From Sentiment to Markets: Understanding Public Reactions to Interest Rate Cuts on Twitter

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1. Introduction

On September 18th, 2024, the U.S. Federal Reserve announced a 2.5% interest rate cut, aiming to counter inflation and stimulate economic growth. This decision sparked widespread debate, with some experts viewing it as necessary and vital to stimulate growth, while others raised concerns about economic stability and vulnerabilities, with the rate cut risking asset bubbles due to prolonged low rates (Borio & Zhu, 2012; Stein, 2014). These different interpretations of policy outcomes and economic uncertainty are important factors contributing to differences in sentiment.

Understanding public sentiment during major economic events is crucial for policymakers and investors. Public sentiment not only captures society's immediate reactions but also significantly influences market expectations and investor confidence (Lamla & Vinogradov, 2019). Negative sentiment often signals doubts about economic stability and policy effectiveness, potentially increasing market volatility and risk aversion (Conrad et al., 2021). In contrast, positive sentiment can boost market confidence and encourage capital flows, aiding economic recovery (Baker & Wurgler, 2007). Analyzing public sentiment also helps policymakers like the Federal Reserve adjust communication strategies, reducing misperceptions and stabilizing markets (Shiller, 2017).

This study analyzes public sentiment on Twitter, a key platform for capturing real-time reactions to major economic decisions. Our goal is to provide insights into public perceptions of this monetary policy decision and contribute to the understanding of how social media sentiment relates to significant economic events. We collected tweets from September 11th to September 25th, 2024, using keywords including "Fed rate cut," "U.S. federal rate cut," and "U.S. rate cut." By analyzing these tweets, this study hopes to reveal the difference in sentiment expression between different topics of posts, and the relationship between changes in sentiment of Twitter posts and economic indices, providing insights into the public reaction and how organizations can respond to these reactions.

The key research questions that guide this study are:

i. How does the sentiment expressed by Twitter users differ across main topics discussed during the Fed's rate cut?

ii. How does sentiment change over time, and how do these changes correlate with the Nasdaq index?

iii. How does the sentiment of highly liked posts compare to that of low-liked posts?

2. Literature Review

Social media platforms, particularly Twitter, have become vital tools for analyzing public sentiment during significant social events. Studies have utilized Twitter data to assess public reactions to many important social events. For example, Osakwe et al. (2021) analyzed 7,000 tweets to identify public concerns during COVID-19. Burnap et al. (2015) analyzed Twitter activity during the London 2012 Olympics to understand public sentiment towards different sports and athletes. Similarly, Kryvasheyeu et al. (2016) analyzed Twitter activity during Hurricane Sandy to assess public responses to the disaster. These demonstrated Twitter's utility in capturing real-time public reactions.

Advancements in Natural Language Processing (NLP) have significantly enhanced the analysis of social media texts, which often contain informal language and abbreviations. Traditional machine learning algorithms like Naïve Bayes, Decision Trees, and SVMs were initially employed for sentiment classification on Twitter data (Sahayak et al., 2015; Wakade et al., 2012). However, the emergence of deep learning models has improved performance. Transformer-based models such as BERT (Devlin et al., 2018), XLNet (Yang, 2019), and DistilBERT (Sanh et al., 2019) have shown superior ability to capture contextual nuances in language, making them effective for sentiment analysis and topic modeling on Twitter data. For example, Hsieh et al. (2023) discussed how distilled models like DistilBERT can outperform larger models with less training data and computational resources, which is advantageous for processing large volumes of social media data in our context. In financial sentiment analysis, domain-specific models like FinBERT have shown substantial improvements over general-purpose models. FinBERT is a variant of BERT fine-tuned on large financial corpora, including earnings reports, analyst notes, and financial news (Liu et al, 2020). Kumar and Chaturvedi (2024) highlight the effectiveness of FinBERT in financial sentiment analysis, outperforming its counterparts DistilBERT and DistilRoBERTa on various metrics such as accuracy, precision, recall, and F1 score. FinBERT's superior performance is particularly evident in its precision of 0.974, recall of 0.973, and F1 score of 0.973, which distinctly surpass the metrics achieved by DistilBERT and DistilRoBERTa.

In the context of economic events, Azar and Lo (2016) examine the use of Twitter data to predict stock market reactions to Federal Open Market Committee (FOMC) meetings. Their findings highlight the predictive power of social media sentiment for market returns, emphasizing the link between public sentiment and financial indicators. Conrad et al. (2021) validate the use of social media data as a reliable alternative to traditional surveys for measuring public economic perceptions using topic modeling and sentiment analysis. FinBERT has also been applied to a variety of financial analytics tasks, particularly in forecasting market sentiment and stock price movements. For example, Kim et al. (2023) used FinBERT to analyze the sentiment in earnings conference call transcripts to predict the S&P 500 index, and the root mean square error (RMSE) was reduced by 20-25% compared to other models, highlighting its strong performance in financial market prediction. In addition, Huang et al. (2022) utilized FinBERT to assess sentiment in financial news and corporate reports with 10-15% higher accuracy than generalized models such as BERT. FinBERT is also used to label ESG-related discussions in corporate disclosures with 89.5% accuracy, which underscores its ability to process domain-specific financial texts (Shen et al., 2023).

3. Methodology

3.1 Data Collection

The data for this study was collected from Twitter using the Twitter API. Tweets were retrieved between September 11th and September 25th, 2024, encompassing the days leading up to and immediately following the Federal Reserve's September 18th announcement of a 2.5% interest rate cut. The keywords "Fed rate cut," "U.S. federal rate cut," and "U.S. rate cut" were selected to ensure comprehensive coverage of relevant public discussions. In total, 38,405 tweets were initially collected. Each tweet was accompanied by metadata such as timestamp, text content, and likes and, to facilitate subsequent analysis.

3.2 Data Cleaning

We performed data cleaning to ensure the accuracy of the dataset, reducing the number of records from 38,405 to 37,167.

3.2.1 Removing Duplicate Data:

The data cleaning process began by removing duplicate tweets from the dataset. This step is essential to avoid biases caused by repeated information.

3.2.2 Handling Missing Data

To address any missing data in the dataset, Tweets with missing text fields were excluded from the analysis to maintain the reliability of sentiment analysis. For missing metadata such as account names or the number of likes, reasonable default values were used to fill in these gaps.

3.2.3 Handling Multilingual Content

Since the dataset may include tweets in multiple languages, we used a language detection tool to filter out non-English tweets, retaining only English-language content for analysis, which ensured consistency in future analysis and prevented errors due to language differences. Multilingual content may introduce semantic differences and sentiment misclassification, especially when dealing with non-English tweets. The model's ability to analyze sentiment may be significantly reduced. In addition, since the study focused primarily on the policy responses of the US Federal Reserve, English tweets were able to more accurately reflect the views of the target group.

3.2.4 Removing Irrelevant Tweets

To further improve the quality of the dataset, we removed irrelevant tweets, including advertisements and spam, using a keyword-based filter to identify and exclude tweets with potential promotional content. We employed a spam words list containing terms "buy now," "call now," "discount," "limited time," "buy today," and "order status" (Desyllas, 2024). Given the economic context of this study, some commonly used financial keywords like "buy" and "cash" were intentionally excluded from the filter, as they could also appear in genuine discussions related to the Fed's interest rate cuts.

3.2.5 Text Preprocessing

Removing URLs and Mentions: We removed links, and user mentions from the tweets to reduce noise, as they generally do not contribute to sentiment-related information (Zhao & Gui, 2017). The methods used are regular expressions (re.sub()) to remove URLs (http\S+) and user mentions (@\w+).

Handling Emojis and Special Characters: According to Sahayak et al. (2015), we removed emojis and special characters from the tweets, as they can introduce noise into sentiment analysis and affect classification accuracy. The method used is regular expressions (re.sub()) to remove all characters that are not alphanumeric ([^A-Za-z0-9\s]).

Text Normalization: We converted all text to lowercase to minimize the impact of word variants. Additionally, we removed stop words, which typically do not carry substantial sentiment information (Zhao & Gui, 2017). We used the Natural Language Toolkit (NLTK) to remove common stop words, such as "the" and "is."

3.3 Sentiment Analysis Model

Sentiment analysis was conducted using FinBERT (Yang et al, 2020). FinBERT was selected due to its superior performance compared with other sentiment analysis models in capturing nuanced sentiments in financial contexts where this research set in.

Before conducting FinBERT analysis, an accuracy test was conducted for this sentiment model in our dataset. After randomly choosing 250 post records from the dataset, we manually classified each post record ~~it~~ into three sentiment categories and compared it with FinBERT sentiment classification results. The result showed that the FinBERT achieved a 95% accuracy with only 12 incorrect classifications.

3.4 LDA

To explore the primary themes discussed on Twitter during the Federal Reserve's rate cut, Latent Dirichlet Allocation (LDA) (Blei, Ng, and Jordan, 2003) was employed as the topic modeling technique. This method was selected for its interpretability and its ability to handle overlapping themes, which is particularly relevant for short Twitter texts. By assigning probabilities for each document to belong to different topics, LDA enables a nuanced exploration of thematic structures without requiring pre-labeled data (Zhao et al., 2011).

The input data consisted of preprocessed tweets that had been cleaned, tokenized, and transformed into a document-term matrix using CountVectorizer. High-frequency noise terms and extremely rare terms were excluded by setting frequency thresholds (min_df=2, max_df=0.95). While analyzing word frequency and performing the word cloud analysis shown in the Analysis section, the number of topics was set to four, capturing the most coherent and relevant themes in the dataset.

4. Analysis

4.1 Research Question 1: How does the sentiment expressed by Twitter users differ across main topics discussed during the Fed's rate cut?

4.1.1 Word Frequency

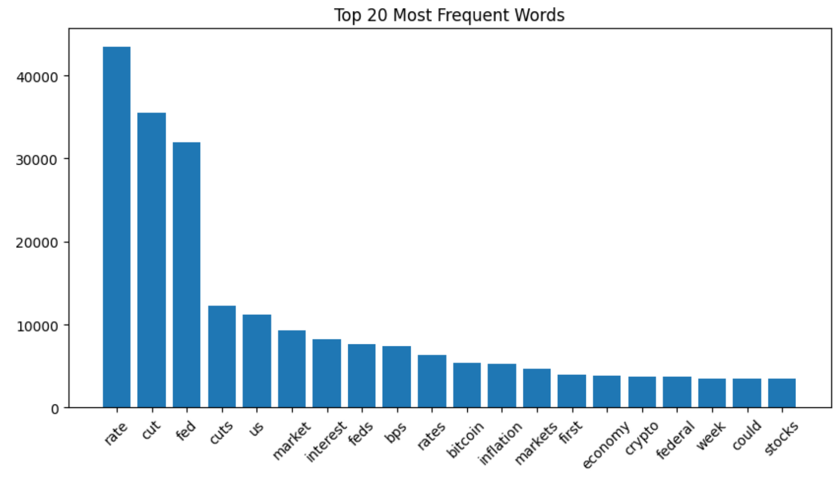

Figure 1: Term Frequency Analysis

Figure 2: Word Cloud

These top 20 words and word cloud analyses were conducted to gain a preliminary understanding of the key topics discussed in Twitter posts following the Federal Reserve’s interest rate cut. From the top 20 most frequent words analysis, the most used words were some of the most obvious and expected words. The tweets mainly contained the words: “rate,” “cut,” “fed,” “market,” and “inflation”. This is reasonable as these are common words associated with federal rate cuts. Therefore, we also excluded these direct references in the word cloud. The most prominent terms include: “market,” “Bitcoin,” “inflation,” “crypto,” “stocks,” and “bps”. Based on the analysis of these two charts, it can be inferred that the topics including crypto, investment market, general economic influence. Therefore, we set the number of topics in LDA to be four to best capture these three potential topics and add one hidden topic.

4.1.2 Topic Modeling

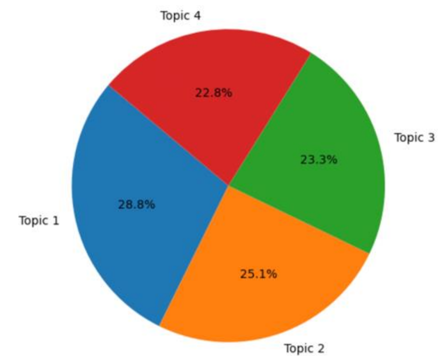

Figure 3: Distribution of Topic Frequency

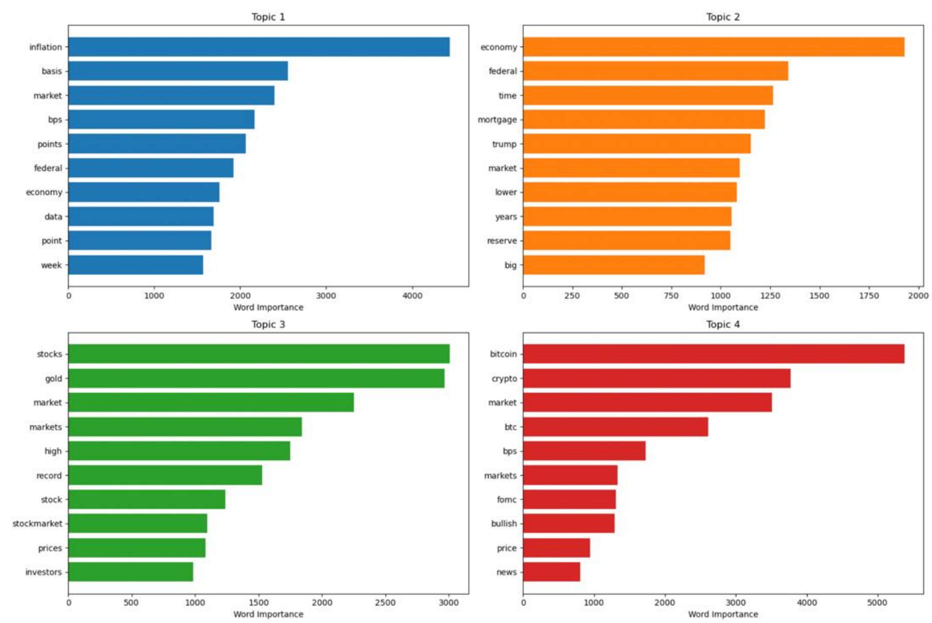

Figure 4: Term Frequency Analysis of Each Topic

When conducting LDA, we also eliminated Fed interest rate cut topic related words including "fed", "feds", "cut", "cuts" and "rate". Based on the results of the LDA analysis, we identified four distinct topics that capture prominent themes within the dataset. Each topic reflects a unique perspective on public discourse surrounding the Federal Reserve's rate cut decisions and their economic implications.

The topic 1 is **Macroeconomic**, accounting for 28.8% of the terms, centers on macroeconomic discussions related to inflation and market dynamics. Key terms like "inflation," "basis," "market," "bps," and "points" suggest a thematic emphasis on how Federal Reserve decisions impact broader economic conditions. This topic reflects discourse around the interconnectedness of monetary policy, inflationary pressures, and the stability of the economy.

Topic 2, titled **Policy**, comprising 25.1% of the terms, emphasizes the role of economic policies in shaping various sectors. Key terms such as "economy," "federal," "mortgage," and "Trump" reflect discussions on how policy decisions, particularly rate cuts, influence financial systems. This topic highlights public interest in the Federal Reserve and governments' further policy actions and their broader implications on mortgages, long-term economic strategies, and overall financial stability.

The topic 3 is **Investment**, representing 23.3% of the terms, focuses on traditional investments. Words such as "stocks," "gold," "markets," and "investors" reveal discussions around traditional investment strategies and the influence of Federal rate cut decision on asset valuations. This topic indicates heightened public interest in how Fed rate cut may shape public investments decisions and financial market reactions.

The topic 4 is **Cryptocurrency**, accounting for 22.8% of the terms, discussed about cryptocurrencies and digital markets. Salient terms like "bitcoin," "crypto," "markets," and "bullish" underscore the growing prominence of digital assets in discussions about this monetary policy. This topic highlights the increasing significance of cryptocurrencies as an alternative investment class.

4.1.3 Sentiment Analysis

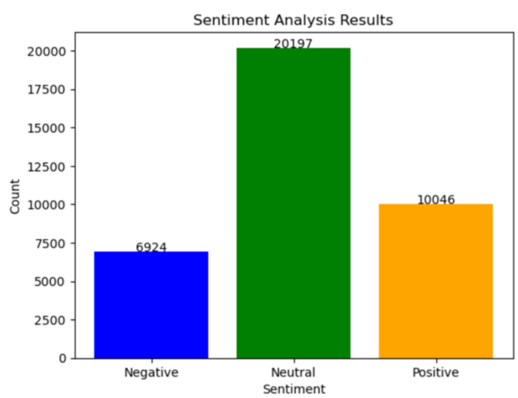

Figure 5: Overall Sentiment Analysis

The sentiment analysis of the whole dataset was conducted using FinBERT (Yang et al, 2020), dividing the sentiment of tweets into three categories: neutral, negative, and positive, which can help us understand the general sentiment distributions of this events before conducting in different topics. Most tweets, around 20,000, were classified as neutral, making up the largest portion of the dataset. Approximately 10,000 tweets expressed positive sentiment, while negative sentiment accounted for the smallest category with around 6,000 tweets.

4.1.4 Sentiment Analysis with Topic

Topic 1: Macroeconomic

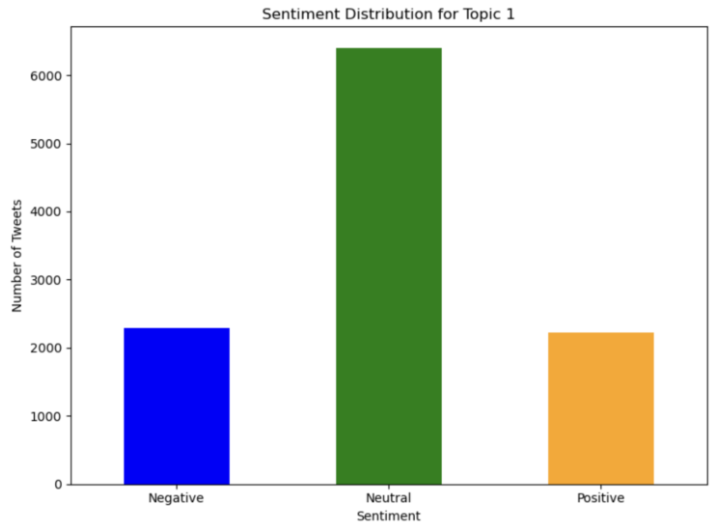

Figure 6: Sentiment Analysis of Topic 1

The sentiment distribution for Topic 1 shows that most tweets exhibit a neutral tone, suggesting that discussions related to this topic are predominantly objective or fact-based. This aligns with the nature of the topic, which focuses on macroeconomic conditions and market dynamics, as reflected by keywords such as "inflation," "basis," and "market." The relatively balanced proportions of positive and negative sentiments further indicate a mixed public perception, with optimism regarding certain policy measures counterbalanced by concerns over their potential economic implications.

Topic 2: Policy

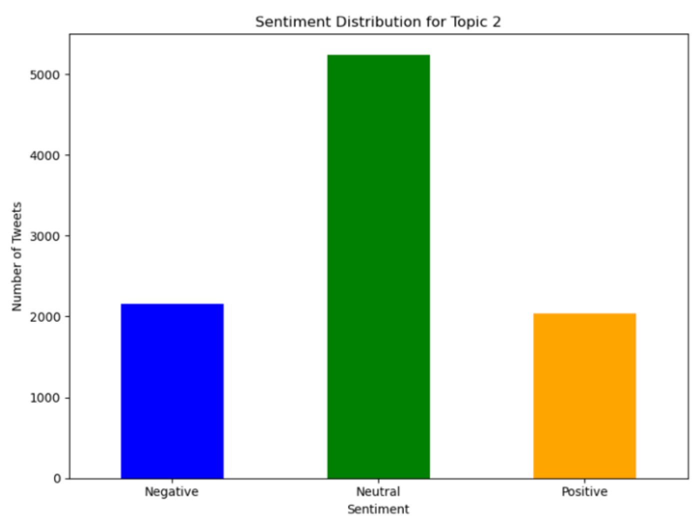

Figure 7: Sentiment Analysis of Topic 2

The sentiment distribution for Topic 2 has the same distribution as topic 1 which shows that most tweets express a neutral sentiment, suggesting that discussions primarily involve factual or descriptive content related to economic policies. This topic's neutral tone may reflect analytical or explanatory discourse on how policies, such as rate cuts or other monetary actions, affect various financial systems, including mortgage rates and long-term economic performance. Similarly, the balanced number of negative and positive sentiments show a general uncertain attitude about rate cut in policy related topics.

Topic 3: Investments

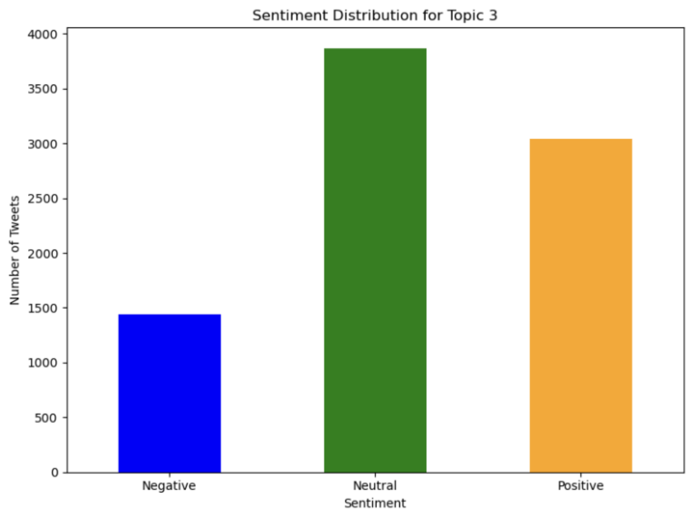

Figure 8: Sentiment analysis of topic 3

The sentiment distribution for Topic 3 shows that despite the predominance of neutral sentiments, positive sentiments are significantly higher than negative sentiments, suggesting that the public's perception of this topic is skewed towards optimism. Given the focus on traditional investments and market performance in Topic 3, the high percentage of positive sentiment reflect public enthusiasm for investments or asset performance in traditional market.

Topic 4: Cryptocurrencies

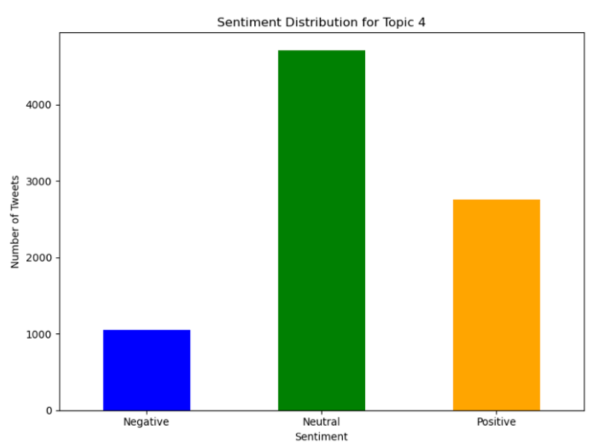

Figure 9: Sentiment analysis of topic 4

The sentiment distribution of Topic 4 is predominantly neutral, indicating that the discussion on this topic is mainly objective or descriptive. Positive sentiment is significantly higher than negative sentiment, indicating that the public is optimistic about buying cryptocurrencies. Given the focus of Topic 4 on cryptocurrencies and digital markets, high positive sentiment may reflect public enthusiasm and confidence in the growth potential of digital assets.

Research Question 2: How does sentiment evolve over time, and how do changes in specific topics correlate with fluctuations in related economic indices?

It is not enough to understand the sentiment distributions in different topics. It is more important to explore how economic status shifts with these sentiments. Therefore, this research chose investment and cryptocurrencies topic which are more specific to investigate whether they have impact on related economic indicator.

4. 2. 1. Sentiment Distribution Over Time

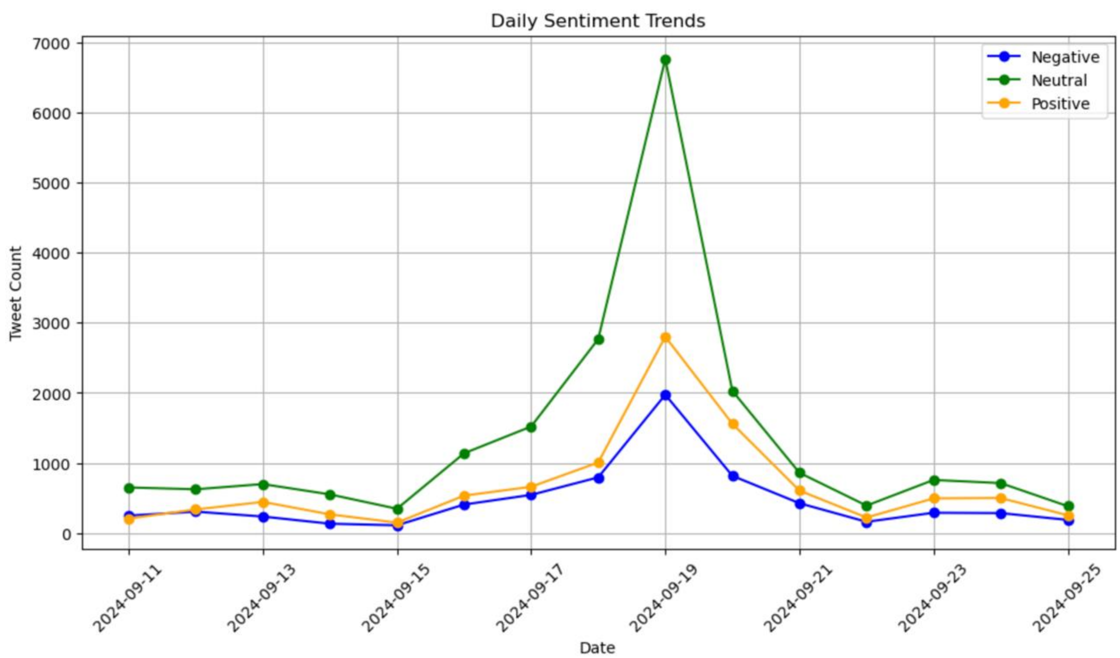

Figure 10: An analysis of sentiment over time

This chart shows how overall public sentiment on Twitter changed over time following the Federal Reserve's announcement of an interest rate cut. The sentiment distribution of tweets over time from September 11th to September 25th, 2024. The neutral sentiment category dominates, reaching its peak on September 19 with nearly 7000 tweets, while positive sentiment also rises significantly to around 2800 tweets, and negative sentiment shows a smaller but noticeable increase, peaking at around 2000 tweets. But before and after the announcement, the number of tweets from all three sentiments remained roughly the same.

4.2.2 Sentiment Dynamics and Nasdaq Index Correlation in Investment-Related Topics

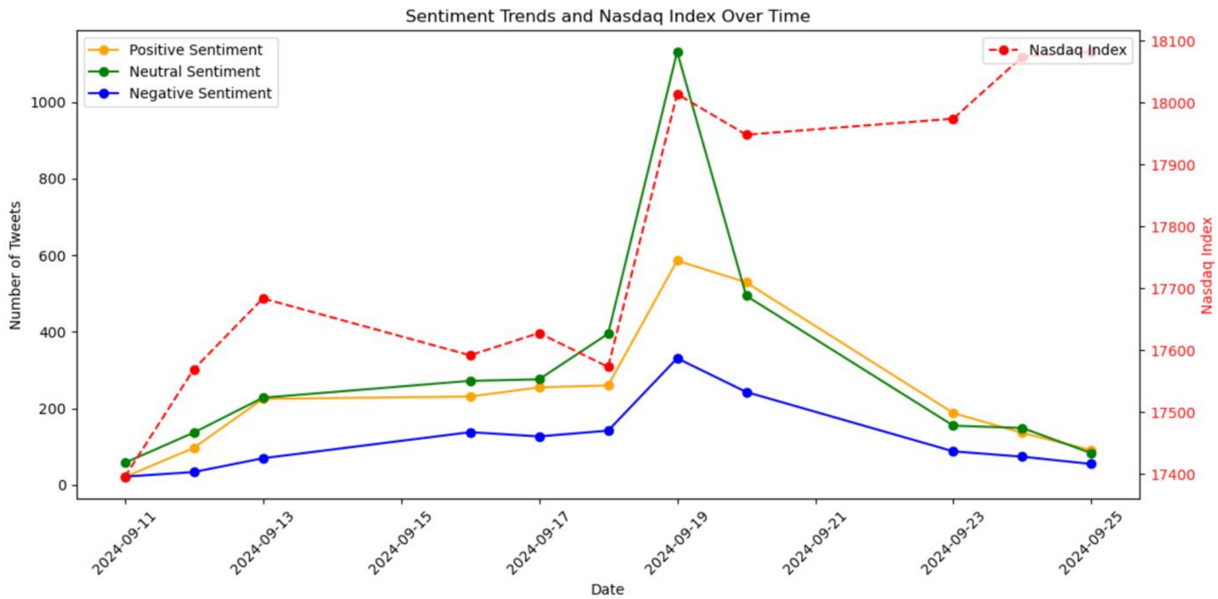

Figure 11: Sentiment analysis compared to Nasdaq Index (Yahoo Finance, 2024)

The Nasdaq Composite Index is a widely recognized benchmark that tracks the performance of more than 3,000 publicly traded companies listed on the Nasdaq Stock Exchange, with a focus on technology and growth industries. As a key indicator of market sentiment and investment health, a rise in the Nasdaq reflects investor confidence (Simon, 2003). The Nasdaq index is very relevant to investment-related discussions.

The analysis reveals a significant correlation between neutral and positive sentiment in traditional investment topic and fluctuations in the Nasdaq Index, while negative sentiment has minimal influence on public discourse. During periods of substantial Nasdaq growth, such as on September 19th, 2024, when the index peaked at $18,013.98, positive sentiment also reached its highest level. Similarly, during the period of sustained index growth from September 12th to September 18th, positive sentiment gradually increased, reflecting a strong alignment between rising investor confidence and market performance. However, after September 19th, the volume of positive sentiment discussions began to decline, mirroring the subsequent downward trend in the Nasdaq Index. As the index stabilized between September 23th and September 25th, the correlation between positive sentiment and the Nasdaq became less pronounced. In contrast, negative sentiment remained relatively stable throughout the observation period, showing minimal responsiveness to both upward and downward trends in the Nasdaq Index. On the other hand, neutral sentiment consistently dominated the timeline, with a significant spike during periods of sharp index movement, such as September 19th, 2024.

4.2.3 Sentiment Dynamics and Nasdaq Index Correlation in Investment-Related Topics

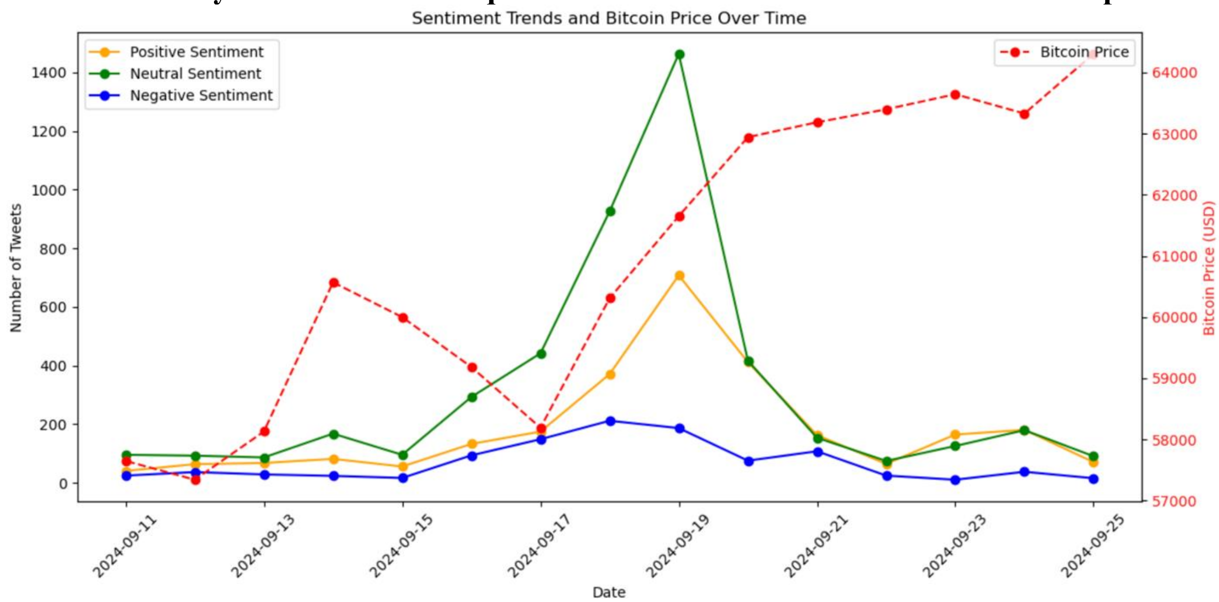

Figure 12: Sentiment analysis compared to Bitcoin Price (Yahoo Finance, 2024)

In this study, Topic 4 is defined as discussions centered around the cryptocurrency market. As the most prominent cryptocurrency globally, Bitcoin's price serves not only as a barometer for the entire cryptocurrency market but also as a significant driver of public sentiment (Kaya, 2018) Therefore, comparing the sentiment trends of Topic 4 with Bitcoin price fluctuations provides valuable insights into how public attitudes toward the cryptocurrency market evolve with Bitcoin's price movements.

The analysis reveals a significant correlation between Bitcoin price fluctuations and public sentiment trends for cryptocurrency market. The graph illustrates a consistent upward trend in Bitcoin prices over the observed period, peaking on September 25th, 2024. This price increase closely aligns with fluctuations in positive sentiment, particularly between September 17th and September 19th, when a rapid rise in Bitcoin prices coincides with a sharp increase in positive sentiment. However, as the Bitcoin price stabilized after September 19th, the volume of positive sentiment discussions declined, potentially reflecting a reduction in public uncertainty regarding future price movements. Neutral sentiment remained dominant throughout the timeline, peaking significantly on September 19th alongside the rapid Bitcoin price increase. In contrast, negative sentiment exhibited minimal fluctuations and remained at consistently low levels throughout the observation period. This suggests that even during periods of significant price changes, the discussion of risks or unfavorable perspectives on the market was relatively limited.

Research Question 3: How does the sentiment of highly liked posts compare to that of low-liked posts?

Understanding the relationship between a post's mood and their level of engagement, measured by the number of likes, provides valuable insight into how public sentiment shapes online discourse and influences audience reception. Posts with high likes often reflect key public narratives or resonate strongly with the audience, likely forming collective perceptions and driving further engagement. By analyzing the distribution of emotions in highly and poorly liked posts, we can determine which types of emotions are more likely to gain traction and influence public opinion.

4.3.1 High-liked and low-liked post

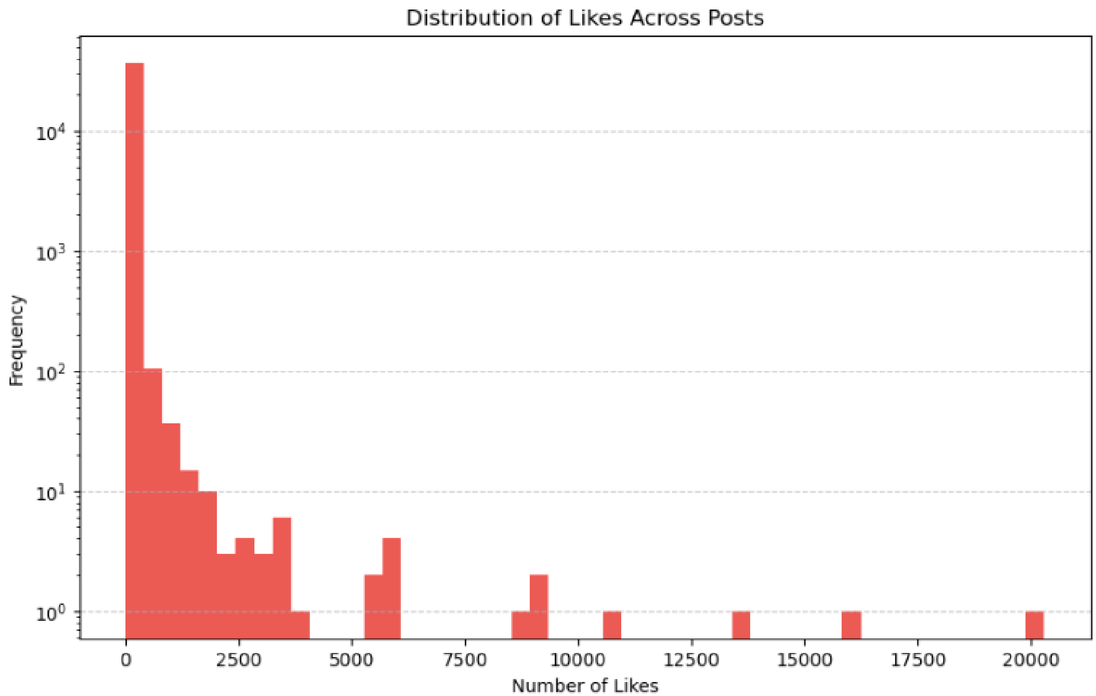

Figure 13: Distribution of frequency of tweet likes

Based on the distribution of likes across posts, as shown in the histogram, most tweets have a relatively low number of likes, with a significant concentration below 1000. This indicates that most posts receive limited engagement. The tail of the distribution, however, shows a small but distinct group of tweets with likes exceeding 1000.

To capture this distinction, the threshold for high-liked posts was set at 1000 likes. Posts with likes greater than 1000 are categorized as high-liked posts, as they belong to the long tail of the distribution and likely reflect more impactful or widely shared content. Conversely, posts with 1000 likes or fewer are classified as low-liked posts, representing most of the dataset and typical user engagement.

4.3.2 Sentiment of highly liked posts compare to that of low-liked posts

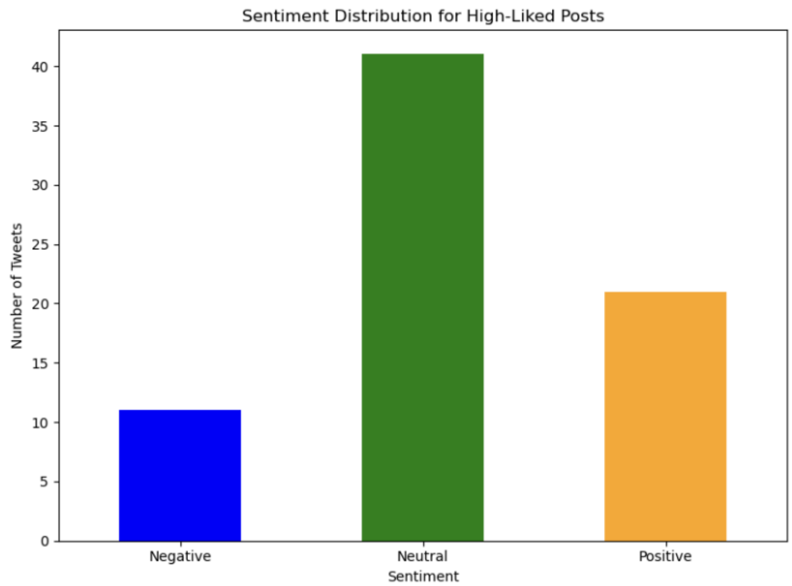

Figure 14: Sentiment distribution of high liked posts

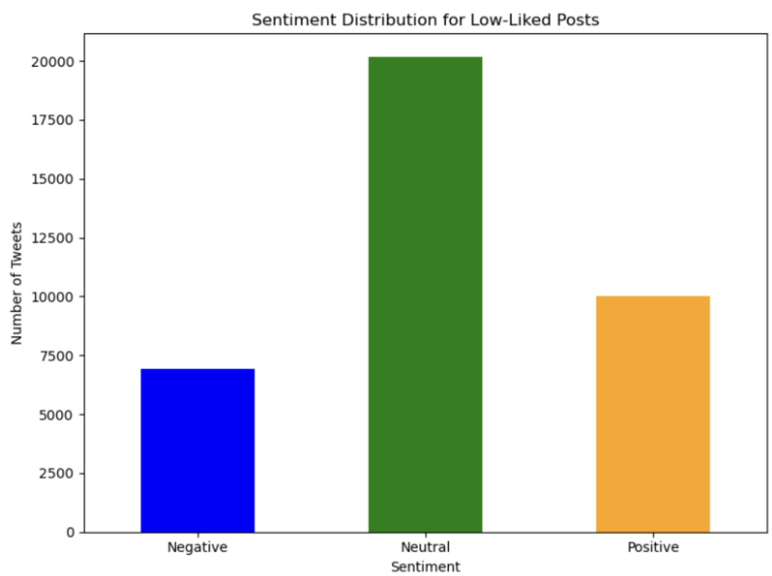

Figure 15: Sentiment distribution of low-liked posts

The sentiment distribution of highly liked posts reveals that neutral sentiment dominates, followed by positive sentiment, with negative sentiment being the least represented. In contrast, the sentiment distribution for low-liked posts mirrors the overall sentiment trends observed in the dataset, with neutral sentiment dominating, followed by positive sentiment, and finally negative sentiment. Overall, the sentiment distribution between high- and low-liked posts demonstrates difference in numbers.

5. Discussion and Contributions

5.1 Topics and Public Sentiment

The sentiment analysis across the four primary topics—Macroeconomic Conditions, Policy, Investment, and Cryptocurrency—reflects the varied public interpretations and reactions to the Federal Reserve's monetary policy decision.

The sentiment analysis on the whole dataset provided evidence that most of the posts has a neutral and subjective opinions. Twitter is often used as a platform for disseminating factual and news updates and analytical content rather than emotional expression, especially in financial contexts. The dominant of positive sentiment out of negative sentiment shows the overall optimistic attitude towards fed rate. These analysis can provide governments and financial organizations with preliminary insights of public perception to make further decisions.

5.1.1 Macroeconomic and Policy Topic

These two topics have overlapping patterns like mostly including broader discussion on the policy and similar sentiments distributions. Therefore, this research combined them in discussion. The predominance of neutral tweets (over 50%) reflects the descriptive nature of social media discourse during economic events. Many users shared factual information, such as Federal Reserve announcements or market updates, rather than expressing explicit emotions. This aligns with findings from Conrad et al. (2021), who observed that during major policy announcements, neutral sentiment often dominates due to the prevalence of information-sharing posts."

However, within these two topics, there exists a balance between positive and negative sentiments. Positive sentiments often highlight optimism about the benefits of rate cuts, such as stimulating economic activity, while negative sentiments express concerns over potential consequences, including inflationary pressures or financial market distortions. This mixed sentiment distribution highlights the public's nuanced perspective on macroeconomic policies, shaped by both immediate economic relief and apprehensions about systemic risks.

These findings provide critical insights into public sentiment as a multidimensional indicator of policy reception. They emphasize the necessity for transparency and enriched explanatory content in policy communication. For instance, central banks could enhance policy credibility and public trust by openly sharing the rationale behind their decisions, including detailed plans to manage inflation expectations and mitigate associated risks. Effective communication not only informs but also alleviates public concerns, fostering a more balanced understanding of policy objectives.

Moreover, the observed sentiment distribution can serve as a predictive tool for evaluating policy impact. By analyzing sentiment trends, policymakers can anticipate potential public reactions and adjust their strategies accordingly. For example, if negative sentiment intensifies, it may indicate the need for supplementary measures to reassure stakeholders and maintain economic stability. In this context, integrating real-time sentiment analysis into policy evaluation frameworks can provide a dynamic feedback mechanism, enabling more adaptive and responsive governance.

5.1.2 Investment Topic

In this topic, in addition to its neutral posts, the predominance of positive sentiment in discussions surrounding traditional investments, such as stocks and gold, underscores the public's perception of falling interest rates as a catalyst for enhancing the appeal of these assets. This reaction aligns with economic theory, where lower interest rates reduce the opportunity cost of holding investments, thereby increasing the present value of future cash flows and making assets like equities and gold more attractive (Keir & Keir, 1983). Moreover, this finding is consistent with modern financial theory (Kerins, et al, 2004) which suggests that low interest rates boost capital liquidity, encouraging greater risk-taking among investors. The data reveal that public optimism regarding traditional assets is closely tied to fed rate cut, particularly in the context of safe-haven investments, which tend to benefit from heightened market confidence during periods of economic expansionary policy.

These findings provide valuable insights for market forecasting and the design of policy feedback mechanisms. In similar context like fed cut, with higher positive posts proportion, central banks can better predict the immediate effects of policy announcements on capital markets.

Furthermore, the ability to track public sentiment offers significant utility for businesses and investment institutions. Analyzing sentiment data enables these entities to forecast investor behavior more accurately, providing critical insights for optimizing capital allocation strategies. In this context, an increase in positive sentiment toward equities following a rate cut could signal a window of opportunity for issuing new shares or reallocating portfolios toward growth-oriented assets. Similarly, understanding the public's emotional response to safe-haven assets like gold could help institutions develop tailored investment products that align with prevailing market sentiment.

5.1.3 Cryptocurrency Topic

The observed emotional trends in cryptocurrency discussions highlight the growing importance of these assets, particularly Bitcoin, in public economic narratives. Within this topic, in addition to neutral sentiment, the predominance of positive sentiment reflects a direct relationship between rate cut and the appeal of cryptocurrencies as alternative assets. According to Fraser-Sampson (2010), when traditional monetary policies create uncertainty or dissatisfaction—such as concerns over inflation or systemic financial risks—investors seek non-traditional assets that can serve as safe havens. The rise in positive sentiment can be attributed to Bitcoin’s unique characteristics as a decentralized and inflation-resistant asset which independently of central banks, appealing to individuals seeking alternatives to perceived shortcomings in conventional monetary policies. Additionally, as mentioned in the Investment topic section, falling interest rates reduce the opportunity cost of investment while increasing the present value of future cash flows encouraging more investors to take risks. Thus, the positive sentiment toward cryptocurrency reflects public uncertainty of current policy market expectations for rising asset prices driven by low-interest-rate policies.

These findings have significant implications for financial regulation and monetary policy. Public optimism toward cryptocurrency like Bitcoin is not only an attitude to its price performance but also an indicator of shifting trust dynamics. Policymakers must recognize that cryptocurrencies are increasingly being viewed as viable alternatives to traditional financial instruments, particularly during periods of monetary instability. This sentiment-driven shift could have impacts on investment behavior and financial market structures. Regulatory bodies need to establish frameworks that balance oversight with innovation, ensuring that the growth of cryptocurrencies does not compromise the stability of the broader financial system. Moreover, understanding the drivers of positive sentiment in cryptocurrency markets can help policymakers anticipate shifts in public trust and investor preferences, enabling more proactive and informed regulatory responses.

5.2 Public Sentiments and Economic Index

5.2.1 Nasdaq and Investment Sentiment

The synchronicity observed between investment sentiment and the Nasdaq Index during the observation period highlights a nuanced relationship between public sentiment and market performance. When the Nasdaq Index peaked at $18,013.98 on September 19th, positive sentiment also reached its highest level. According to Sturm (2023), robust market performance fuels investor confidence, leading to increased optimism in public sentiment. This, in turn, creates a feedback loop that can further boost the market upward. For instance, as the Nasdaq climbed steadily between September 12th and September 19th, positive sentiment also rose, reflecting widespread optimism about policy-driven economic growth and favorable market conditions. At the same time, with increase public confidence, the stock price will then increase.

However, this relationship is dynamic and evolves as market conditions stabilize. Between September 23th and September 25th, when the Nasdaq exhibited minimal fluctuations, positive sentiment showed a noticeable decline. This suggests that investors reassess their positions during periods of stability, shifting from optimistic outlooks to more cautious interpretations of market signals with a greater focus on potential risks.

These findings illuminate the direct linkage between investment sentiment and Nasdaq performance, providing valuable implications for both market forecasting and economic policy. Tracking changes in positive sentiment can serve as an early indicator of invest market increase or turning points. For example, the surge in positive sentiment preceding the Nasdaq's peak on September 19th could have been used to anticipate heightened market activity and prepare for potential adjustments. Financial institutions can leverage this relationship to design risk management strategies, such as reallocating assets or implementing hedging measures during sentiment-driven market expansions.

From a policy perspective, this connection shows the importance of understanding how policy announcements influence both investor sentiment and market behavior. When positive sentiment aligns with rapid market growth, regulatory bodies could implement stabilization mechanisms, such as tightening financial conditions or issuing cautionary statements, to prevent overheating and speculative bubbles

5.2.2 Bitcoin Price and Cryptocurrency Sentiment

In the analysis, there is a strong correlation between positive and neutral sentiment and rising bitcoin prices. The rise in Bitcoin prices during the observation period, particularly between

September 17th and September 19th, coincided with a significant rise in positive sentiment. This suggests that Bitcoin's role as an alternative investment asset attracts investor optimism when the price climbs, creating a feedback loop where rising prices reinforce public enthusiasm and further stimulate demand as mentioned above.

This relationship between sentiment and bitcoin price movements provides practical insights for market participants. For example, monitoring trends in positive sentiment can serve as an early indicator of potential price spikes in the cryptocurrency market. Investors can use this information to optimize their entry and exit strategies, especially during bullish trends. Conversely, a stabilization or decline in market confidence may signal an imminent slowdown in price momentum, helping to prevent losses in volatile markets.

From a policy perspective, the tight link between positive sentiment and bitcoin prices highlights the speculative nature of cryptocurrency investments. Policymakers should consider the implications of such emotion-driven market behavior when designing regulatory frameworks. For example, a sharp rise in positive sentiment coupled with a rapid rise in prices may indicate that a speculative bubble is forming and therefore intervention is necessary to ensure market stability. Understanding these emotional dynamics can also inform public communication strategies and help investors understand the risks associated with speculative trading in the cryptocurrency space.

5.3 Sentiments and Public Likes

The sentiment distribution of highly liked pattern suggests that posts with high engagement tend to provide objective and analytical information, focusing on the Federal Reserve's policy decisions and their potential economic impacts. Highly liked posts often include fact-based narratives, such as updates on Federal Reserve policy decisions or economic impacts, which are more likely to resonate with a broader audience. Additionally, the significant proportion of positive sentiment among highly liked posts highlights the optimism of influential accounts toward the benefits of the rate cuts, such as stimulating economic growth, improving market liquidity, and increasing investment opportunities. According to Berger & Milkman (2012), uplifting narratives or those projecting positive expectations tend to generate greater interaction and resonance with audiences.

In contrast, the sentiment distribution of low-liked indicates that the general public's reaction to the rate cuts leans towards neutrality and positivity. However, the sheer volume of low-liked posts suggests that, despite widespread discussions about the rate cuts, most posts failed to attract significant attention or engagement. This may indicate a lack of resonance with public sentiment or the inability of such posts to effectively communicate important policy-related information.

These findings highlight a dual perspective on public sentiment: high-liked posts provide a snapshot of influential narratives, often driven by expert or authoritative accounts, while low-liked posts offer a lens into the more dispersed, grassroots reactions of ordinary users. Policymakers and financial institutions should consider both levels of engagement in their analyses—leveraging high-liked posts to identify dominant narratives and low-liked posts to understand widespread, individual-level sentiment. Furthermore, the analysis emphasizes the representational value of low-liked posts, as their abundance reflects the collective mood of the public. By analyzing this broader dataset, researchers can uncover dominant patterns of public concern or optimism that may not be immediately apparent in high-engagement posts. This approach provides a more inclusive view of public sentiment.

6. Implications for Text Mining or NLP Applications

The dominance of neutral tweets in sentiment analysis emerged as a significant characteristic in our analysis. Additionally, accuracy analysis revealed instances where FinBERT misinterprets contextual nuances, highlighting limitations in its understanding.

6.1 Sarcasm Challenges

The analysis of tweets revealed that a significant portion of posts were classified as neutral by FinBERT. Upon closer examination, we identified that some tweets contained surface-level positive words while expressing sarcasm or dissatisfaction. For instance, a tweet like "Thank you, Fed, for ensuring my mortgage rates skyrocket. Great job!" might be labeled as positive by FinBERT due to phrases like "Thank you" and "Great job." However, the true intention is clearly negative. The challenge in detecting sentiment in such tweets lies in their use of sarcasm, where the linguistic structure deliberately contradicts the implied sentiment. FinBERT, like many traditional sentiment analysis models, heavily relies on explicit emotional keywords rather than contextual or semantic cues, making it difficult to handle complex rhetorical devices such as sarcasm, irony, or metaphor. These tweets uniquely mask their sentiment through wordplay and contextual ambiguity, exposing a core limitation of keyword-based analysis in understanding nuanced emotional intent. Models like FinBERT struggle particularly when the apparent meaning diverges sharply from the true emotional context, as sarcasm often depends on extralinguistic and cultural understanding to decode (González-Ibánez et al., 2011; Joshi et al., 2017).

6.2 Multimodal Contents

Another challenge lies in the misclassification of tweets as neutral, which stems from the informal and multimodal nature of Twitter as a platform (Kumar & Grag, 2019). Many tweets use non-textual elements such as emojis, GIFs, or images to amplify emotional expression, creating complexities for text-based sentiment analysis models like FinBERT. For example, a tweet with a very positive photo conveys strong optimism, while the textual content alone lacks sufficient emotional keywords for classification. FinBERT's reliance on purely textual analysis limits its ability to capture the sentiment embedded in these multimodal expressions (Rahate et al., 2022). As a result, tweets with dominant visual elements are often incorrectly categorized as neutral, underscoring the challenge of adapting text-focused models to the multimodal characteristics of social media interactions.

6.3 Descriptive tweets

Descriptive tweets, such as policy interpretations or market news, make up a significant portion of those classified as neutral by FinBERT. For example, a tweet like *"Fed cuts rate by 2.5%. Nasdaq rises by 2%."* may appear purely factual but implicitly conveys optimism through the word *"rises"*. FinBERT often struggles to detect such nuanced emotional signals because it relies heavily on explicit emotional words, thereby neglecting the semantic and contextual cues embedded in descriptive content. This limitation is particularly critical, as descriptive tweets frequently carry subtle emotional undertones that can shape public perception and influence market dynamics (Birjali et al, 2021). Their objectivity and information make them central to the spread of public opinion on social media. While FinBERT demonstrated a high degree of accuracy in analyzing the sentiment of such tweets, it was difficult to determine the sentiment and underlying message they brought to the public (Word Count: 5990).

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