Analyzing the Influence of Presidential Candidates' Tweets on Stock Market Volatility: A Dynamic Topic Modeling Approach

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Abstract: This study investigates the impact of presidential candidate Donald Trump's tweets on stock market volatility during the 2020 election period. Utilizing Dynamic Topic Modeling and high-frequency(minute-by-minute) trading data, we analyzed the correlation between tweet frequency and market movements. Our findings indicate that while Trump's tweets initially caused significant market reactions, repeated tweets on similar topics led to diminishing responses from investors, highlighting a desensitization effect. This research underscores the importance of incorporating both immediate and long-term impacts of political communications in financial analysis and suggests directions for future studies to enhance understanding of social media's influence on market behavior.

Keywords: Stock Market Volatility, Presidential Tweets, Donald Trump, Financial Market Analysis, Social Media Influence

1. Introduction

1.1 Background

Predicting the stock market is crucial because it directly impacts the economic stability and financial planning of individuals, companies, and governments. Accurate predictions can lead to better investment decisions, enhanced risk management, and overall economic growth. The ability to forecast stock market trends allows investors to allocate resources more efficiently, avoid potential losses, and capitalize on profitable opportunities. This topic is particularly important as it combines the challenges of financial analysis with the potential to significantly improve economic outcomes for various stakeholders.

Twitter is an invaluable tool for predicting the stock market due to its real-time dissemination of information and widespread usage among influential individuals and organizations[1]. Unlike other social media platforms or traditional news outlets, Twitter allows for the rapid spread of market-relevant news, opinions, and sentiment. Tweets from corporate accounts, financial analysts, and influential figures can quickly influence public perception and market movements. The concise nature of tweets also facilitates the analysis of sentiment and trends through natural language processing and machine learning techniques.

Presidential candidates' tweets, particularly those from high-profile figures like Donald Trump, are significant in predicting the stock market due to their potential to introduce impactful news and sentiments into the market[2]. According to the Efficient Market Hypothesis[3] (EMH), stock prices only move when new, meaningful information is introduced; otherwise, they follow a random walk pattern. Trump's tweets, often conveying policy announcements, economic decisions, or geopolitical stances, provide new information that can influence investor behavior and market volatility.

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[1] Gjerstad, P., Meyn, P. F., Molnár, P., & Næss, T. D. (2021). Do President Trump's tweets affect financial markets?. Decision Support Systems, 147, 113577.
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Therefore, we aim to examine the relationship between presidential candidate's, Donald Trump in our research, tweets and stock market volatility to better understand how such communications affect financial markets and to potentially improve predictive models of market behavior.

1.2 Related Work

Previous studies have extensively analyzed the correlation between President Trump's tweets and stock market movements. These works have primarily focused on understanding how different aspects of his tweets influence market behavior. For instance, Ge et al.[4], Born et al.[5], and Juma'h et al.[6] investigated the impact of firm-specific tweets from Trump, finding significant effects on the stock returns of the targeted companies. Similarly, Ajjoub et al.[7] and Brans el al.[8] explored the broader market reactions, noting considerable impacts on stock prices when Trump mentioned certain companies or economic policies in his tweets.

Furthermore, researchers have examined the influence of Trump's tweets on overall financial markets. Studies by researchers like Ge[9], Born[10], and Juma'h[11] revealed that Trump's tweets led to notable fluctuations in the US stock market, particularly when they involved key economic terms such as "tariffs" and "trade wars." Other investigations extended this analysis to international markets, demonstrating that Trump's tweets also affected the Chinese and European stock markets. Bianchi et al.[12] specifically highlighted the impact of Trump's tweets related to the Federal Reserve, showing changes in market expectations regarding monetary policy.

1.3 Limitation of Previous Literature

Most of the studies mentioned rely on daily price data to analyze the impact of Trump's tweets on the stock market. This approach poses significant challenges in establishing a causal relationship due to the problem of omitted variables. For example, if new US unemployment rate data is released and it is much lower than expected, the stock market may rise. Subsequently, Trump might tweet about the lower unemployment rate, claiming credit for it. In this scenario, a strong correlation might be observed between Trump's tweet and the market's performance on that day. However, this correlation does not imply causation, as both the financial markets and Trump's tweet are responding to the same underlying news. Thus, the true causal impact of Trump's tweets on the market remains unclear. To address these limitations, similar to the approach by Gjerstad et al.[13], we utilize high-frequency

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(minute-by-minute) financial data to more precisely time the market reactions to Trump's tweets. This method allows us to isolate the direct impact of his statements from other concurrent news events, providing a clearer picture of the true causal effects of Trump's tweets on financial market behavior.

Additionally, while classifying tweets based on specific target words provides useful insights, this method has its limitations. Gjerstad et al.[14] used specific keywords and Latent Dirichlet Allocation (LDA) topic modeling to identify topics within Trump's tweets that influence stock market volatility. However, this static analysis has limitations in capturing the trends in volatility related to changes in the political timeline. A more comprehensive analysis would take into account the broader political context at the time of posting. Such an approach could capture the dynamic interplay between political events and market volatility, offering a deeper understanding of the relationship between politicians' tweets and stock market instability. Focusing solely on specific words may lead to an oversight of how the political timeline influences market behavior. Therefore, integrating temporal political factors into the analysis could yield a more holistic perspective on the impact of politicians' social media activity on financial markets.

1.4 Research Hypothesis

Drawing on the findings from the referenced studies, our hypothesis posits that although new information initially impacts the market, repeated announcements of the same content lead to diminishing reactions from the market and investors. Zhou et al.[15] found that while initial disclosure of environmental violators revealed by China's Pollution Blacklist Program had a negative impact on stock prices, this effect diminished over time. Similarly, research[16] on stock market reactions to multiple announcements of accounting restatements showed that investors who viewed restatements positively reacted more slowly as restatements became more frequent.

Based on these insights, our research hypothesizes that as President Trump repeatedly tweets about the same topics, the market's reaction will diminish. In other words, the more frequently Trump uploads tweets on similar subjects, the less impact these tweets will have on market volatility. This suggests that the market and investors become desensitized to information that is no longer perceived as new or surprising, leading to reduced market fluctuations.

2. Data

2.1 Donald Trump Tweet Archive

The tweet archive dataset of Donald Trump[17], includes precise time information for tweets posted between February 2020 and November 2020, covering the presidential election period. We selected tweets that were posted during NASDAQ trading hours (weekdays 9:30 AM to 4 PM Eastern Time), resulting in a total of 9,868 tweets during this period. Our study examines the stock market's response to tweets within the trading hours, excluding off-hours to ensure data reliability, aligning with Hu et al. (2011)[18].

Selecting data within the NASDAQ trading hours ensures that the tweets are analyzed in the context of active market conditions when traders and investors are most likely

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[17] Twitter Stance Election 2020 [website] : https://paperswithcode.com/dataset/twitter-stance-election-2020 (accessed April 05, 2024)
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to respond to new information. During trading hours, market participants have the opportunity to react immediately to any new information, such as a tweet from a high-profile figure like Donald Trump. This real-time reaction is crucial for capturing the true impact of the tweets on market behavior. Off-hours data might not accurately reflect the immediate market response due to lower trading volumes and potential delays in reaction time. Thus, focusing on tweets posted during active trading hours enhances the reliability and relevance of our analysis in understanding the direct effect of political communications on financial markets.

2.2 Financial Market Data

We utilized high-frequency (1 minute basis) price and volume data from market indices such as the S&P 500 and 11 sector ETFs, including XLE (Energy), XLF (Financial), XLK (Technology), XLI (Industrial), XLY (Consumer Discretionary), XLP (Consumer Staples), XLC (Communication Services), XLU (Utilities), XLV (Health Care), XLRE (Real Estate), and XLM (Materials). This data was obtained from the Alpha Vantage Stock API[19] and covers the same period from February 2020 to November 2020, during NASDAQ trading hours (weekdays 9:30 AM to 4 PM Eastern Time). The dataset includes 81,806 records for the S&P 500 and 897,602 records for the sector ETFs.

Table1. Data Description

Data	**Source**	**Records**	**Features**
Donald Trump Tweet Archive	Twitter Stance Election 2020	9,868	- **`text`:** The content of the tweet. - **`isRetweet`:** A flag indicating if the tweet is a retweet. - **`isDeleted`:** A flag indicating if the tweet has been deleted. - **`device`:** The device used to post the tweet. - **`favorites`:** The number of likes the tweet received. - **`retweets`:** The number of retweets the tweet received. - **`date`:** The timestamp when the tweet was posted. - **`isFlagged`:** A flag indicating if the tweet was flagged.
S&P 500	Alpha Vantage Stock API	81,806	- **`timestamp`:** The date and time of the data point. - **`open`:** The opening price. - **`high`:** The highest price during the time interval. - **`low`:** The lowest price during the time interval. - **`close`:** The closing price. volume: The trading volume.
ETFs (11 sectors)	Alpha Vantage Stock API	897,602	- **`timestamp`:** The date and time of the data point. - **`open`:** The opening price. - **`high`:** The highest price during the time interval. - **`low`:** The lowest price during the time interval. - **`close`:** The closing price. volume: The trading volume.

[19] Alpha Vantage Stock API [website]: https://www.alphavantage.co/ (accessed April 05, 2024)

3. Method

3.1 Tweet Topic Modeling

We first conducted topic modeling using BERTopic (Topic model with class-based IF-IDF) to find meaningful topics in Trump's tweets. We directly selected meaningful topics using words related to the extracted topics, listed up the words for the topics, and counted tweets containing related words. Through two stages of preprocessing, we were able to find 20 topics at a meaningful level.

3.2 Macro - Dynamic Topic Modeling

Our study enhances previous research by integrating Dynamic Topic Modeling (DTM) to analyze the evolution of topics in tweets from Donald Trump, especially during the last U.S. presidential elections period. DTM surpasses traditional static models like LDA by considering the temporal dimension, offering insights into how topics change in response to political events, public sentiment, and global issues. Among the topics obtained from the topic model, we analyzed the frequency of tweets by period (14 days) by adding up the statistical frequencies for the 20 topics with the highest frequency. In addition, we compared the market volume and index fund price of the S&P 500 during the analyzed frequency period, and additionally calculated their gradient values to compare the “tweet frequency-market volume” and “tweet frequency-market price” correlation coefficients.

3.3 Micro - Market Sector ETF Analysis based on Topic

Following the application of DTM to understand the temporal shifts in topics discussed by Donald Trump, our research further investigated the specific impact of these evolving topics on the financial markets. We examined the volatility of Market Sector ETFs associated with each identified topic. This entailed a detailed analysis of how different sectors react to the topics prominent in the tweets, correlating political discourse with market movements.

Before analyzing the data, it was necessary to define the frequency of mentions of certain topics. In this study, to set intervals identical to those used in macro-level analysis, the frequency of a given topic at a specific time was defined as the number of tweets on the same topic that existed in the 14 days prior to the time of the tweet. Based on this definition, the average trading volume for tweets on the same topic was plotted on a graph according to their frequency, examining various cases from 10 minutes to maximum 3 hours after the tweet to see how long the influence of each tweet lasted. Then, linear regression analysis was performed to analyze the correlation using the Pearson correlation coefficient and p-value.

4. Results

4.1 Tweet Topic Modeling Results

Using BERTopic, we conducted topic modeling on tweets posted during trading hours throughout the previous election period. As shown in Figure 1, we extracted the top 20 topics. For each topic, we compared the content with the original tweets to verify the specific themes they represent.

We excluded topics such as Topic 0 and Topic 1, which were primarily related to self-promotion and party endorsements during the election, and were deemed less relevant to the stock market. Consequently, we focused on the following topics for more detailed macro and micro analysis:

- Topic 4: China
- Topic 5: Airport
- Topic 6: Covid
- Topic 7: Economy Market
- Topic 8: Great America

- Topic 11: Israel
- Topic 12: Fake News
- Topic 13: Healthcare
- Topic 14: Wall Border
- Topic 15: Book Bestseller
- Topic 17: MAGA
- Topic 18: Education
- Topic 19: North Korea

These selected topics were analyzed further to understand their impact on the stock market, allowing us to delve into both broad patterns and specific instances of market reaction to political communication during the election period.

Figure 1.Topic Modeling Results of Donald Trump Tweets

4.2 Macro Results

The graph above shows tweet frequency, S&P 500 average price and volume over a specific period of time. As you can see from the graph, there is no discernible trend. However, we found that S&P 500 volume was relatively low when tweet frequency peaked after April 2020. Conversely, we see that the volume of the S&P 500 is relatively high at the local minimum of tweet frequency. However, this trend does not appear to apply to the S&P 500 average price.

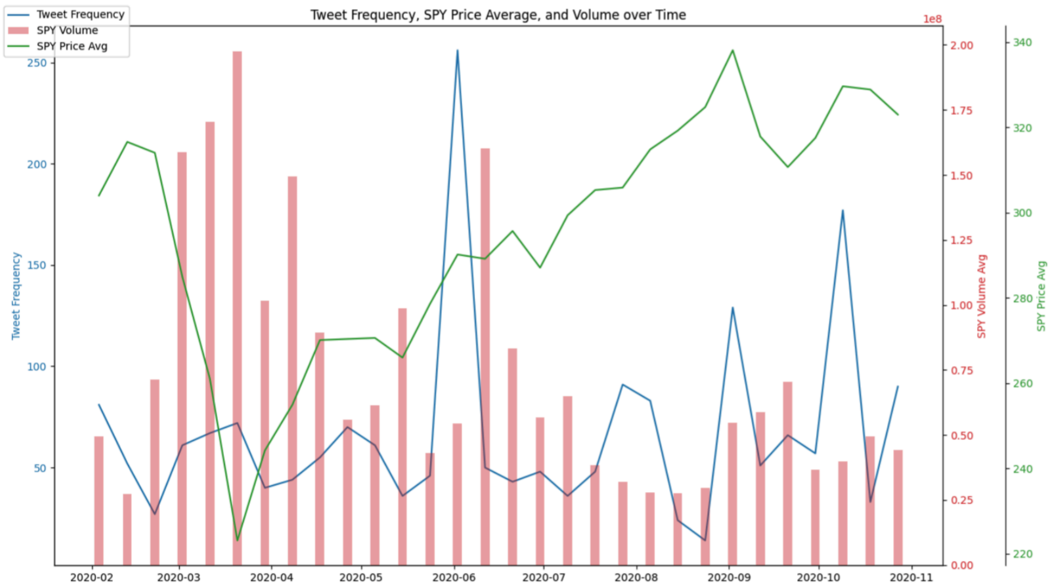


Figure 2. Tweet Frequency, S&P 500 Price and Volume Graph

Figure 3 is a graph that plots the gradient values. Observing the graph, it can be seen that the gradient of tweet frequency shows a similar pattern to the gradient of stock volume at intervals. However, the trends between tweet frequency and the S&P 500 price are not very similar. In fact, when we checked the correlation coefficient of the gradients, it was confirmed that the correlation between tweet frequency and the S&P 500 volume (-0.113) was higher than the correlation between tweet frequency and the S&P 500 price (0.062). This phenomenon motivated us to examine the correlation between tweet frequency by topic and S&P 500 volume on a smaller scale.

Figure 3. Gradient of Tweet Frequency, S&P 500 Price and Volume

4.3 Micro Results

4.3.1 Regression on S&P 500

Figure 4 represents scatter plots of the average SPY ETF (iShares S&P 500) trading volume 10 minutes, 20 minutes, 30 minutes, and 60 minutes after tweets, based on the tweet frequency of four topics (China, Airport, and Economy Market, Great America) obtained through topic modeling, where the number of tweets was sufficient. Figure 5 also shows the correlation coefficients and p-values between this data.

A strong negative correlation was observed for the topics of China, Airport, and Economy Market, while a relatively weak correlation was observed for the topic of Great America. This indicates that tweets with fewer recent mentions tended to cause greater market volatility, suggesting that the market no longer perceives frequently repeated topics as new information. The weaker correlation observed for the Great America topic is thought to be because this topic has less significant economic implications.

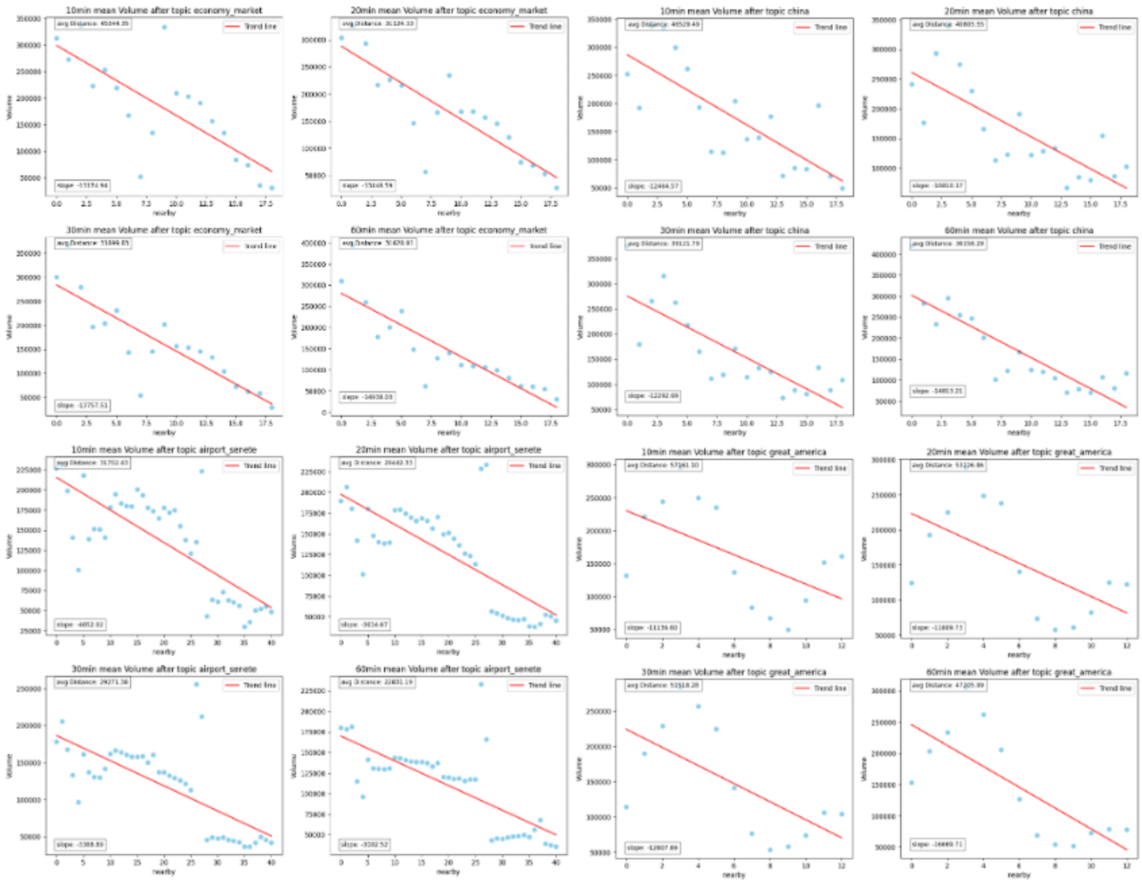
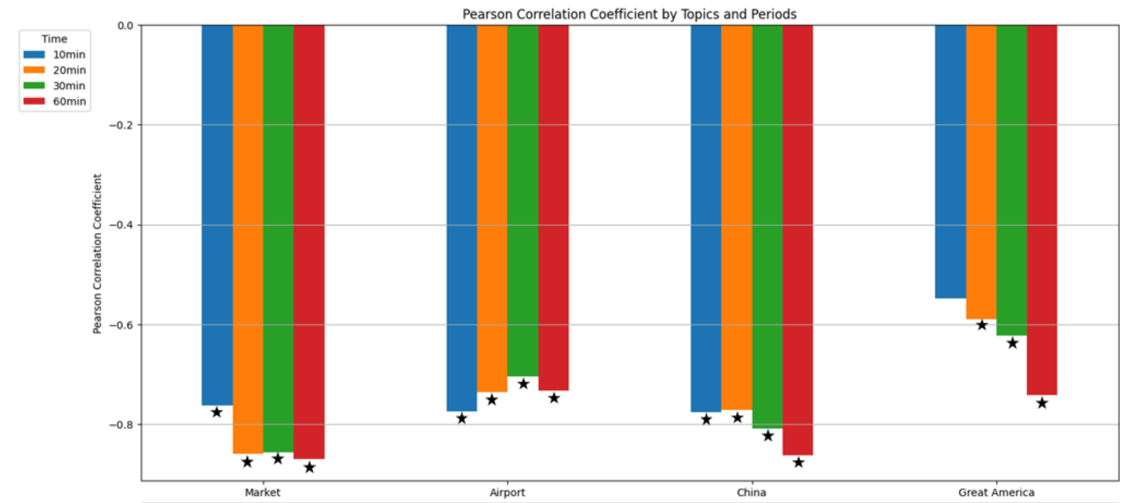


Figure 4. Frequency-Avg_volume (4 topic, 10min - 1h)



	10min	20min	30min	60min
Market	-0.763	-0.86	-0.857	-0.87
Airport	-0.775	-0.735	-0.704	-0.733
China	-0.776	-0.772	-0.809	-0.862
Great America	-0.548	-0.589	-0.623	-0.742

Figure 5. Correlation Coefficient, p-Value for Figure 4

4.3.2 Regression on ETF

Unlike the SPY ETF, which reflects the top 500 stocks listed on the NASDAQ, analyzing how the trading volumes of sector-specific ETFs move in response to tweets was a more challenging task. The first challenge was that identifying the sectors directly related to each topic relied on qualitative methods. Secondly, the relatively lower trading volumes of these ETFs increased the likelihood of frequent errors. Therefore, this study will only address two cases: those with high correlation and those with low correlation between topics and sector.

Figure 5 and Figure 6 analyze the XLF (iShares Finance ETF) with the economy topic and the XLC (iShares Communication ETF) with the airport topic using the same method as the SPY ETF, examining the data from 10 minutes to 3 hours after the tweet. In the former case, a significant negative correlation can be observed up to 3 hours after the tweet. This can be interpreted as the financial sector, which is sensitive to Federal Reserve statements and economic conditions, naturally reacting strongly to tweets about the economy by then-President Trump. In the latter case, concerning the airport topic related to defense and aviation legislation, there was no correlation with the communication sector, showing a consistent lack of correlation from immediately after the tweet up to 3 hours later.

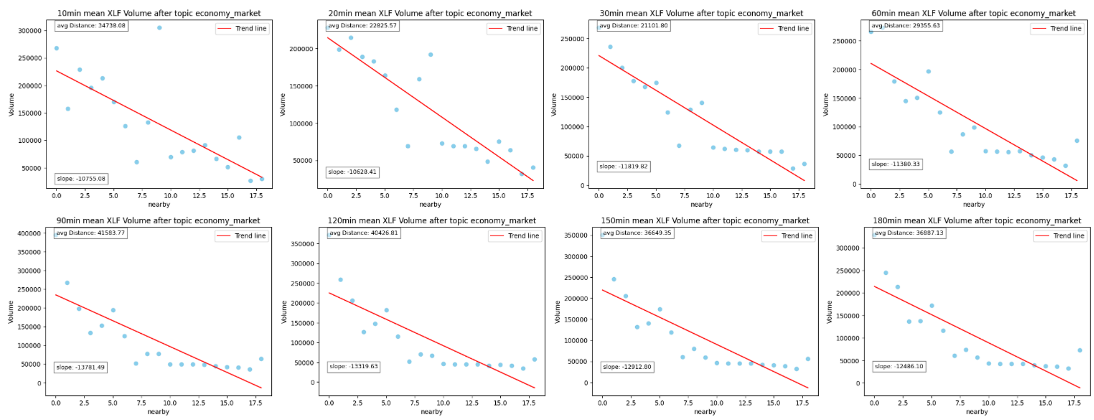


Figure 5. Frequency-Avg_XLF_volume (economy, 10min - 3h)

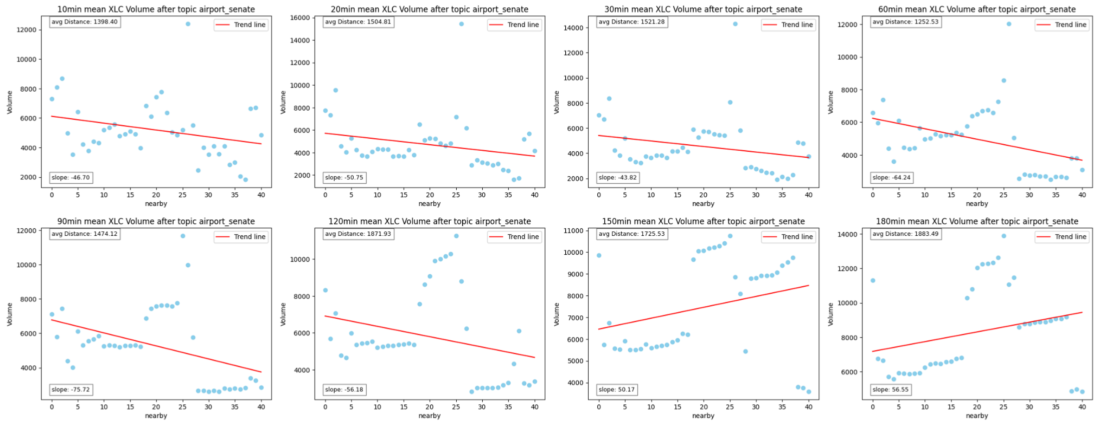


Figure 6. Frequency-Avg_XLC_volume (Airport, 10min - 3h)

5. Discussion

5.1 Interpretation of Results

Our study provides insights into the impact of Donald Trump's tweets on stock market volatility, revealing both immediate and gradual effects. Initially, Trump's tweets were observed to significantly influence market movements, consistent with the Efficient Market Hypothesis (EMH), which states that stock prices respond to new and meaningful information. However, our analysis showed that as the frequency of similar tweets increased, the market's reaction diminished. This aligns with our hypothesis that repeated information becomes less impactful over time as investors become desensitized to it.

5.2 Limitations

5.2.1 Exclusion of Other Social Media Platforms or News Outlets

While Twitter is a powerful tool for real-time information dissemination, it is not the sole medium influencing market behavior. Traditional news outlets and other social media platforms also play significant roles in shaping market sentiment. The omission of these sources might have introduced bias into our findings, as we focused solely on Twitter, potentially overlooking other influential factors.

5.2.2 Off-Hour and Opening Hour Market Dynamics

Our analysis was confined to NASDAQ trading hours (9:30 AM to 4:00 PM Eastern Time). This limitation excludes the impact of tweets posted during off-hours and their potential effect on market opening volatility. Tweets posted during off-hours can accumulate and cause significant market movements when trading resumes, a factor not captured in our study.

5.2.3 Challenges in Analyzing Detailed Content of Tweets

The use of topic modeling, while effective for categorizing tweets, may not fully capture the nuanced content of each tweet. Topic models generalize content based on word patterns, which might miss the specific context or sentiment of individual tweets. This limitation could lead to an oversimplification of the tweets' impact on the market.

5.3 Future Research Directions

5.3.1 Inclusion of Other Social Media and News Outlets

Future studies could address the limitations identified in our research by incorporating data from other social media platforms and news outlets. This broader scope would provide a more comprehensive understanding of how different sources of information collectively influence market behavior. Additionally, analyzing off-hour tweets and their effects on market openings could yield valuable insights into the timing and magnitude of market reactions.

5.3.2 Analysis of Joe Biden's Tweets

Our research did not analyze Joe Biden's tweets due to the limited number of tweets posted during trading hours (approximately 261 tweets) in the same period. Future research should consider including Biden's tweets when more data becomes available to provide a comparative analysis of different political figures.

5.3.3 Correlation with Stock Returns

In this study, we focused on the correlation between tweet frequency and market volatility (trading volume). However, stock returns are also a crucial indicator of market performance. Future research should examine the relationship between tweet frequency and stock returns to provide a more comprehensive analysis of the tweets' impact on financial markets. Integrating stock returns into the analysis could offer deeper insights into how political communications affect different aspects of market behavior.

5.4 Practical Implications

Understanding the diminishing impact of repeated tweets has practical implications for investors and market analysts. Recognizing that markets become desensitized to repeated information can help in developing more sophisticated trading strategies that account for the changing influence of political communications over time. This knowledge can also inform policymakers and public figures about the potential long-term effects of their communication strategies on financial markets.

6. Conclusion

This study aimed to explore the impact of presidential candidates' tweets, specifically those of Donald Trump, on stock market volatility. Utilizing dynamic topic modeling and high-frequency trading data, we provided a detailed analysis of how Trump's tweets influenced market behavior during the 2020 election period.

Our findings revealed that Trump's tweets initially had a significant impact on market movements, consistent with the Efficient Market Hypothesis. However, as the frequency of similar tweets increased, the market's reaction diminished. This supports our hypothesis that repeated information leads to desensitization among investors, resulting in reduced market volatility.

The study identified several limitations, including the exclusion of other social media platforms and news outlets, the confinement of analysis to NASDAQ trading hours, and challenges in capturing the nuanced content of tweets through topic modeling. These limitations suggest that future research should adopt a broader scope, including additional information sources and considering off-hour market dynamics.

Moreover, our analysis did not include Joe Biden's tweets due to insufficient data during the trading hours. Future studies should aim to incorporate Biden's tweets to provide a comparative analysis of different political figures. Additionally, while we focused on the correlation between tweet frequency and market volatility, it is equally important to examine the relationship between tweet frequency and stock returns, as returns are a crucial indicator of market performance.

Understanding the diminishing impact of repeated tweets has practical implications for investors and market analysts. It highlights the need for sophisticated trading strategies that account for the changing influence of political communications over time. Furthermore, this knowledge can inform policymakers and public figures about the potential long-term effects of their communication strategies on financial markets.

In conclusion, our research provides valuable insights into the interplay between political communications and market behavior, underscoring the importance of considering both immediate and long-term effects in financial analysis. Future research expanding on these findings can contribute to a more comprehensive understanding of how social media activity by influential figures shapes market dynamics.

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