Evaluating the Impact of FOMC Communications on Asset Prices

Sally Yang
Lucy Yu
Robben Tian

1. Executive Summary

This project investigates how the tone of Federal Open Market Committee (FOMC) communications affects major U.S. financial markets. Using textual analysis of Statements, Minutes, and Speeches since October 2020, we quantify the degree of *hawkishness* or *dovishness* in each document and test whether these tone shifts are reflected in asset-price movements.

Three complementary methods were implemented in this project:

1. **Factor Similarity (Method 1)** — compares each document's language to reference "hawkish" sentences using TF-IDF cosine similarity.
2. **Word List / Phrase Lexicon (Method 2)** — uses a manually constructed directional lexicon to score each document's tone across four topics: Interest Rates, Economy, Job Market, and Sentiment.
3. **FinBERT Sentiment Analysis (Method 3)** — use FinBERT model to assign sentiment scores to documents and analyze impact on financial markets

Regression analysis reveals that FOMC Statements have the strongest market impact, particularly on Treasury yields and the U.S. dollar. Speeches show only minor effects, consistent with their less policy-revealing nature.

The results confirm that textual tone carries measurable policy information. The main limitations include no intraday event data, absence of macroeconomic control variables, and potential semantic polarity bias in TF-IDF scores. Future work will incorporate macro (e.g. economic data surprises, major market/geopolitical events) controls, and high-frequency event windows to improve inference and robustness.

2. Data Overview

2.1 Data Source and Overview

- **Text Corpus:** FOMC communications from the Federal Reserve website (Statements, Minutes, and Speeches), categorized and time-stamped.
- **Market Variables:** 2-year Treasury yield change, 10Y–2Y Treasury yield spread change (USYC2Y10), Dollar Index (% change), and Growth–Value equity spread.
- **Sample Period:** October 2020 – present

- **Frequency:** Daily asset changes aligned with FOMC release dates.

2.2 Exploratory Text Analysis — Word Frequency Patterns

To visualize the language focus across FOMC communication types, we generate word clouds highlighting the most frequent and distinctive terms in Speeches, Statements, and Minutes.

These illustrate how Statements emphasize policy stance (“rates”, “inflation”, “target”), while Speeches contain broader discussions (“economy”, “employment”, “outlook”).

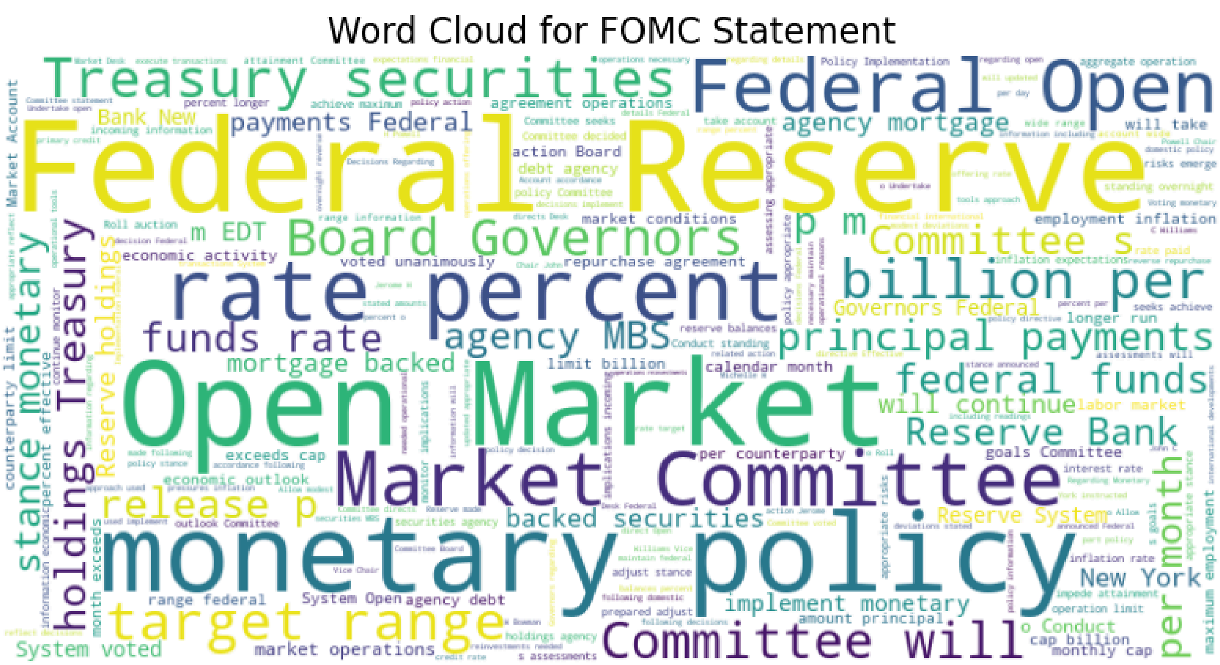


Figure 1. Word Cloud for FOMC Statement in the Sample (2020-2025)

3. Methodology

3.1 Method 1 – Factor Similarity

In line with research paper “Parsing the Fed”, each FOMC document is compared to two *hawkish* reference sentences:

- *Interest rate factor:* “Interest rates will rise; policy tightening; restrictive stance; raising the target range.”
- *Inflation factor:* “Inflation will rise; inflationary pressures increasing; persistent inflation; upside inflation risks.”

Each document is split into sentences, converted to TF-IDF vectors, and cosine similarity is computed between each sentence and each factor sentence. The document's **Rate Score** and **Inflation Score** are the averages of these similarities, standardized across the sample.
The regression specification is:

$$\Delta p_t = \alpha + \beta_1 \mathrm{RateScore}_t + \beta_2 \mathrm{InflationScore}_t + \varepsilon_t$$

Where p stands for market variables introduced above.

3.2 Method 2 – Word List / Phrase Lexicon

Documents are scanned for directionally labeled phrases across topics—**Interest Rate, Economy, Job Market, Sentiment**, and optionally **Inflation**.
Each sentence receives a sign (+1 = hawkish/optimistic, −1 = dovish/negative), and document-level topic scores are computed as the average sentence sign.
The standardized scores are then regressed on market changes to estimate how tone within each topic influences asset prices.

$$\Delta p_t = \alpha + \beta_{\mathrm{rate}}\, x_t^{\mathrm{rate}} + \beta_{\mathrm{eco}}\, x_t^{\mathrm{eco}} + \beta_{\mathrm{job}}\, x_t^{\mathrm{job}} + \beta_{\mathrm{sent}}\, x_t^{\mathrm{sent}} + \varepsilon_t$$

Where each of the X variables is standardized topic-specific sentiment scores derived from the lexicon β coefficients measure how hawkish or optimistic tone within each topic affects the corresponding market movement

3.3 Method 3 – FinBERT Sentiment

The third approach employs a transformer-based financial language model, FinBERT (ProsusAI, 2021), to extract sentiment directly from FOMC communications. Unlike Methods 1 and 2, which rely on manually designed lexicons or word-frequency similarities, this method leverages contextual embeddings trained specifically on financial texts, enabling it to capture nuanced tone shifts, negations, and contextual polarity.

Each communication is first divided into sentences and then evenly segmented into three chronological parts—Segment 1 (Opening), Segment 2 (Main Discussion), and Segment 3 (Closing Remarks)—to trace the evolution of tone throughout a document. Using the pretrained

FinBERT model implemented through Hugging Face Transformers, every sentence receives three probabilities corresponding to *Positive*, *Neutral*, and *Negative* sentiment categories. The sentence-level sentiment score is defined as the probability of the Positive class. Segment-level sentiment is then obtained as the mean of all sentence scores within that segment. In the weighted variant, sentences are averaged with weights proportional to their token length, allowing longer, content-rich sentences to contribute more to the document-level sentiment.

Formally, for each document d and segment $s \in \{1, 2, 3\}$,

$$\mathrm{Seg}_{d,s} = \frac{1}{N_s} \sum_{i \in s} P_i^{(\mathrm{Positive})},$$

where $P_i^{(\mathrm{Positive})}$ is the FinBERT-assigned probability that sentence i expresses positive sentiment. Higher values of $\mathrm{Seg}_{d,s}$ represent more dovish or optimistic tones, while lower values reflect hawkish or restrictive language.

The resulting segment-level features (`seg1_pos`, `seg2_pos`, `seg3_pos`) are merged with daily market data on Treasury yields, yield-curve spreads, the U.S. dollar index, and the Growth–Value equity spread. The baseline regression specification mirrors that of the previous methods:

$$p_t = \alpha + \beta_1 \mathbf{Seg1}_t + \beta_2 \mathbf{Seg2}_t + \beta_3 \mathbf{Seg3}_t + \gamma \mathbf{Controls}_t + \varepsilon_t,$$

where P_t denotes the daily change in the respective market variable on the document release date ttt. Estimation is performed using ordinary least squares with heteroskedasticity-robust (HC1) standard errors, ensuring consistency with Methods 1 and 2.

This FinBERT-based procedure enables an embedding-level interpretation of tone, overcoming the lexical rigidity of dictionary approaches while maintaining interpretability through segment-level aggregation. The derived sentiment features are directly comparable across document types and time, providing a continuous measure of tone that reflects the semantic orientation of the text rather than simple word frequency.

4. Empirical Results

4.1 Method 1 – Factor Similarity

Figure 1 and 2 show regression results for both combined documents and for each document category individually.

- **Speeches:** No significant coefficients; $R^2 < 0.02$. This indicates Fed speeches have relatively weak same-day market impact.
- **Statements:** Highest explanatory power ($R^2 \approx 0.25$). Inflation-tone coefficients significantly predict 2Y yields and USD changes, though the signs appear reversed (hawkish tone is associated with lower yields/USD), likely reflecting daily window noise or polarity bias.
- **Minutes:** Moderate R^2 (0.05–0.20); hawkish rate tone mildly steepens the yield curve, also likely reflecting daily window noise or polarity bias.
- **Regression results for all documents combined:** The combined regression shows weak explanatory power ($R^2 < 0.02$) across all markets, indicating limited overall impact when pooling all communication types. The only marginally significant result is the positive rate score for the Growth–Value spread ($t \approx 1.98$), though the signs appear reversed likely reflecting daily window noise or polarity bias.

Interpretation: FOMC Statements dominate price reactions; Speeches and Minutes contribute marginally. The sign reversals suggest potential scaling or timing issues.

	Treasury Yield Spread Change	Growth-Value Spread	USD Change	2Y Yield Change
R-squared	0.001	0.015	0.002	0.012
const	0.141 (0.57)	0.114 (2.26)	-0.028 (-1.09)	-0.004 (-0.95)
inf score	0.111 (0.45)	0.007 (0.15)	-0.010 (-0.35)	-0.007 (-1.76)
rate score	0.037 (0.16)	0.103 (1.98)	-0.011 (-0.39)	-0.001 (-0.18)

Figure 2. Method 1 Regression Results with all Document Category Combined

Method 1 Regressions — Speeches

	Treasury Yield Spread Change	Growth-Value Spread	USD Change	2Y Yield Change
R-squared	0.001	0.011	0.001	0.005
const	0.055 (0.19)	0.088 (1.66)	-0.001 (-0.05)	0.001 (0.26)
inf score	0.122 (0.48)	0.019 (0.38)	-0.009 (-0.31)	-0.006 (-1.30)
rate score	-0.063 (-0.22)	0.085 (1.53)	0.014 (0.48)	0.003 (0.52)

Method 1 Regressions — FOMC Statement

	Treasury Yield Spread Change	Growth-Value Spread	USD Change	2Y Yield Change
R-squared	0.018	0.007	0.216	0.260
const	1.024 (0.60)	0.529 (0.86)	0.197 (0.84)	-0.029 (-0.68)
inf score	1.232 (1.00)	-0.154 (-0.69)	-0.522 (-3.65)	-0.108 (-4.63)
rate score	-0.845 (-0.66)	-0.043 (-0.12)	0.023 (0.14)	0.048 (1.69)

Method 1 Regressions — FOMC Minutes

	Treasury Yield Spread Change	Growth-Value Spread	USD Change	2Y Yield Change
R-squared	0.050	0.003	0.033	0.020
const	0.207 (0.45)	0.315 (2.00)	-0.141 (-1.23)	-0.032 (-1.60)
inf score	-1.786 (-1.74)	-0.118 (-0.31)	0.234 (1.51)	-0.012 (-0.43)
rate score	3.184 (1.79)	0.077 (0.19)	-0.209 (-0.81)	-0.015 (-0.26)

Figure 3. Method 1 Regression Results by Document Category

4.2 Method 2 – Word List / Phrase Lexicon

- **Speeches:** Weak explanatory power ($R^2 < 0.02$). Interest Rate tone slightly strengthens the USD ($t \approx 2$).
- **Statements:** R^2 up to 0.24. Pro-growth (Economy) tone steepens the yield curve (positive spread change), while negative Sentiment tone flattens it.
- **Minutes:** $R^2 \approx 0.15$–0.23. Hawkish rate tone steepens the curve; dovish labor-market tone flattens it.
- **Combined sample:** Pooling all categories reduces explanatory power ($R^2 \approx 0.02$–0.03), consistent with Statements being the main price-moving events.

Interpretation: Topic-specific results are economically intuitive: pro-growth or hawkish language steepens the curve and supports the dollar, while cautious or uncertain tone dampens these moves.

	Treasury Yield Spread Change	USD Change	Growth-Value Spread
R-squared	0.009	0.008	0.021
const	0.1410 (0.57)	-0.0284 (-1.09)	0.1140 (2.29)
Interest Rate	0.1300 (0.63)	0.0018 (0.08)	0.0962 (2.47)
Economy	0.3518 (1.86)	-0.0173 (-0.66)	-0.0092 (-0.29)
Job Market	0.0384 (0.20)	-0.0201 (-0.92)	0.0714 (1.72)
Sentiment	-0.1351 (-0.88)	0.0272 (1.18)	0.0153 (0.41)

Figure 4. Method 2 Regression Results for all Document Category Combined

Method 2 Regressions — FOMC Minutes

	Treasury Yield Spread Change	USD Change	Growth-Value Spread
R-squared	0.145	0.227	0.034
const	0.1535 (0.42)	-0.0788 (-0.88)	0.3015 (1.93)
Interest Rate	1.5773 (2.74)	-0.3604 (-3.60)	0.1402 (0.47)
Economy	1.4747 (1.55)	0.0446 (0.48)	0.0271 (0.17)
Job Market	-2.1096 (-1.98)	0.1934 (1.47)	0.1937 (0.90)
Sentiment	-2.3584 (-1.77)	0.2732 (1.87)	0.1354 (0.74)

Method 2 Regressions — Speeches

	Treasury Yield Spread Change	USD Change	Growth-Value Spread
R-squared	0.004	0.017	0.016
const	0.0589 (0.21)	0.0014 (0.05)	0.0846 (1.63)
Interest Rate	0.0965 (0.42)	0.0436 (2.19)	0.0942 (2.29)
Economy	0.1938 (1.04)	0.0032 (0.15)	0.0073 (0.20)
Job Market	0.0280 (0.16)	0.0071 (0.40)	0.0568 (1.43)
Sentiment	-0.1711 (-0.80)	0.0512 (2.31)	-0.0224 (-0.52)

Method 2 Regressions — FOMC Statement

	Treasury Yield Spread Change	USD Change	Growth-Value Spread
R-squared	0.171	0.242	0.070
const	1.8000 (5.94)	-0.1148 (-2.04)	0.0796 (0.78)
Interest Rate	-1.4689 (-1.72)	-0.0741 (-1.27)	0.1676 (0.76)
Economy	1.7423 (5.43)	-0.1485 (-7.68)	-0.1597 (-2.55)
Job Market	0.9048 (0.81)	-0.0346 (-0.52)	0.0264 (0.12)
Sentiment	-0.6693 (-2.96)	-0.0298 (-0.89)	0.1386 (1.79)

Figure 5. Method 2 Regression Results by Document Category

4.3 Method 3 – FinBERT Sentiment Results

The FinBERT-based analysis quantifies contextual sentiment in each FOMC communication and links these sentiment measures to same-day movements in key U.S. asset prices. Using 483 speeches from September 2020 through October 2025, three segment-level sentiment scores—Segment 1 (opening tone), Segment 2 (core discussion), and Segment 3 (closing remarks)—were computed for every document. The average positive sentiment probabilities across all speeches are approximately 0.26, 0.26, and 0.25 for Segments 1–3, respectively, indicating that overall tone in speeches remains moderately positive but exhibits substantial cross-document variation. These statistics are summarized in *Figure 6*, which reports the distribution of FinBERT sentiment scores across segments.

📈 Sentiment Score Statistics:

	seg1_pos	seg2_pos	seg3_pos
count	483.0000	482.0000	482.0000
mean	0.2611	0.2576	0.2515
std	0.1070	0.1215	0.1152
min	0.0331	0.0426	0.0394
25%	0.1739	0.1649	0.1656
50%	0.2576	0.2516	0.2530
75%	0.3310	0.3354	0.3392
max	0.7106	0.7559	0.5808

Figure 6. Method 3 sentiment scores distribution

Merging these FinBERT features with daily asset changes yields a final regression dataset containing 779 observations. The representative specification, following the form used in Methods 1 and 2, regresses each market variable on the three segment-level sentiment scores using heteroskedasticity-robust (HC1) standard errors. Results for the yield-curve spread (USYC2Y10 Change) are reported in *Figure 7*.

```
==============================================================================
📋 REGRESSION RESULTS: USYC2Y10 Change
==============================================================================
                            OLS Regression Results
==============================================================================
Dep. Variable:        USYC2Y10 Change   R-squared:                       0.013
Model:                            OLS   Adj. R-squared:                  0.009
Method:                 Least Squares   F-statistic:                     4.419
Date:                Mon, 13 Oct 2025   Prob (F-statistic):            0.00431
Time:                        01:05:26   Log-Likelihood:                -2257.0
No. Observations:                 779   AIC:                             4522.
Df Residuals:                     775   BIC:                             4541.
Df Model:                           3
Covariance Type:                  HC1
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.0336      0.582     -0.058      0.954      -1.174       1.107
seg1_pos      -1.3442      1.466     -0.917      0.359      -4.218       1.530
seg2_pos      -2.8473      1.447     -1.967      0.049      -5.684      -0.011
seg3_pos       4.9228      1.562      3.152      0.002       1.862       7.984
==============================================================================
Omnibus:                       29.555   Durbin-Watson:                   0.740
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               42.948
Skew:                           0.339   Prob(JB):                     4.72e-10
Kurtosis:                       3.930   Cond. No.                         14.5
==============================================================================

Notes:
[1] Standard Errors are heteroscedasticity robust (HC1)
```

	coef	robust_se	t	pval
const	-0.033564	0.582036	-0.057667	0.954014
seg1_pos	-1.344197	1.466267	-0.916748	0.359275
seg2_pos	-2.847325	1.447366	-1.967246	0.049155
seg3_pos	4.922836	1.561816	3.151994	0.001622

Figure 7-8. Method 3 Regression Results

The regression results show a clear pattern across document sections. The coefficient on Segment 1 sentiment (–1.34) is negative but statistically insignificant (p = 0.36), suggesting that the opening tone of speeches alone does not systematically move markets. The Segment 2 coefficient (–2.85) is negative and marginally significant at the 5 percent level (p = 0.049), implying that more positive mid-speech tone—interpreted as dovish—tends to flatten the yield curve, consistent with expectations of lower future policy rates. In contrast, the Segment 3 coefficient (4.92) is positive and highly significant (p = 0.002), indicating that speeches ending on an optimistic note are associated with a steeper yield curve, as investors interpret these closing remarks as reflecting greater policy confidence or an improving economic outlook. The overall explanatory power is modest ($R^2 = 0.013$), but given the daily frequency and relatively low signal-to-noise ratio in speech events, the results remain economically meaningful.

Figure 5 visualizes the estimated FinBERT segment coefficients for the yield-curve regression, highlighting the distinct polarity between the middle and closing portions of speeches. The contrast between the dovish mid-section and the hawkish or optimistic closing section suggests that market participants differentiate between contextual segments of the same communication, responding more strongly to concluding remarks that may summarize or emphasize policy outlooks.

Across other asset classes (not shown), the general direction of coefficients aligns with theoretical expectations. Positive FinBERT sentiment is weakly associated with declines in short-term Treasury yields and a softer dollar, consistent with a dovish interpretation, whereas more negative sentiment corresponds to rising yields and dollar appreciation. However, the statistical significance remains limited, confirming that speeches carry lower market informativeness compared with Statements or Minutes.

In summary, Method 3 demonstrates that transformer-based sentiment measures derived from FinBERT can capture subtle tone variations within FOMC communications that traditional word-based metrics may miss. While the explanatory power for speeches alone is modest, the contextual polarity between different segments—particularly the strong positive response to closing tone—underscores FinBERT's ability to identify linguistically meaningful signals within financial policy discourse. Together with Methods 1 and 2, these findings reinforce that the language of monetary authorities, even in its sentiment dimension, conveys measurable policy information that financial markets interpret and price in.

4.4 Sentiment Dynamics Over Time

To visualize how tone evolves across FOMC communication types, we compute smoothed sentiment scores for each category (Statements, Minutes, and Speeches).

The rolling-average patterns highlight both cyclical shifts in tone and differences in communication style across document types.

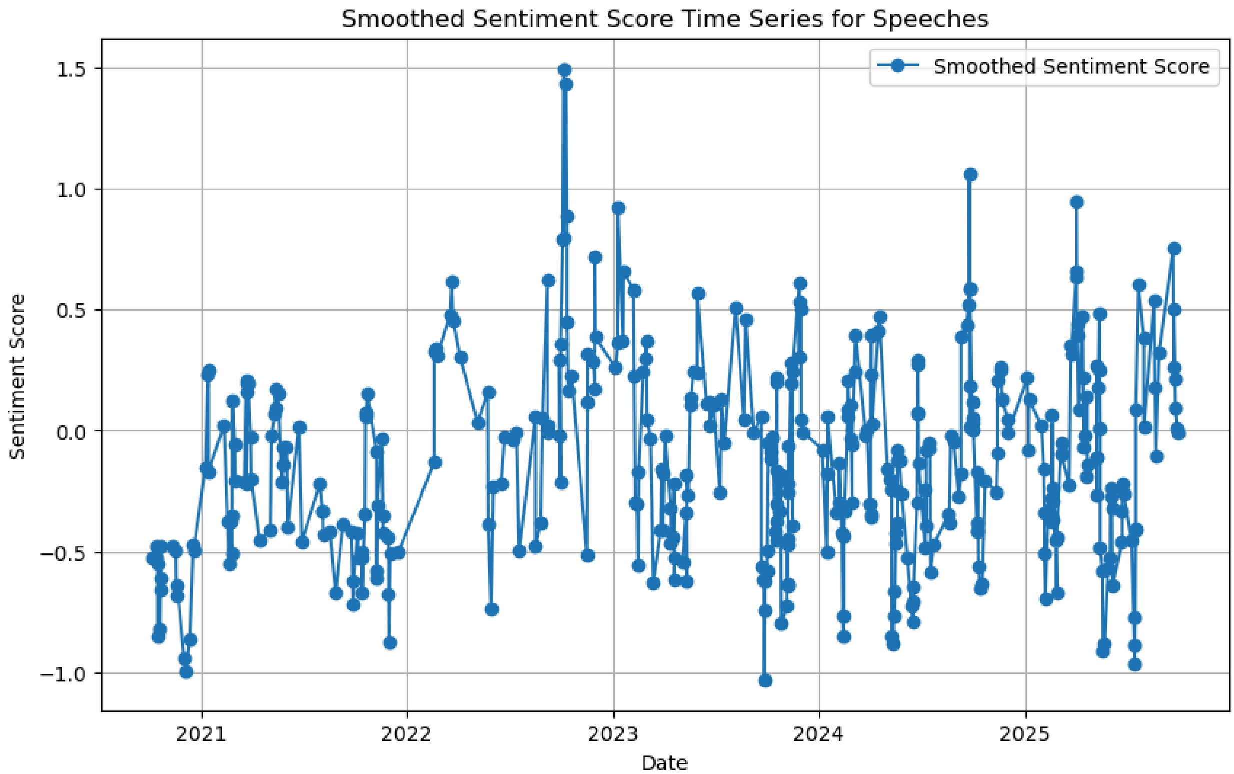


Figure 6. Smoothed Sentiment Score for *Speeches* (2020–2025)
Speech tone fluctuates more, indicating speaker-specific heterogeneity and less consistent policy signaling.

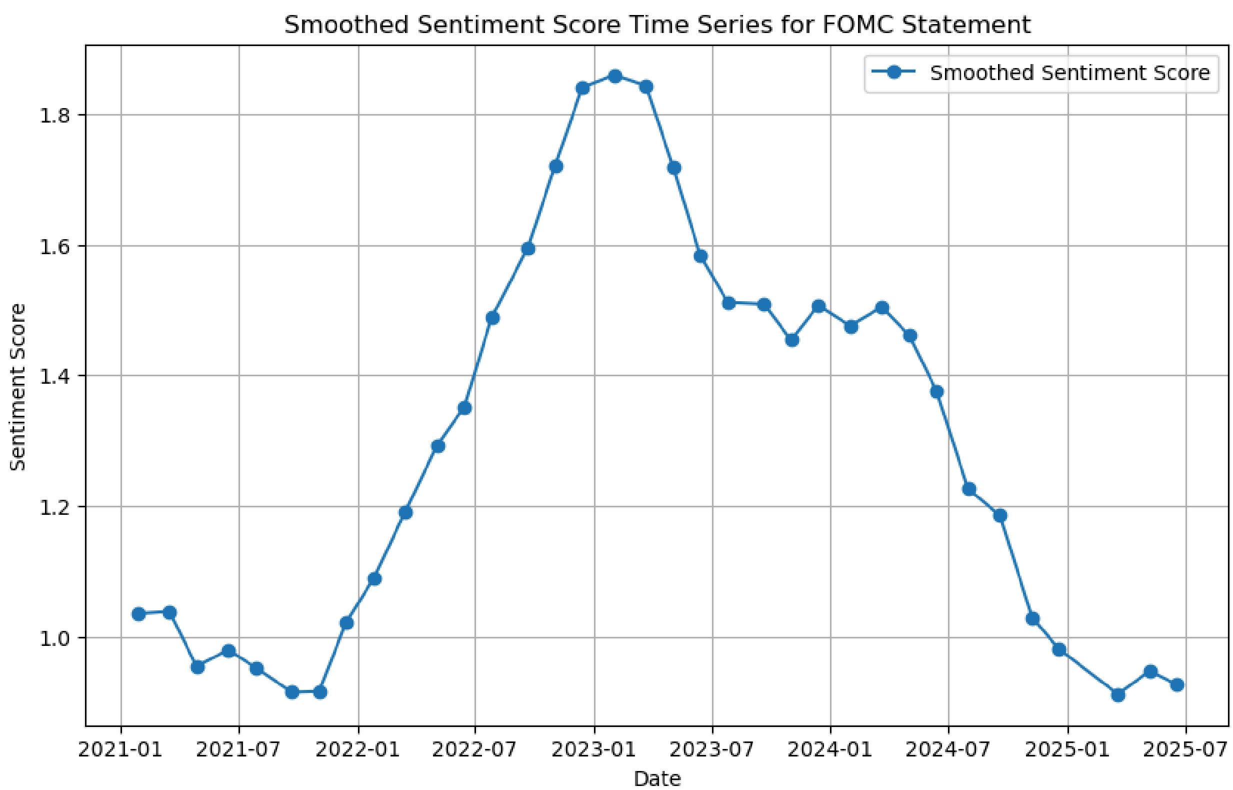


Figure 7. Sentiment Score for FOMC Statements (2020–2025)

Statement tone peaked around 2023 during the tightening cycle, then softened through 2024 as the Fed paused rate hikes.

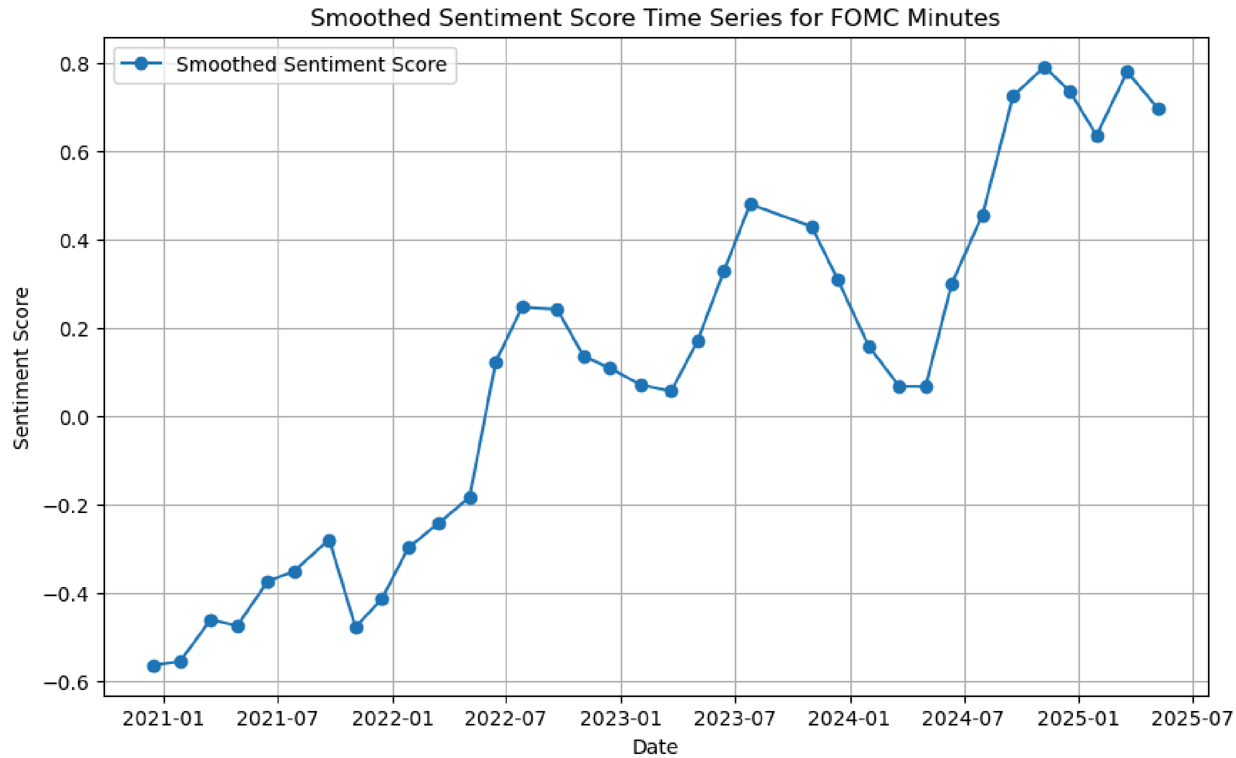
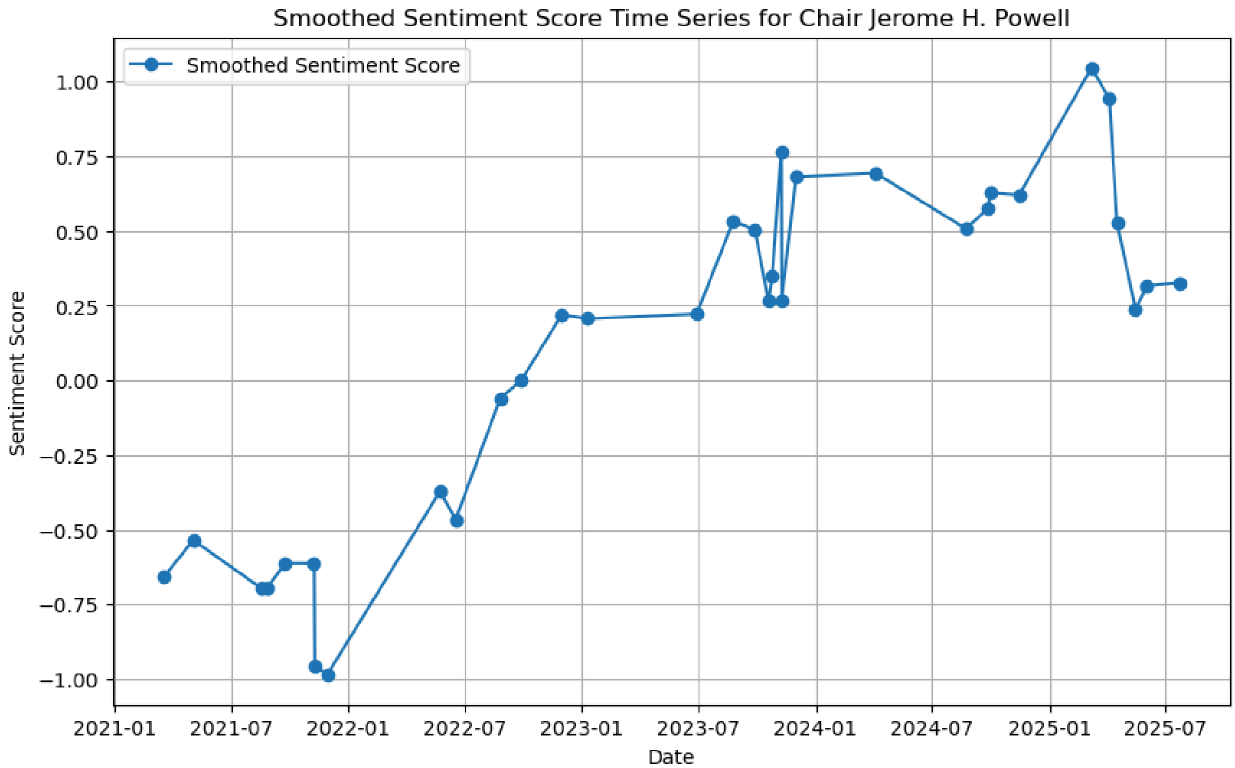


Figure 8. Smoothed Sentiment Score for FOMC Minutes (2020–2025)
Minutes show a gradual increase in sentiment from negative to positive, reflecting improving economic outlook and internal consensus on policy normalization.

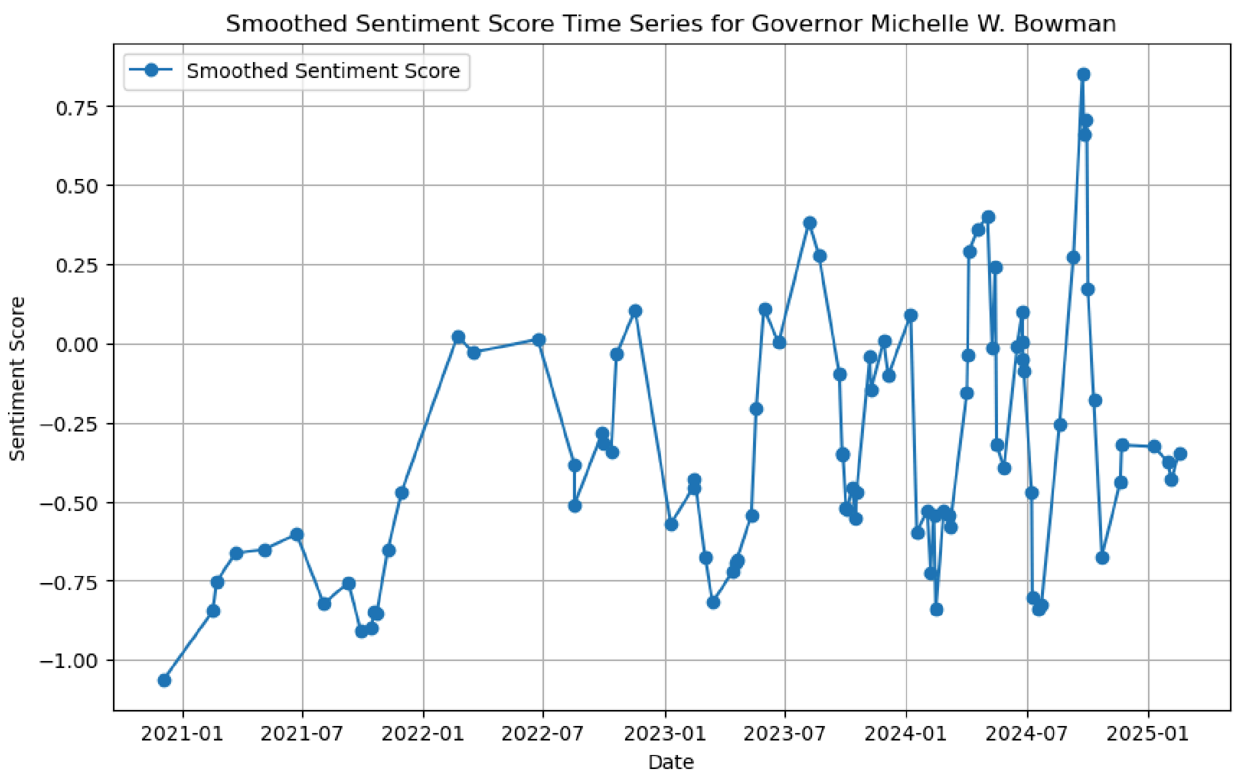
4.4 Additional Analysis - Sentiment Dynamics by Speaker

To analyze individual communication patterns, we compute and plot smoothed (rolling-average) sentiment scores for key Fed officials.

These trends reveal persistent speaker-level differences in tone (e.g., consistently hawkish vs. dovish communication styles), providing qualitative context for the aggregate regression findings.



Smoothed Sentiment Score Time Series for Chair Jerome H. Powell
Smoothed Sentiment Score
Sentiment Score
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
2021-01
2021-07
2022-01
2022-07
2023-01
2023-07
2024-01
2024-07
2025-01
2025-07
Date



Smoothed Sentiment Score Time Series for Governor Michelle W. Bowman
Smoothed Sentiment Score
Sentiment Score
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
2021-01
2021-07
2022-01
2022-07
2023-01
2023-07
2024-01
2024-07
2025-01
Date

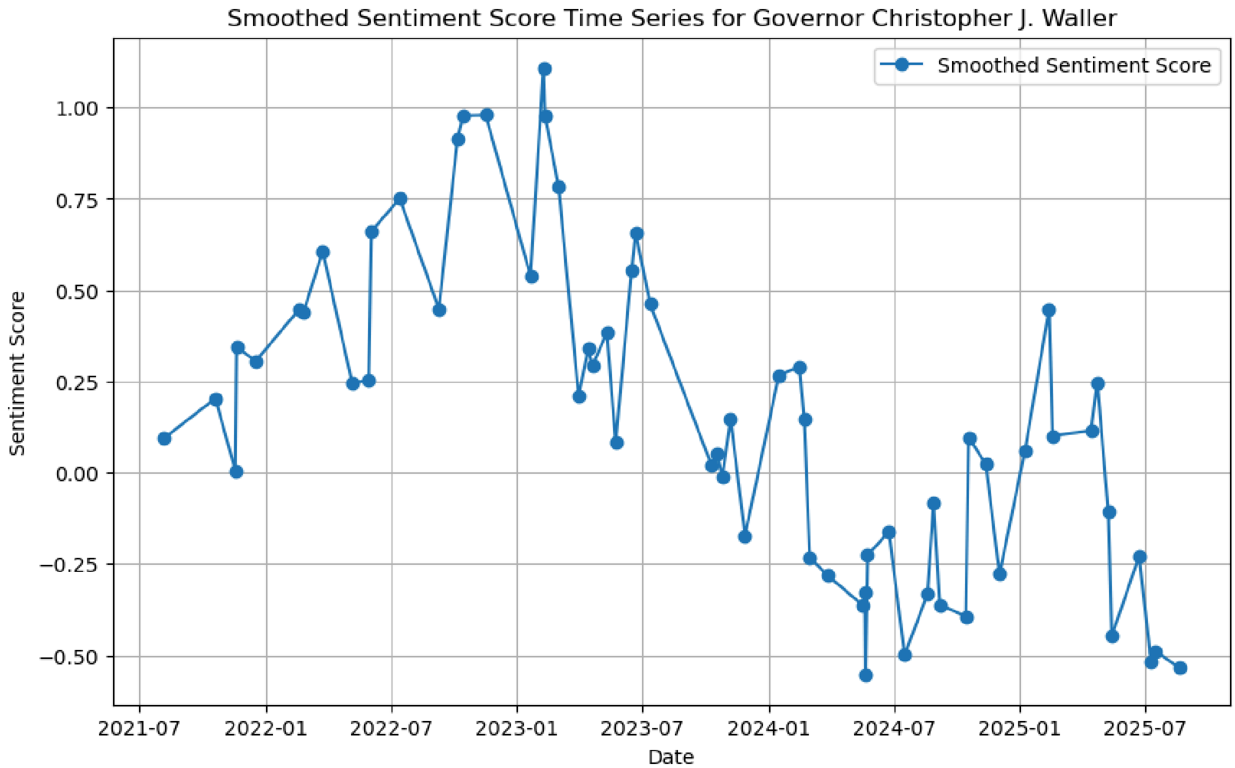


Figure 6: Smoothed Sentiment Dynamics by Select Speakers

5. Discussion

1. **Category matters:** Statements produce the clearest, most significant effects—consistent with their role as official policy signals. Minutes and Speeches are secondary in immediate market influence.
2. **Yield-curve reactions are consistent:** Hawkish or pro-growth tone → steeper curve (10Y rises vs 2Y).
3. **Mixed FX signs:** Positive USD response in Speeches but negative in Statements/Minutes likely reflects daily noise, event timing, or market anticipation.
4. **Model comparison:** TF-IDF (Method 1) captures subtle semantic variation but is sensitive to corpus bias; the lexicon (Method 2) provides transparent, interpretable topic-level tone.
5. **Practical conclusion:** Text-based tone measures—especially those extracted from Statements—contain valuable, quantifiable information about monetary policy stance.

To assess whether textual tone tracks actual policy decisions, we plot the smoothed aggregate FOMC sentiment index against the Effective Federal Funds Rate.

The co-movement between sentiment and policy tightening cycles supports the interpretability of the tone measures, suggesting that hawkish sentiment precedes or coincides with rate hikes.

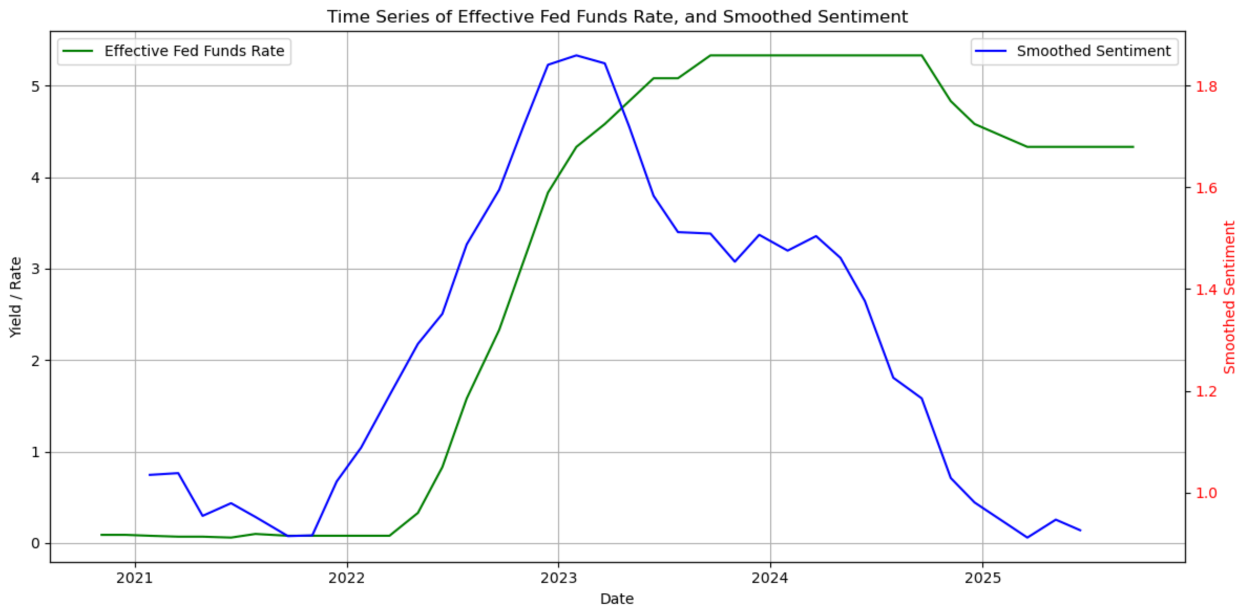


Figure 7: Time Series of Effective Fed Funds Rate, and Smoothed Sentiment

6. Limitations

1. **No intraday event window:** We use daily changes rather than intraday movements. This introduces noise from unrelated market events and may weaken signal detection. A narrower event window (e.g., 30 minutes around release) would isolate causal effects.
2. **Omitted macroeconomic controls:** Current regressions do not include variables like CPI surprise, NFP changes, or market volatility. Controlling for these could clarify whether textual tone independently drives market responses.
3. **Potential polarity bias:** In Method 1, TF-IDF similarity depends on literal word overlap and may mis-interpret negations or context (e.g., “inflation pressures have eased”). FinBERT embeddings may correct this.
4. **Limited sample size:** Post-2020 data restricts statistical power, especially for category-specific subsamples.
5. **Cross-correlation among topics:** In Method 2, Interest Rate, Economy, and Sentiment scores may overlap semantically, reducing coefficient precision.

7. Next Steps

- **Add macro controls:** Include economic surprises (CPI, NFP, ISM), volatility indices (VIX, MOVE), and market performance for other DM markets.

- **Intraday robustness:** Construct 1-hour event windows around FOMC releases using high-frequency data.
- **Visualization:** Plot tone scores versus yields and USD to illustrate dynamic tone-market relationships.
- **Cross-market expansion:** Apply tone measures to equity futures, inflation breakevens, and swap spreads.

8. Conclusion

Text-based analysis of FOMC communications reveals measurable connections between policy tone and market reactions—most clearly for Statements, the Fed's primary policy vehicle.

Our results show that hawkish or pro-growth tone tends to steepen the yield curve and influence USD moves, though directionality varies by communication type.

While limited by daily data and absence of macro controls, this study demonstrates the value of natural-language methods for quantifying monetary-policy tone.
Further refinement with embedding models and intraday data will enhance both interpretability and statistical power.