovish tone of Federal Open Market Committee (FOMC) statements. By analyzing specific terms and phrases that indicate a more aggressive (hawkish) or accommodative (dovish) stance, Tadle's scoring mechanism assigns a sentiment score that attempts to quantify the overall tone of the statement. A higher score typically corresponds to a hawkish tone, implying a tighter monetary stance, while a lower score reflects a dovish or more accommodative policy stance.

Scoring Mechanism and Limitations

Tadle's method relies heavily on predefined keywords and phrases associated with hawkish and dovish sentiments. This reliance on specific terms, while providing a straightforward scoring model, introduces certain limitations. First, it may lack adaptability to variations in language used across different FOMC statements over time. Additionally, it may miss subtleties in sentiment that are not captured by simple keyword matching, resulting in a less nuanced interpretation of the FOMC's tone. Moreover, this approach assumes that certain words always carry the same sentiment, which can ignore context-specific meanings.

Proposed Model Explanation

The model used below is a BERT-based sentiment analysis pipeline to assess the tone of FOMC statements. BERT, a transformer-based language model, is capable of understanding the context around words, which allows for a more nuanced analysis compared to simple keyword-based approaches. By analyzing the entire text and not just isolated terms, this model can capture subtleties and contextual shifts within each statement. The scores range from 0 to 1, with higher scores indicating a stronger sentiment toward hawkishness. Additionally, the model classifies tones as hawkish, dovish, or neutral based on score thresholds, providing a structured interpretation of sentiment. BERT is a fine tuned model developed by Google, meaning that it has already been trained on large general language or large text. The limitation of this model might be the fact that the model has not been trained specifically on financial terms and language.

Advantages over Tadle's Method

This BERT-based approach addresses several limitations of Tadle's model. First, its context-awareness allows it to discern the meaning of words based on surrounding context, which is particularly valuable for FOMC statements that may use nuanced or evolving language. Second, the model is adaptable to changing language patterns and does not rely on static keyword lists.

The new approach uses a pre-trained BERT model capable of handling multilingual text sequences. First, the sentiment-analysis pipeline is initialized with a model that can analyze longer text sequences. A custom function, classify_tone, is then defined to categorize sentiment scores into three categories: "Hawkish" (for high scores), "Dovish" (for low scores), and "Neutral" (for moderate scores). The model analyzes each statement's text, assigning a sentiment score to it, and then applies the classify_tone function to determine the statement's tone.

```
                Date                                     Statement Text  \
0   2000-01-19  Reports from most Federal Reserve Districts in...
1   2000-03-08  Reports from the twelve Federal Reserve Distri...
2   2000-05-03  Reports from the twelve Federal Reserve Distri...
3   2000-06-14  Reports from the Federal Reserve Districts ind...
4   2000-08-09  The information collected for these reports su...
..         ...                                                ...
120 2024-03-20  March 20, 2024\nFederal Reserve issues FOMC st...
121 2024-05-01  May 01, 2024\nFederal Reserve issues FOMC stat...
122 2024-06-12  June 12, 2024\nFederal Reserve issues FOMC sta...
123 2024-07-31  July 31, 2024\nFederal Reserve issues FOMC sta...
124 2024-09-18  September 18, 2024\nFederal Reserve issues FOM...

     Sentiment Score     Tone
0           0.283983  Neutral
1           0.353083  Neutral
2           0.348307  Neutral
3           0.474146  Neutral
4           0.414483  Neutral
..               ...      ...
120         0.287085  Neutral
121         0.262520  Neutral
122         0.264218  Neutral
123         0.296913  Neutral
124         0.265947  Neutral

[170 rows x 4 columns]
```

Figure 7: BERT Model Sentiment Output.

Section 2.5

In this section, we generated three scatter plots in order to analyze and compare patterns between Tadle's sentiment scoring methodology, BERT Model Scoring and the Target changes.

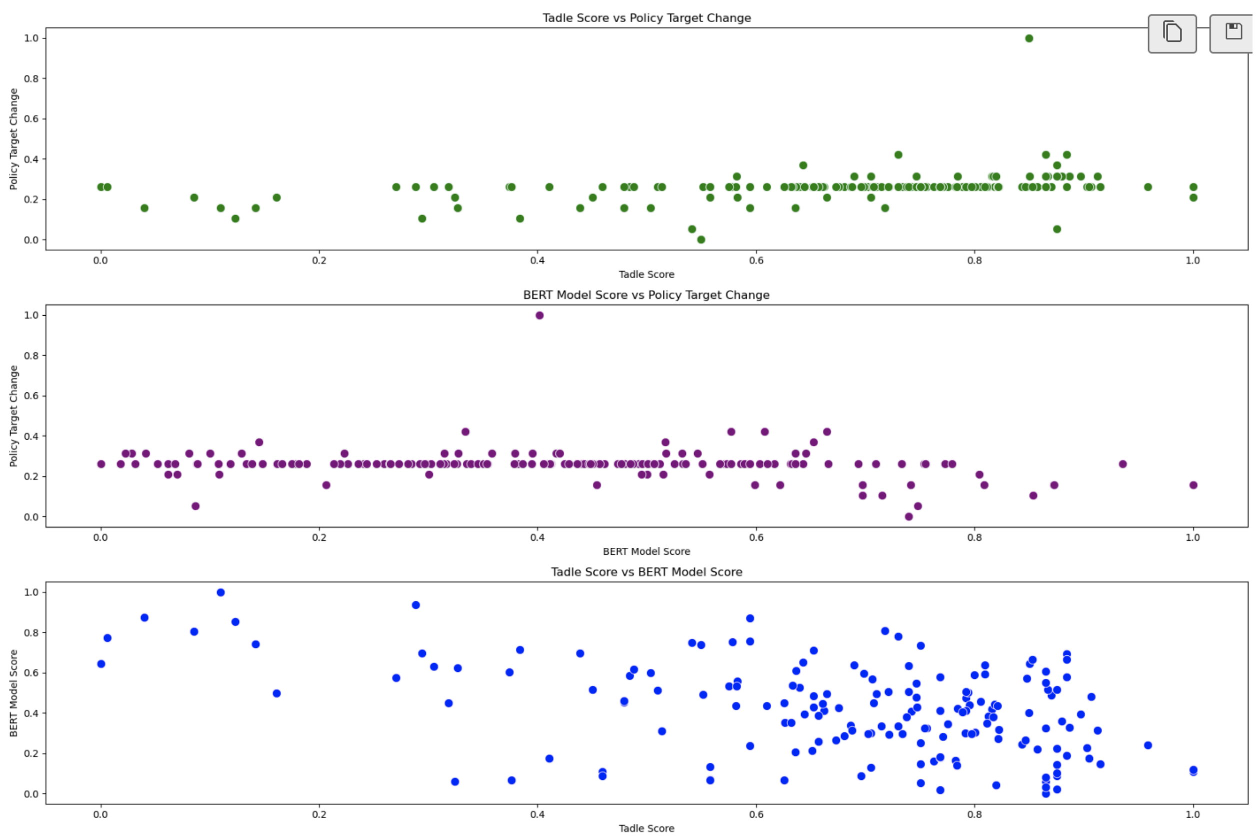

Figure 8: Scatter plots comparing Tadle Score, BERT Model Score, and Policy Target Change.

Tadle Score vs. Policy Target Change

This plot examines the relationship between the Tadle Score and the Policy Target Change. The distribution of points suggests a relatively spread-out pattern, with no strong linear correlation. The lack of a clear trend or clustering implies that variations in Tadle Score may not have a consistent impact on the Policy Target Change. The data points are spread across various Tadle Score levels without showing a distinct directional impact on policy adjustments.

BERT Model Score vs. Policy Target Change

In this plot, the BERT Model Score is plotted against Policy Target Change. Similar to the first scatter plot, there doesn't seem to be a strong pattern or relationship. The Policy Target Change values do not appear to vary in a systematic way with changes in BERT Model Score. This suggests that while the BERT model provides sentiment insights, these do not directly correlate with policy rate adjustments, at least within this data's scope.

Tadle Score vs. BERT Model Score

This scatter plot shows the relationship between the Tadle Score and the BERT Model Score. Here, we observe a more diverse spread across the axis, indicating that while both metrics attempt to capture sentiment, they may measure slightly different aspects or respond differently to the same underlying data. There's a slight clustering in certain areas, suggesting some level of agreement in sentiment interpretation between Tadle and BERT, but not a strong correlation. This implies that the two scores might complement each other by offering distinct perspectives on sentiment.

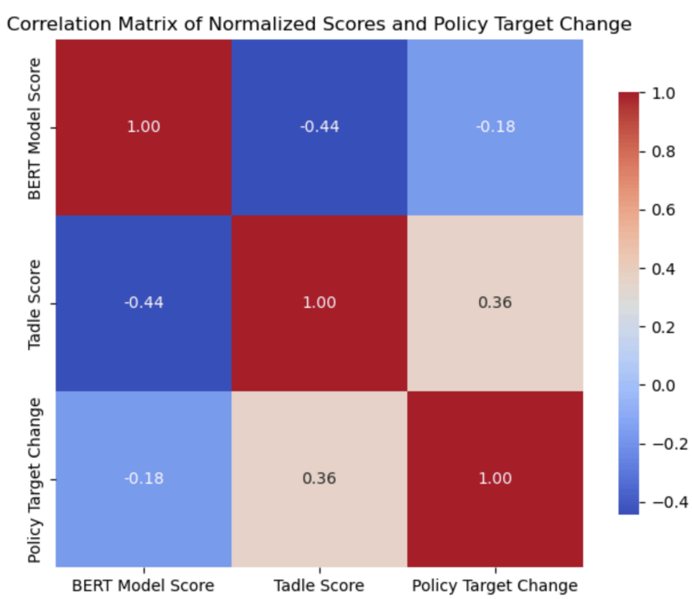

Figure 9: Correlation Matrix.

The heatmap above presents the correlation of the normalized values of the BERT model Sentiment Score, Tadle Score, and Policy Target Changes. The strongest correlation here is a negative one between the BERT model Sentiment Score and Tadle Score (-0.44), indicating that when one sentiment score is high, the other tends to be lower, suggesting a possible divergence in how sentiment is interpreted between the two models. This may imply that each sentiment measure captures different nuances in FOMC statements. Additionally, we observe a mild positive correlation (0.36) between Tadle Score and Policy Target Change. This suggests that as the Tadle Score becomes more hawkish (or dovish), there is a slight tendency for policy adjustments to align, potentially hinting at Tadle's score being more sensitive to economic shifts that result in policy changes. The weaker negative correlation (-0.18) between BERT Model Sentiment Score and Policy Target Change indicates that while BERT model sentiment measure also reacts to the tone of FOMC statements, it may be less directly aligned with the actual policy changes, emphasizing its potential as an independent perspective on sentiment that complements Tadle's model. It may also be explain by the fact that the BERT model is a fine-tuned model that has been trained on general language not solely on Financial language.

Section 3.1

In this section, we began by retrieving three economic time series from the Federal Reserve Economic Data (FRED) API: the Effective Federal Funds Rate (EFFR), the 1-Month Treasury Yield (DGS1MO), and the 10-Year Treasury Yield (DGS10). The data was filtered to include only records from the year 2000 onwards, and missing values were removed to ensure a clean dataset. We then calculated the daily changes in each indicator using the .diff() function, which measures the difference between consecutive days. By matching these changes with the exact dates of FOMC announcements, we focused our analysis on the specific periods when these announcements were made.

After filtering for FOMC announcement dates, we calculated comprehensive summary statistics for the changes in the three financial indicators. The summary statistics show that the mean change in the Effective Federal Funds Rate (EFFR) was slightly positive at 0.015, while the 1-Month (DGS1MO) and 10-Year (DGS10) Treasury Yields had small negative mean changes of around -0.011. The median changes for all indicators are close to zero, indicating that changes were generally balanced between increases and decreases. The standard deviation is lowest for EFFR (0.037), indicating relatively stable changes, while the Treasury Yields have slightly higher variability (around 0.064 each). The minimum and maximum values show that the 1-Month Treasury Yield experienced the largest decrease (-0.4) and increase (0.14), indicating that short-term yields were more prone to significant fluctuations around FOMC announcements compared to the other indicators.

	EFFR_change	DGS1MO_change	DGS10_change
count	133.000000	133.000000	133.000000
mean	0.015188	-0.011278	-0.011128
median	0.000000	0.000000	-0.010000
std	0.036775	0.064929	0.063944
min	-0.110000	-0.400000	-0.210000
max	0.140000	0.140000	0.180000

Figure 10: Section 3.1 Summary Statistics.

Section 3.2

In Section 3.2, the primary objective was to isolate periods with hawkish sentiment and analyze the impact of FOMC announcements on key financial indicators. We began by filtering the combined dataset (doc_index_score_ffr_target_df) to focus on dates where the FOMC statements exhibited hawkish sentiment. Using a pre-defined threshold for hawkishness, we created a new DataFrame named hawkish_score_df containing only the rows where the sentiment index score exceeded this threshold. We renamed the sentiment score column as 'HAWK' to make it clear that these values represent a hawkish sentiment index.

With the filtered hawkish sentiment data ready, the next step was to merge it with a DataFrame that contained changes in key financial indicators around FOMC announcement dates. After merging the DataFrames, we defined the independent and dependent variables for our regression analysis. We identified three dependent variables representing changes in financial indicators (EFFR_change, DGS1MO_change, and DGS10_change) to understand how these indicators reacted to hawkish sentiment and target rate changes. Similarly, we specified three sets of independent variables: changes in the target rate (MPOL), hawkish sentiment scores (HAWK), and a combination of both (MPOL and HAWK).

Section 3.3

The three specifications focus on different combinations of independent variables to explain changes in key financial indicators. In Specification 1, only the changes in the target rate (MPOL) are considered. This specification isolates the direct impact of the Federal Reserve's monetary policy changes. Specification 2, on the other hand, focuses solely on the sentiment of the FOMC statements (HAWK). This specification aims to capture the market's response to the tone of the FOMC's communication, independent of actual changes in monetary policy. Specification 3 combines both variables (MPOL and HAWK), recognizing that financial markets react to a combination of policy changes and the tone of communication. This specification acknowledges the dual role of FOMC statements in influencing market behavior: actual decisions and the communicated outlook.

Among these three, Specification 3 was our favorite specification as it was the most insightful and realistic model to use as it incorporates both the actual changes in the policy rate (MPOL) and the sentiment conveyed in the statements (HAWK).

In the analysis, Specification 3 for the dependent variable EFFR_change achieved the highest R-squared value, approximately 0.224. Both MPOL and HAWK showed statistically significant coefficients, indicating that changes in the target rate and the tone of FOMC statements independently affect the federal funds rate. Specifically, an increase in MPOL or a stronger hawkish sentiment (HAWK) is associated with slight decreases in EFFR, suggesting that both concrete policy actions and communicated sentiment influence market expectations and behavior.

Section 3.4

In the regressions for specification 3, the coefficients (β) represent the influence of changes in the target rate (MPOL) and hawkish sentiment (HAWK) on each financial indicator. For the dependent variable EFFR_change, the coefficient of MPOL is approximately -0.011976, indicating a small negative effect of changes in the target rate on the Effective Federal Funds Rate. Meanwhile, the coefficient of HAWK is also slightly negative at around -0.001959, suggesting that increased hawkish sentiment is associated with a minor decrease in the EFFR. The t statistics for EFFR_change are the highest when compared to the other two dependent variables.

For DGS1MO_change, the coefficient for MPOL is around -0.019321, while the coefficient for HAWK is -0.003821. Both coefficients are larger in magnitude compared to EFFR_change, which indicates that changes in short-term Treasury yields (1-Month Yield) are more sensitive to both actual policy changes and hawkish sentiment in FOMC statements, however, the results are less significant. In contrast, the coefficients for DGS10_change are even smaller: -0.007625 for MPOL and -0.002144 for HAWK. This indicates that changes in long-term yields (10-Year Yield) are less sensitive to immediate policy adjustments and hawkish sentiment, as these yields are influenced more by broader economic expectations and long-term inflation outlooks.

The regression results suggest that different financial indicators respond to monetary policy changes and FOMC communication in different ways. But overall, the observed differences are consistent with expectations based on economic theory. Policy changes (MPOL) directly impact the Effective Federal Funds Rate, which is reflected in the stronger coefficient for EFFR_change. The larger coefficients for DGS1MO_change indicate that short-term yields react more sharply to immediate policy decisions and hawkish sentiment, which aligns with the market's tendency to adjust short-term expectations quickly. On the other hand, the smaller coefficients for DGS10_change are indicative of the long-term nature of 10-year yields, which are less influenced by short-term policy changes and more by macroeconomic factors.

Section 4.1

In Section 4.1, we began by loading a dataset containing daily returns for 49 different industries from an Excel file. After cleaning and standardizing the date format, we merged this dataset with the hawkish sentiment scores (HAWK) extracted from FOMC announcements. We then implemented a function named run_industry_regressions to perform regression analysis for each of the 49 industries. The independent variable in each regression was the hawkish sentiment score (HAWK), while the dependent variable was the return for each industry. The function calculated the intercept (Alpha), slope (Beta), p-value, and R-squared value for each industry. The results were sorted by the Beta coefficient to identify which industries exhibited the most significant sensitivity to hawkish sentiment. The figure below shows a partial screenshot of the resultant output.

```
Number of Industries: 49
Regression Results for Each Industry:
```

	Industry	Alpha	Beta	p-value	R-squared
0	Coal	-10.743819	0.122917	0.043648	0.056878
1	Mines	-7.773243	0.093158	0.056797	0.050867
2	FabPr	-7.111154	0.083902	0.118474	0.034461
3	Steel	-6.795575	0.080478	0.118525	0.034451
4	Oil	-4.413552	0.049817	0.327815	0.013682
5	BldMt	-4.056668	0.049551	0.250187	0.018845
6	Agric	-3.493450	0.040561	0.340025	0.013013
7	Ships	-3.109823	0.036922	0.373956	0.011309
8	Whlsl	-2.886126	0.036041	0.290263	0.015963
9	Paper	-2.549373	0.031379	0.406166	0.009879
10	Mach	-2.230470	0.027552	0.438266	0.008607

Figure 11: Regression Results for Top 10 Industries.

Section 4.2

In Section 4.2, we read and cleaned a dataset containing monthly industry portfolio returns. The cleaned data was then transposed so that industry portfolios could be efficiently processed for regression analysis. Then, we performed a batch regression analysis by running Ordinary Least Squares (OLS) regressions for each industry portfolio for every month. The batch regression function iterated through each dependent variable (industry portfolio returns), running regressions and calculating key statistics such as Alpha, Beta, and R-squared values. The results were consolidated into a single DataFrame as shown below.

Monthly Regression Results:

	Alpha	Beta	R-Squared
2000-01-01	-3.716282	60.084491	0.091654
2000-02-01	-1.990965	-5.695914	0.000910
2000-03-01	7.605094	9.730121	0.003965
2000-04-01	0.024228	-24.250160	0.029509
2000-05-01	-1.599273	-24.484262	0.025609
...	...	...	...
2024-04-01	-3.766888	-30.156663	0.109104
2024-05-01	3.681793	-5.476297	0.005526
2024-06-01	-1.248090	-19.031190	0.044106
2024-07-01	5.965741	-45.085255	0.111938
2024-08-01	1.766290	-49.356497	0.305323

296 rows × 3 columns

Figure 12: Regression Results for Monthly Returns.

Section 4.3

λT represents the price of the monetary risk premium / sensitivity to FOMC statements on a monthly basis across all industries during that time period. Higher λT values may suggest more sensitivity to changes in monetary policy, suggesting that investors would demand a higher return to compensate for the increased risk they take.

Based on the plot, there seems to be no apparent trend with significant fluctuations between positive and negative values as shown in the plot below. However, there does seem to be higher λT values during economic crises (dot com crash, financial crisis), indicating the higher premium demanded by investors due to the higher risk they were taking during those times.

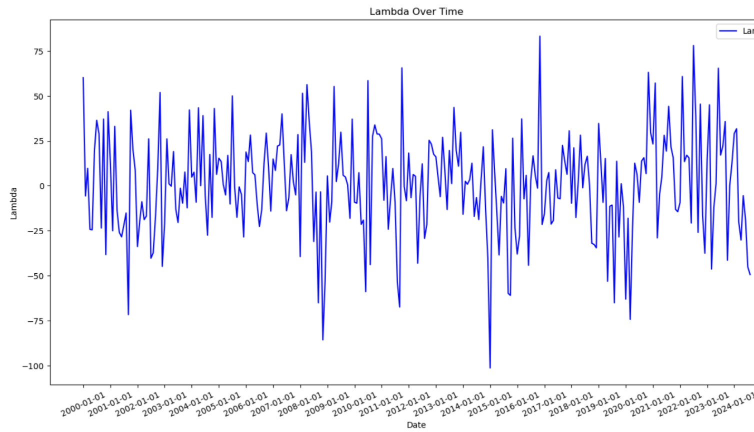

Figure 13: Lambda over Time.

Section 4.4

R-squared measures how well our model explains variability in industry returns. The plot of R-squared over time also shows a high level of variability, with values ranging mostly between 0 and 0.3, and occasional spikes reaching as high as 0.6. The low R-squared values seen throughout most of the period suggest that the independent variables used in these regressions have limited explanatory power, suggesting that the model is relatively ineffective at capturing the broader relationship between betas and industry returns. This is expected as returns across industries are affected by various factors beyond the ones used in the model.

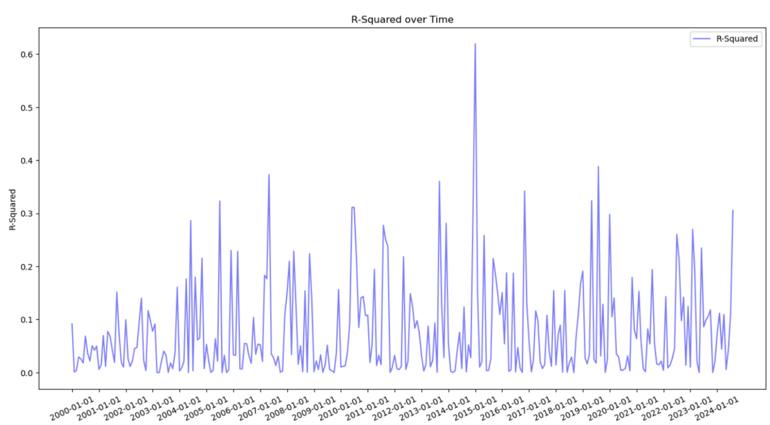

Figure 14: R-Squared over Time.

Conclusions

The project concluded that the Federal Open Market Committee (FOMC) statements from 2000 to 2024 reveal patterns in sentiment that correlate with economic events and policy shifts. Key findings include:

(1) FOMC statements exhibit varied sentiment, with dovish tones prevailing during economic downturns and hawkish tones aligning with economic recovery periods.
(2) There is a mild positive correlation between policy target changes and sentiment, particularly for hawkish tones. However, the overall relationship between sentiment scores and actual policy changes remains weak, suggesting that further analysis is needed to draw definitive conclusions. Incorporating other macroeconomic indicators, such as GDP growth rates, market expectations, and unemployment rates, could help clarify the model's relationship with sentiment and policy adjustments
(3) Regression analysis indicated that certain industries are more sensitive to FOMC sentiment changes, with hawkish tones impacting returns across various sectors differently.

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