Trump's Tweets on Market Volatility

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Abstract

In this short paper, we aim to asses to what extent financial markets may react to Donald Trump's social media posts, and specifically the effect on average realised volatility. We do so using both ARMA-X and VAR models, with data spanning the 1st of January 2014, to the 7th of May 2025, over various time horizons and independent variables. We find limited evidence that there is a significant positive effect, and provide some explanations as to why this could be the case.

Contents

1 Introduction

1.1 Motivation

Over the past 15 years social media has become an important communication tool for politicians. One of the pioneers of this novel approach has been Donald Trump, the 45th and 47th President of the United States. Since his ban on Twitter after the January 6th riots, his quantity of social media posts has drastically increased[1].

The content of his posts can sometimes have announcements or teases of future political decisions. Note the recent infamous "THIS IS A GREAT TIME TO BUY!!! DJT" post sent just an hour before lifting his reciprocal tariffs. It is then not improbable that agents in financial markets might take this information into account in their decision making. This question has been asked before in the literature, focusing rather on his first term.

This brings us to our research question: Do Donald Trumps Posts impact market Volatility?

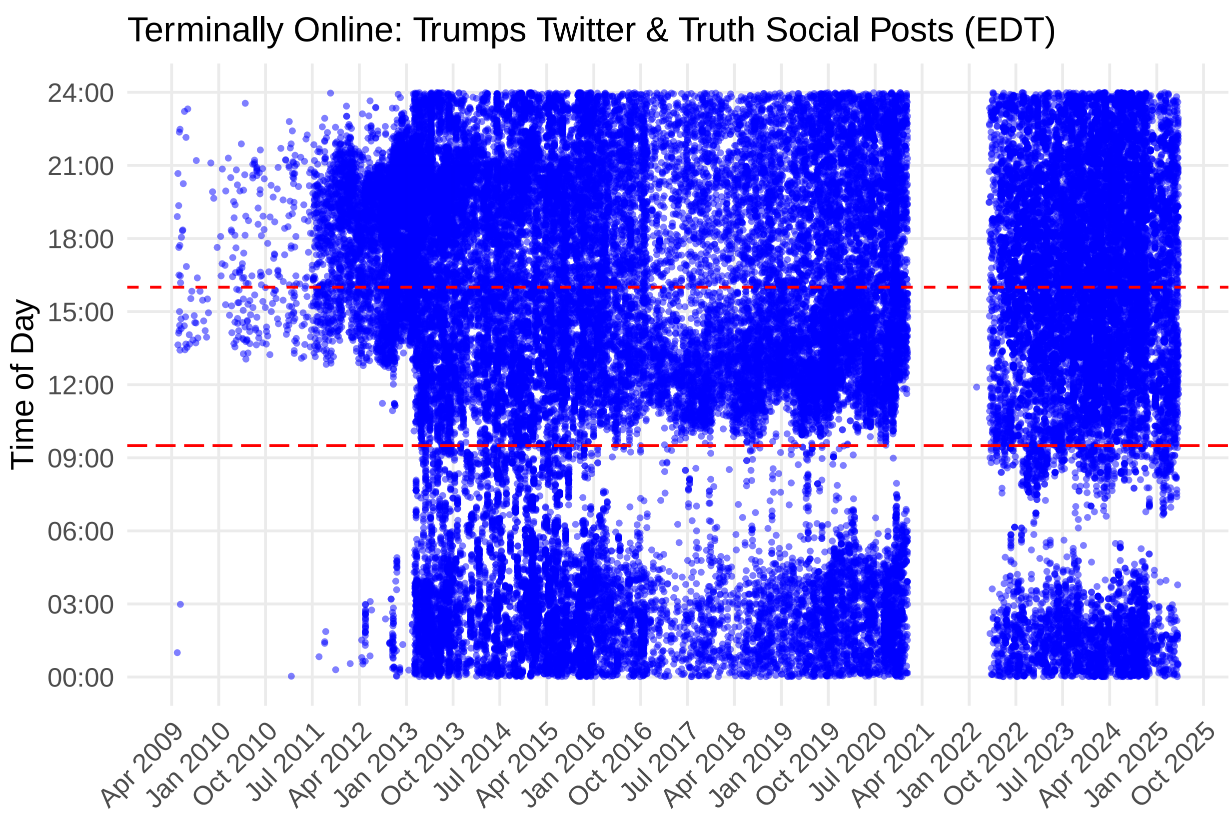

Figure 1: Terminally Online: Trump's Twitter & Truth Social Posts (EDT)

1.2 Literature Review

Information is one of the most valuable assets in the financial market. Its importance lies at the core of the "Efficient Market Hypothesis", which states that the prices of assets fully reflect all available information, adjusting immediately to any new data Fama et al. (2003) , and thereby creating a strong demand for

[1] Includes both Posts and Reposts

information flow. In addition, the "Mixture of Distribution Hypothesis" states that the release of new information is closely linked to movements in both realized and implied volatility Andersen (1996), French & Roll (1986), Vlastakis & Markellos (2012).

Consequently, a large part of the literature had focused on the relation between announcements, news and market activity. For example, Schumaker & Chen (2009) use various linguistic and textual representations derived from financial news to predict stock market prices. Similarly, Ederington & Lee (1993) analyze the impact of macroeconomic news announcements on interest rate and foreign exchange futures markets, particularly in terms of price changes and volatility. Both studies, among others, find that prices— such as stock prices—react primarily within minutes after the release of new information.

Recently, the world has witnessed the rise of the Internet which revolutionized the dissemination and accessibility of information. Social media enable investors, analysts or politicians to instantly share their information, news or opinions. This led some studies to focus on the communication dynamics of social platform to predict changes in the returns of financial assets De Choudhury et al. (2008) & Bartov et al. (2018). In this context, the impact of Trump's tweets on various financial and macroeconomic variables has been analysed by several studies, especially during his first mandate.

Using high-frequency financial data, Gjerstad et al. (2021) found an increase in uncertainty and trading volume, along with a decline in the U.S. stock market—regardless of the tweet's content. However, the effect was stronger when Trump used confrontational words such as "tariff" or "trade war." Some of his announcements also influenced the U.S. dollar exchange rate Vlastakis & Markellos (2012) and certain market indices within minutes of the tweet being posted Colonescu (2018) & Kinyua et al. (2021).

Other scholars have shown that negative Trump tweets about specific companies tended to reduce demand for their stocks Brans & Scholtens (2020) & Mendels (2019), whereas some other have shown that they also impact market volatility indices such as the VIX Fendel et al. (2019) or the Volfele Klaus & Koser (2021). The effects of his tweets also extended beyond the U.S.. For example, Nishimura & Sun (2025) shows a positive relationship between volatility in European stock markets and tweeter activity of Trump, and this effect tends to intensify as public intention for his tweet grows Nishimura & Sun (2025).

Our paper is built as follows: Section 2 describes the data, their sources, and the several transformations applied. Section 3 focuses on ARMA-X models, describing both our methodology and results. Section 4 does the same, though for our VAR models. Section 5 concludes.

2 Data

2.1 Financial Data

For our financial data, we decided to try to find minute-by-minute prices for broad market indices. While the actual indices do not update their prices so often, we had to take proxies under the form of ETF's that track them. Our 3 markets of analysis are: SPY to track the S&P500, VGK to track the FTSE Developed Europe All Cap Index, and finally ASHR to track the CSI 300 China. We accessed this data through a free stock API, Alpha Vantage. Our timeframe is from the first of January 2014 to the 7th of May 2025.

We then had to transform this data to get our main variable of interest, Average Hourly Volatility (AHV). Note that this is realised market volatility. We did so with the following formula:

$$v_t = \frac{1}{N}\sum_{i=1}^{N}(\Delta p_{t,i})^2$$

Where Δp_t is the difference in price (open - close) and i represents every minute.

We used a custom function in order to get the AHV for each open market hour. Note that the first hour is from 9:30 am to 10:00 am since the market opens on a half-hour but closes at 4:00 pm.

We can clearly see that the last few months show a new era of never seen before levels of volatility. Shocks on volatility recently have reached, and even surpassed (for a few data points) levels seen during the COVID-19 pandemic.

2.2 Political Data

We have two sources for Trump's posts. The Tweets are from Kaggle Shantanu (n.d.) and go until the 8th of January 2021. Since he switched his primary posting platform to Truth Social we use only that Data from 2021 onwards. All Truth Social posts were scrapped from trumpstruth.org, a webpage that aims to conserve all his posts. Note that we have had to use web-scrapping methods in order to download all his Truth Social posts in a dataset.

A big problem we had in our analysis was what to do with social media posts which appeared outside market hours. We first decided to simply ignore them, but it turned out to remove a lot of observations. We finally decided to push all the social media information outside market hours to the next open hour. This comes as an assumption[2].

Since our financial data is hourly, we aggregate the social data by hour. We then construct multiple variables from the social media data. These include a dummy for whether there was a post, the number of posts an hour and counts for certain words ("tariffs","trade","china"). Further we applied some simple sentiment analysis algorithms on the data to see if there are certain sentiments in his tweets that move the markets. Details on all our data management procedures can be found in the GitHub repository.

[2] For instance, if Trump tweets on Good Friday (market holiday), then the market will only react to this new information on Monday at 9:30 am.

Andersen, T. G. (1996). Return Volatility and Trading Volume: An Information Flow Interpretation of Stochastic Volatility. *The Journal of Finance*, *51*(1), 169–204. https://doi.org/10.2307/2329306

Bartov, E., Faurel, L., & Mohanram, P. S. (2018). Can Twitter Help Predict Firm-Level Earnings and Stock Returns? *The Accounting Review*, *93*(3), 25–57. https://doi.org/10.2308/accr-51865

Brans, H., & Scholtens, B. (2020). Under his thumb the effect of president Donald Trump's Twitter messages on the US stock market. *PLOS ONE*, *15*(3), e0229931. https://doi.org/10.1371/journal.pone.0229931

Colonescu, C. (2018). The Effects of Donald Trump's Tweets on US Financial and Foreign Exchange Markets. *Athens Journal of Business & Economics*, *4*(4), 375–388.

De Choudhury, M., Sundaram, H., John, A., & Seligmann, D. D. (2008). Can blog communication dynamics be correlated with stock market activity? *Proceedings of the Nineteenth ACM Conference on Hypertext and Hypermedia*, 55–60. https://doi.org/10.1145/1379092.1379106

Ederington, L. H., & Lee, J. H. (1993). How Markets Process Information: News Releases and Volatility. *The Journal of Finance*, *48*(4), 1161–1191. https://doi.org/10.2307/2329034

Fama, E. F., Fisher, L., Jensen, M. C., & Roll, R. W. (2003). The Adjustment of Stock Prices to New Information. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.321524

Fendel, R., Burggraf, T., & Huynh, T. L. D. (2019). *Political News and Stock Prices: Evidence from Trump's Trade War* ({{SSRN Scholarly Paper}} No. 3479822). Social Science Research Network.

French, K. R., & Roll, R. (1986). Stock return variances: The arrival of information and the reaction of traders. *Journal of Financial Economics*, *17*(1), 5–26. https://doi.org/10.1016/0304-405X(86)90004-8

Gjerstad, P., Meyn, P. F., Molnár, P., & Næss, T. D. (2021). Do President Trump's tweets affect financial markets? *Decision Support Systems*, *147*, 113577. https://doi.org/10.1016/j.dss.2021.113577

Kinyua, J. D., Mutigwe, C., Cushing, D. J., & Poggi, M. (2021). An analysis of the impact of President Trump's tweets on the DJIA and S&P 500 using machine learning and sentiment analysis. *Journal of Behavioral and Experimental Finance*, *29*, 100447. https://doi.org/10.1016/j.jbef.2020.100447

Klaus, J., & Koser, C. (2021). Measuring Trump: The Volfefe Index and its impact on European financial markets. *Finance Research Letters*, *38*(C).

Mendels, G. (2019). Stanford Research Series: Making Trading Great Again: Trump-based Stock Predictions via Doc2vec.... In *Comet*.

Nishimura, Y., & Sun, B. (2025). Impacts of Donald Trump's tweets on volatilities in the European stock markets. *Finance Research Letters*, *72*, 106491. https://doi.org/10.1016/j.frl.2024.106491

Schumaker, R. P., & Chen, H. (2009). Textual analysis of stock market prediction using breaking financial news: The AZFin text system. *ACM Trans. Inf. Syst.*, *27*(2), 12:1–12:19. https://doi.org/10.1145/1462198.1462204

Shantanu, R. (n.d.). *Donald Trump Tweets Dataset*. https://www.kaggle.com/datasets/codebreaker619/donald-trump-tweets-dataset.

Vlastakis, N., & Markellos, R. N. (2012). Information demand and stock market volatility. *Journal of Banking & Finance*, *36*(6), 1808–1821. https://doi.org/10.1016/j.jbankfin.2012.02.007