# FOMC PRESS CONFERENCE SENTIMENT ANALYSIS – FinBERT

# 1. Introduction

One of the most crucial instruments for contemporary monetary policy has become central bank communication. Transparency and forward guidance have emerged as crucial policy tools in the wake of the global financial crisis, and the Fed has depended more and more on speeches, news conferences, and other forms of communication to control financial market expectations. The Federal Open Market Committee (FOMC) news conference is one of the most important of these since it offers up-to-date information on the Fed's policy position, economic outlook, and possible future policy actions.

Financial markets respond to the tone and attitude of policy pronouncements in addition to their content. Whether dovish or hawkish, little adjustments in rhetoric can have a quantifiable impact on volatility and asset prices. Previous research has shown that central bank communication influences currency rates, equity prices, and yields (Luca and Moench, 2015; Hansen and McMahon, 2016; Ehrmann and Fratzscher, 2007). It is still unclear from empirical research, nevertheless, how much mood expressed in press conferences held after meetings affects market behavior.

This study investigates the relationship between the sentiment conveyed during FOMC press conferences from 2011 to 2019 and anomalous changes in the S&P 500 index and implied volatility as indicated by the VIX. Within a certain event window, we assess sentiment and correlate it with market outcomes using natural language processing algorithms. Our goal is to evaluate the press conference tone's predictive content for volatility and returns.

# 2. Data

The empirical analysis relies on two main data sources: textual transcripts of FOMC press conferences and daily financial market data for the S&P 500 and VIX indices.

**Text Data:** The Federal Reserve's official website provided transcripts of press conferences from 2011 to 2019. Ben Bernanke (2011–2014), Janet Yellen (2014–2018), and Jerome Powell (2018–2019) are the three Federal Reserve Chairs whose terms are covered by these. A Q&A session with media follows the chair's opening remarks in every transcript. The raw text was preprocessed to eliminate repeated boilerplate language, metadata, and non-verbal features like laughter and applause.

**Market Data:** Yahoo Finance provided the daily closing prices for the CBOE Volatility Index (^VIX) and the S&P 500 (^GSPC). Each observation's event date falls on the same day as the news conference. In order to ensure that the metrics capture deviations from recent historical behavior rather than long-term trends, abnormal returns and abnormal volatility are computed in relation to a 60-day pre-event estimation window.

N = 64 press conference events, each associated with a sentiment score and related aberrant market results, make up the final dataset.

# 3. Methodology

## 3.1 Sentiment Extraction

We extract sentiment from each press conference transcript using FinBERT (yiyanghkust/finbert-tone), a financial domain-specific version of the BERT architecture. Three sentiment categories—positive (P\_pos), neutral (P\_neu), and negative (P\_neg)—are represented by the probabilities that FinBERT produces. The definition of the sentiment score is:

Sentiment Score = P\_pos − P\_neg

This formulation measures the net positivity of the text, capturing the balance between optimistic and pessimistic language. We enhance the sentiment measure in two ways:

**• TF-IDF weighting:** Assigns higher weights to words that are informative within the corpus but not overly common.  
**• Position weighting**: Applies greater emphasis to earlier segments of the press conference, based on the assumption that initial remarks are more impactful. This is implemented as:  
 w\_i = TF-IDF\_i × max(1 − i/N, 0.1)

## 3.2 Return and Volatility

We calculate returns (R\_t) and volatility (V\_t) to capture deviations from expected market behavior.

Return:  
 R\_t = R\_t − mean(R\_{t−60:t−1})  
where R\_t is the return on the event day and the mean is computed over the 60 trading days preceding the event.

Volatility:  
 V\_t = σ\_{t:t+5} − σ\_{t−60:t−1}  
where σ\_{t:t+5} is the standard deviation of returns over the 5 days following the event, and σ\_{t−60:t−1} is the pre-event volatility.

# 4. Results

We estimate two OLS regression models:  
 R\_t = α\_R + β\_R · SentimentScore\_t + ε\_t  
 V\_t = α\_V + β\_V · SentimentScore\_t + u\_t

## Table 1. OLS: Return on Sentiment

## A screenshot of a computer AI-generated content may be incorrect.

## Table 2. OLS: Volatility on Sentiment

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AI-generated content may be incorrect.

Scatter plots of sentiment score against return and volatility reveal a modest positive slope for returns and a near-flat slope for volatility. The return regression coefficient (β\_R) is positive and marginally significant at the 10% level, while the volatility coefficient (β\_V) is small and statistically insignificant.

# 5. Discussion

The results suggest that more positive sentiment in FOMC press conferences is associated with higher abnormal returns in the S&P 500 on the day of the event. This aligns with the hypothesis that upbeat tone can boost investor confidence and stimulate equity buying. However, the statistical significance is borderline (p = 0.054), indicating that the effect is not strong enough to be conclusive at conventional significance levels.

For abnormal volatility, the relationship with sentiment is weaker and statistically insignificant. This could reflect the fact that volatility is more sensitive to the substance of policy changes or macroeconomic surprises than to linguistic tone. Alternatively, the market may have already priced in volatility expectations prior to the press conference.

Our findings are broadly consistent with earlier studies showing that sentiment affects returns more than volatility. For instance, Smales and Apergis (2020) find that central bank communication tone influences equity market returns but has less impact on implied volatility measures.

# 6. Limitations & Future Work

This analysis faces several limitations. First, the small sample size (N = 64) limits statistical power and may obscure weaker effects. Second, we rely on daily data, which may miss short-lived intraday reactions. High-frequency (minute-level) data would allow for more precise identification of immediate market responses. Third, the sentiment extraction process, while advanced, may not fully capture the nuances of central bank language, such as conditional statements or forward guidance caveats.

Future research could address these limitations by expanding the dataset to include other forms of Fed communication (e.g., testimony, speeches, FOMC statements), applying more sophisticated NLP models (such as fine-tuned large language models), and integrating macroeconomic control variables to isolate sentiment effects from concurrent economic news.

# 7. Conclusion

This study contributes to the literature on monetary policy communication by quantifying the relationship between FOMC press conference sentiment and financial market reactions. We find modest evidence that positive tone is linked to higher abnormal returns, while volatility appears unaffected. These results underscore the importance of central bank language as a policy tool, even in the absence of concrete policy changes. As central banks continue to refine their communication strategies, understanding the market impact of tone will remain an important area of research.

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