# SEPOL 416 Capstone Project: Decoding Market Reactions: Unveiling the Impact of FOMC Statements with NLP and Machine Learning Methods

Qingyang Tian

Supervisor:

Dr. Ruhan Circi &

Dr. Ruhan Ogut



# **Outline**



I. Background & Research Questions



II. Prior Research



III. Data & Indentification strategy



IV. Descriptive Analysis



V. Prediction Results & Model Evaluation



VI. Policy Insights & Next Steps

#### I. Introduction

- The Federal Open Market Committee (FOMC) plays a crucial role in setting U.S. monetary policy.
- Frequency: 8 times per year
- Market participants closely analyze FOMC statements, which influence investor expectations and risk sentiment.
- These communications impact asset prices in various financial markets.

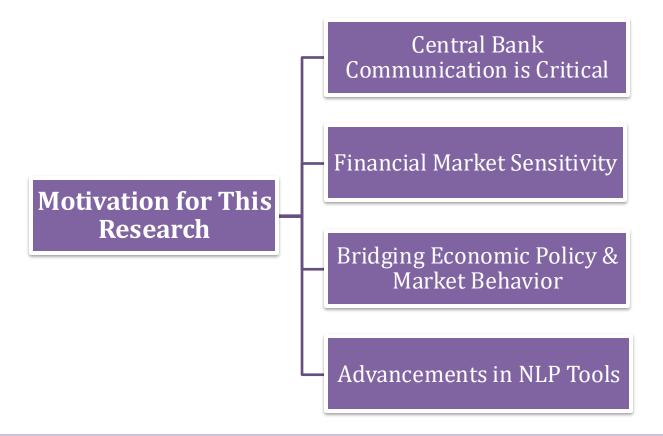
#### **Dovish Tone**

- Lower interest rates and economic support
- Rate cuts or quantitative easing
- boost **stock prices**

#### **Hawkish Tone**

- Inflation control and Economic tightening
- Rate hikes or reduced liquidity
- Leads to market volatility

# I. Research Questions



#### **Research Question:**

How do FOMC meeting statements relate stock prices indices and asset price trends?

#### II. Prior Research

**NLP tools** measure how qualitative economic descriptions in postmeeting statements impact bond prices (Taeyoung et al., 2021).

**Fine-tuned FinBERT** on FOMC minutes to enhance sentiment analysis of monetary policy communications (Ziwei et al., 2023).

**Applied sentiment analysis (Loughran-McDonald, BERT, XLNet)** to FOMC statements, predicting federal funds rate changes and S&P 500 correlations (Tomokuni et al., 2023).

#### My research:

Using various NLP tools to analyze the impact brought by the FOMC statements to the Specific industries of the Stock Market

### II. Prior Research

My research: Stock Market Indices from different industries

Symbol	Index Name	Description
^SP500-60	S&P 500 Real Estate (Sector)	Tracks the <b>real estate sector</b> within the <b>S&amp;P 500</b> , including REITs and property investment firms.
^SP500-50	S&P 500 Utilities (Sector)	Focuses on <b>utility companies</b> (electricity, water, gas) within the S&P 500.
^SP500-25	S&P 500 Consumer Discretionary (Sector)	Represents consumer discretionary stocks (e.g., retail, entertainment, automotive) within the S&P 500.

# III. Data and identification strategy

#### **Data Sources**

- FOMC Meeting Statements (2004-2024) from the Federal Reserve Board
- Stock Market Data For Different Industries (Real Estate, Utilities, Consumer Discretionary) from Yahoo Finance

#### **NLP Techniques Used**

- Text Preprocessing: Tokenization, Lowercasing,
   Stemming/Lemmatization, Stopword Removal, etc
- Text Analysis (TF-IDF): Identifying Hawkish and Dovish Keywords from the FOMC Statements and then apply TF-IDF vectorization.
- Sentiment Analysis (FinBert): Measuring sentiment in FOMC Statements and divided into three groups (Hawkish, Neutral, Dovish Score tell them what is it

# Workflow

Data Collection

Collect 2004 to 2024 FOMC statements from the Federal Reserve Board

Collect Stock Price Indexes from Different industries of S&P 500

# Data Processing

Data Import & Cleaning

Select specific FOMC meeting date from Federal Reserve Board

Calculate the Difference of index closing prices within a day, a week, and 4 weeks

#### **NLP Analysis**

Extract Specific Keywords and Compute TF-IDF

Extract Sentiments Using FinBERT

Extract BERT-Based Features Using FinBERT and PCA analysis

# Exploratory Data Analysis

S&P 500 Index volatility over time

Distribution of market difference after 1 day, 1 week & 4 week

Correlation
between
FinBERT
Sentiment &
Market
Difference

#### Machine Learning

Time series Train-Test Split (80,20), predict the differences for the last 20% of the dataset

Model training with Logistic regression, Random Forest

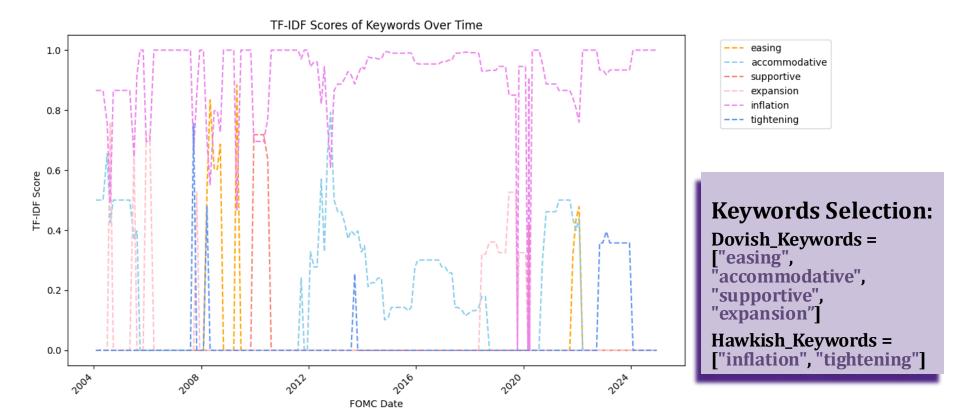
# Model Evaluation

Hyperparameter Tuning & Cross Validation

Confusion Matrix & Accuracy, Recall, Precision, F1 Scores

# IV. Descriptive Analysis:

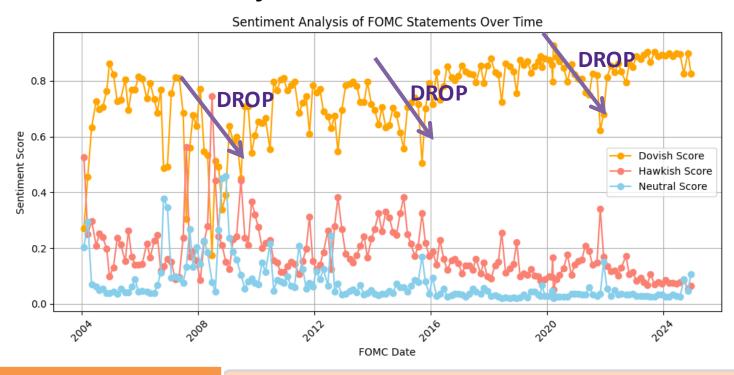
#### NLP ---- TF-IDF



"Inflation" consistently has high relevance, peaking in recent years, but experienced a sudden drop in 2020 year. "Easing" & "Accommodative" were prominent before 2008 & 2020, likely during economic stimulus periods. "Tightening" gained relevance post-2008 and again post-2020, indicating policy shifts toward tightening. "Expansion" & "Supportive" had temporary spikes, aligning with economic stimulus phases.

# IV. Descriptive Analysis:

#### **NLP ---- Sentiment Analysis**



**Dovish sentiment (high values)** 

 dominates, suggesting a preference for lower interest rates and economic support.

Hawkish sentiment (fluctuating)

• spikes during 2008-2010 and 2016-2018, aligning with tightening cycles and rate hikes.

Neutral sentiment (consistently low)

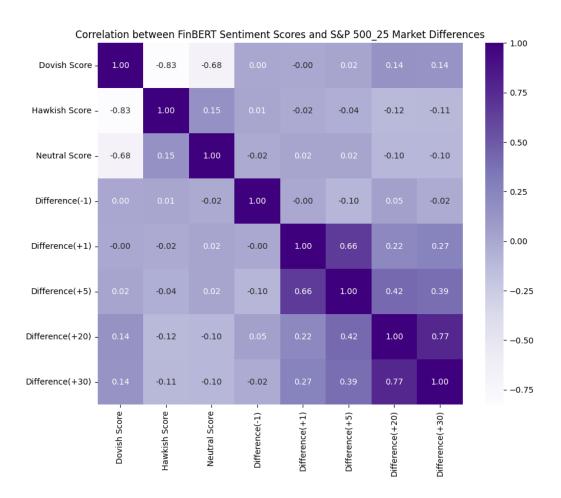
 remains minor, indicating statements generally lean toward a stance rather than neutrality.

# IV. Feature Extraction & Prediction Analysis

NLP Analysis ---- Extract BERT-Based Features Using FinBERT and PCA analysis

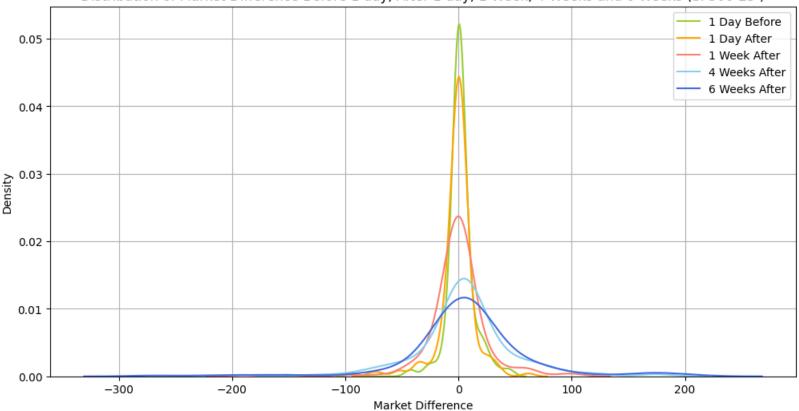
- FinBERT Embeddings (768 Dimensions)
  - FinBERT is a **finance-specific BERT model** used for **NLP in financial texts**.
  - It converts text into **768-dimensional embeddings** for numerical analysis.
- Dimensionality Reduction Using Principal Component Analysis
  - PCA **reduces feature dimensions** while keeping 90% variance.
  - Helps in improving computation efficiency and avoiding overfitting.
- Reduced 768 variables to 30

# IV. Descriptive Analysis



# IV. Descriptive Analysis





## V. Predictive Analysis

- Number of input variables: 39
  - 6 Keywords Selection
  - 3 Sentimental Scores
  - 30 BERT Based Features
- Output variable (for this presentation) S&P 500-25 Difference (+1)

# Input Variables Keywords TF-IDF values Sentiment Scores BERT-based Features by using PCA Analysis

# Output Variables S&P 500-25 Difference (+1)

#### VI. Prediction Results & Model Evaluation

#### Train/test split:

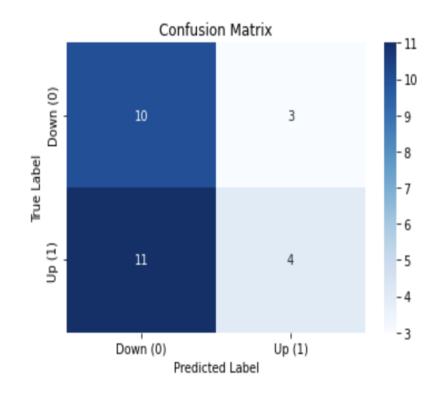
Time Series Split is used to ensure that training always occurs on past data while testing is done on future data

#### **Logistic Regression (Linear Model)**

<b>Evaluation Metrics</b>	Score
Accuracy	0.5
Precision	0.5272
Recall	0.5
F1 Score	0.4679

#### **Potential Reasons for the low Score:**

The non-linear nature of the data and market movements may not be linearly separable



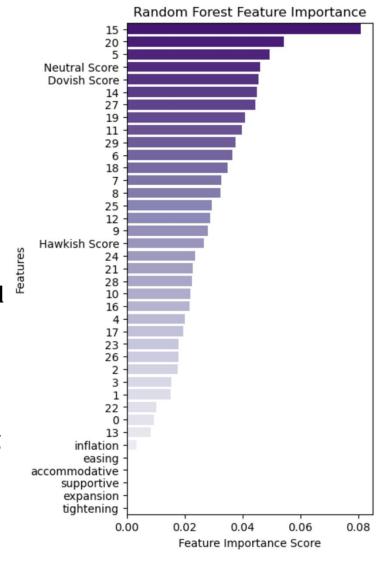
## VI. Models Evaluation

#### **Random Forest:**

<b>Evaluation Metrics</b>	Score
Accuracy	0.9642
Precision	0.9668
Recall	0.9643
F1 Score	0.9643

#### **Feature Importance Insights:**

- FinBERT embedding capture the context well
- Neutral and Dovish Scores are the most influential factors in predicting market movements.
- Policy-related keywords (inflation, easing, tightening, etc.) have minimal impact, indicating that market responses are driven more by sentiment than explicit policy language.



# VI. Conclusion & Policy Insights

#### Conclusion

 BERT model, NLP features and flexible ML method show promise to predict the market movement.

#### **Policy Insights**

- Improve Fed communication strategies to reduce uncertainty.
- Anticipate
   industry-specific
   market
   movements for
   proactive policy making.

# VI. Limitation & Next Steps

Limited effects for the selected keywords due to the rare appearance

Use other NLP techniques

Small datasets, which may lead to **overfitting** 

Increase dataset size

Analyze **broader financial markets** to refine Fed policy strategies.

17

#### References

- Doh, T., Kim, S., & Yang, S.-K. X. (2021, February 11). How You Say It Matters: Text Analysis of FOMC Statements Using Natural Language Processing.

  Kansascityfed.org. https://www.kansascityfed.org/research/economic-review/how-you-say-it-matters-text-analysis-of-fomc-statements-using-natural-language-processing/
- Gössi, S., Chen, Z., Kim, W., Bermeitinger, B., & Handschuh, S. (2023). Finbert-FOMC: Fine-tuned FinBERT model with sentiment focus method for enhancing sentiment analysis of FOMC minutes. *4th ACM International Conference on AI in Finance*, 357–364. https://doi.org/10.1145/3604237.3626843
- Higano, Tomokuni, et al. "Machine Learning and FOMC Statements: What's the Sentiment?" CFA Institute Enterprising Investor, 18 Jan. 2023, blogs.cfainstitute.org/investor/2023/01/18/machine-learning-and-fomc-statements-whats-the-sentiment/.

Q & A

# Thanks for watching~