HOW POLITICAL NEWS MOVES MARKETS

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ABSTRACT

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(Under the Direction of Dr. Gregory Brown)

The United States' position on trade and the Federal Open Market Committee's outlook both govern the pricing of equities, debt, and other derivatives domestically and internationally. Unprecedented executive influence on trade and the Fed, coupled with a president's unpredictable and instantaneous communication on Twitter, inspired banks and trading firms to create indexes, bots, and derivatives to account for this phenomenon. This thesis asks the question: how do President Donald Trump's tweets affect the broader stock market in terms of pricing and volatility? I use intra-day event study analysis on a sample of 2148 President Donald Trump tweets to evaluate the market impact of general tweets. I segmented the tweets into Fed-related tweets, Trade-related tweets, and other tweets before evaluating the pricing and volatility impacts using the SPX index and VIX index respectively. I found significant differences between the market reaction to trade-related tweets and Fed-related tweets and other tweets.

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TABLE OF CONTENTS

LIST OF FIGURES

RESEARCH QUESTION

From his 2017 inauguration through October 2019, President Trump tweeted 11,821 times. On September 9th, 2019, J.P. Morgan launched their Volfefe index. Getting its namesake from a misspelled President Trump tweet, the index used 14,000 tweets, specific keywords, and other insights to model how President Trump's tweets affect volatility in US Treasury bond pricing (Alloway, 2019).

J.P. Morgan's research, as well as conversations with peers, coworkers, and mentors, guided my interest into the potential impact of President Trump tweets on financial markets. This thesis utilizes event study analyses to assess the impact of President Trump tweets on stock market pricing and volatility.

INTRODUCTION

On May 18, 2015, the @POTUS twitter account made its first tweet. While little fanfare accompanied this tweet, a few developments gave new significance to the start of presidential tweets: the election of a president who regularly communicates to his more than 75 million Twitter followers, the multiple trade conflicts involving the threat or use of tariffs, and the abnormally authoritative presidential communication towards the Federal Reserve. Twitter's instantaneous transmission of messages coupled with a president unafraid to articulate his thoughts on companies, tariffs, interest rates, and other entities makes for interesting applications of finance. These changes inspired research from the private sector, academic researchers and others to determine whether the fallout from President Trump's tweets are purely coincidental.

President Trump Tweets and Federal Reserve Independence

On April 18, 2018, President Trump tweeted his first criticism of Fed Policy, "Russia and China are playing the Currency Devaluation Game as the U.S. keeps raising interest rates. Not acceptable!" While the Great Recession in 2008 already eroded most public confidence in central banks, this was the first example of an American president publicly pressuring Fed policy with a tweet. This tweet interrupted decades of central bank independence following the inflationary terms of President Johnson and Nixon.

Their administrations influenced the Federal Reserve chairman to maintain low interest rates, helping create the Great Inflation of the 1970s. The Great Inflation led the

Fed to institute a dual mandate of price stability and maximum employment and establish a more distant relationship with the executive branch to insulate their policy from presidential influence. The end, or perceived end, of this independence, along with intermittent tweet barrages directed at the Fed, create events to gauge the perceived independence of the Fed. As these perceptions reverberate through financial markets, do they influence market pricing and volatility?

President Trump Tweets about Trade

On January 26, 2017 President Trump made his first tweet as president criticizing another country's trade with the US and a prior trade deal, "The U.S. has a 60-billion-dollar trade deficit with Mexico. It has been a one-sided deal from the beginning of NAFTA with massive numbers…" Tweets like these, threats of tariffs, and implementations of tariffs eschewed a half century of US policy movement towards free trade following the formation of the General Agreement on Tariffs and Trade after World War II. The 1987 Canada—U.S. Free Trade Agreement of 1987, the 1994 North American Free Trade Agreement, and the 1994 granting of World Trade Organization Most Favored Nation status to China all reinforced American commitment to free trade (Halloran, 2019). These changes resulted in increased American dependence on international trade, with 42.9% of revenue from S&P 500 companies coming from foreign countries as well as shifts in supply chains (Silverblatt, 2018). With this exposure to international trade, do President Trump's tweets concerning trade, tariffs, and trade deals impact market pricing and volatility.

The Private Sector Reaction to President Trump Tweets

While one instance of a company's stock price dropping following a negative President Trump tweet does not constitute a trend, US banks have developed products, indexes, models and strategies related to his tweets. JPMorgan developed the "Volfefe Index" to measure the impact of President Donald Trump's Tweets on Treasury yields (Alloway, 2019). Bank of America Merrill Lynch researched the connection between the volume of President Trump tweets and stock market performance. They found that days President Trump tweeted more than 35 times resulted in negative returns on average while days President Trump tweeted less than 5 times resulted in positive returns on average (Liu, 2019). These examples of bank research and products only represent the publicly distributed response by the private section to President Trump's tweets.

Research Question

Amid the backdrop of international trade conflicts and renewed public criticism of central banks, do the tweets of a president with 75 million Twitter followers who uses Twitter as his primary form of communication affect market pricing and volatility?

This introduction serves as a roadmap for the rest of my analysis. In section II, I examine the past research surrounding the market impact of presidential tweets, popular news columns, and investing TV shows, as well as other pertinent research. Section III explains my methodology of using event studies to assess market reactions to President Trump Tweets. Section IV discusses each of the three groupings, providing some justification for results. Lastly, section V details the conclusions arrived at from results in the previous section and lays out further research.

LITERATURE REVIEW

In this literature review, I describe the theoretical underpinnings of most modern financial research: the efficient markets hypothesis (EMH) and Random Walk Theory. I then detail the findings from several studies examining the impact of news on asset prices. Next, I examine research surrounding the application of similar methodologies to Twitter communications, highlighting studies discussing President Trump's Twitter activity. I then provide a brief explanation of high frequency trading with an example of one trading bot using President Trump's tweets. I conclude with a recognition of the gap in the current literature and a description of how this research can contribute to the conversation surrounding the impact of news on asset pricing.

Efficient Markets Hypothesis

Serving as a foundation for most modern financial research, the EMH posits that markets quickly and completely incorporate the value of new information into asset prices resulting in the inability of market participants to earn abnormal profits (Fama, 1970). Without friction, instantaneous and complete change in asset prices should follow public release of new information. So, in the case of firm earnings announcements, the market has already used available, public information to price these stocks appropriately, and their subsequent price change, or lack thereof, reflects the market's reaction to earnings releases. Any prior anticipation of this new information may be incorporated into the asset's price prior to the information's release, reducing the impact of the release (Fama, 1970). Fama relies on three models for testing market efficiency: the Fair Game Model, the Submartingale Model, and the Random Walk Model. In addition, EMH can be categorized into three levels based on the available information set: the Weak Form, Semi-Strong Form, and Strong Form.

The fair game model suggests that expected returns are a function of the underlying risk in a security in which all available information is reflected. The Submartingale Model expands on the Fair Game Model stating that security prices tend to rise over time. This model suggests a buy and hold model will result in the highest profits compared to other strategies. In contrast, the Random Walk Theory states that changes in a security's price are random and independent of each other, suggesting that past trends of movements of a security's price cannot be used to predict the security's movement in the future. This theory also implies that it would be difficult to consistently exploit mispriced stocks as price movements are the result of unforeseen events.

These models form the basis of Fama's research of examining the EMH in the weak, semi-strong, and strong forms. In its weak form, the EMH states that security prices are a reflection of all the data in past prices. This form suggests that investors cannot generate superior returns through technical analysis; however, price abnormalities can be exploited through fundamental analysis. Semi-Strong form states all public information is reflected in a security's current stock price, and neither technical analysis nor fundamental analysis will generate excess returns. Only information that is not available to the public will aid investors in achieving excess returns. In its strong form, EMH states that all public and private information is reflected in a security's price and there is no way for investors to achieve returns in excess of the broader market. For researchers, the EMH, especially the assumption that all public information is already incorporated into an assets price, facilitates the evaluation and comparison of the impact of different events on asset prices.

Random Walks in Stock Market Prices

The Theory of Random Walks challenges the traditional approaches of fundamental analysis and technical analysis by relying on the premise that prices in an efficient market accurately reflect the true intrinsic value of the underlying security (Fama, 1995). Research supporting the Random Walk Theory relies on a statistical approach of calculating serial correlation coefficients and an analysis of runs of consecutive price changes of the same sign.

As new information enters the market, the price instantaneously adjusts to reflect an updated intrinsic value, independent of previous price trends or changes (Fama, 1995). The price of the underlying security will resemble a "random walk," rendering the value of the security in the future unpredictable. This theory makes the case for a "buy and hold" strategy of investing rather than a market timing approach that attempts to exploit price anomalies in the market.

In response to the chartist, who relies on technical analysis, Fama emphasizes that one cannot simply rely on patterns in the data to consistently predict future asset prices. Turning to intrinsic value analysis, Fama argues that analysts actually facilitate the market reaction to new information, thus making the market more efficient and supporting the random walk model. However, an analyst attempting to outperform the market through intrinsic value analysis only adds value if they can consistently make meaningful judgements about the purchase and sale of securities compared to random selection. Furthermore, that analyst must beat random selection by an amount sufficient to cover the resources expended in the process of conducting intrinsic value analysis. Fama states that unless an analyst has better insights into a security or new information that is not priced into the security, intrinsic value analysis will not outperform a random selection procedure.

The Impact of News on Asset Prices

Research examining the impact the news has on asset prices varies in relevance, newness, reach, and other factors. This research ranges from measures with clear ties to company performance, such as earnings releases, acquisition announcements, or dividend announcements. This literature review primarily focuses on less directly applicable news, such as general market coverage and the musings of a popular stock-picker because of their less-clear impact on stock prices. I will also walk through research documenting the impact of positive or negative spin on information presented across various sources and audiences.

In terms of news releases with very clear implications to firm valuation, Chan examines stock price reaction to news-related events compared with stocks with similar returns but no news-related event (2003). Chan looked at monthly performance of randomly selected stocks from the CRSP database, sorting them into stocks with no news and stocks with news and then “good” news or “bad” news by grouping the top and bottom third by monthly performance. Chan found that in the case of negative (positive) news, stocks that underperformed (outperformed) after a news event continued to underperform (outperform) without any additional negative news. In the case of negative (positive) performance without news, stocks tended to outperform (underperform) in the following months. In essence, momentum from an actual event persisted more than random momentum with no direct event support.

Beyond the impact of information presented in the news, the level of optimism or pessimism also matters. Dougal, Engelberg, Garcia, and Parsons (2012) inspected the relationship between Dow-Jones Industrial Average (DJIA) returns and the often-rotating author of the Wall Street Journal's "Abreast of the Market" (AOTM) column from 1970 to 2007. They adjusted for earnings releases, day-of-the-week, time effects, volume, volatility and other external events and factors. They found a causal relationship between the author of the column and DJIA returns the day of columns and the day following columns. Their use of signed rather than absolute return data allowed them to discover a relationship between optimistic (pessimistic) authors and subsequent positive (negative) returns. In times of elevated market volatility, the effects of the authors were amplified. The novelty of observing a causal effect between media reporting and stock returns inspired similar research covering different news sources, audiences, and mediums. Disruption in news mediums and audiences, coupled with technological changes that ease market friction, continue to create changes in market dynamics, eliciting research on similar dynamics outside the pages of the Wall Street Journal.

Engelberg et al. (2012) inspected the impact of CNBC's "Mad Money" show, hosted by Jim Cramer, and found that the impact of media attention on stock market returns extends beyond definitive financial reporting sources like the Wall Street Journal, Bloomberg, or New York Times. After adjusting for the newness of the news, earnings events, and other factors, they found a few relevant conclusions. They observed that equal-weighted portfolios of Cramer's recommendations formed immediately before their mention on his show experience no abnormal returns when held for 50, 150, or 250 trading days. Given the lack of a long-term impact, they modified their research to form portfolios the day after recommendations and found they underperformed the market over 50, 150, and 250 day periods.

The discrepancy between portfolios formed before and after the recommendations pointed towards a mispricing of stocks following their mention on “Mad Money”. The researchers surmised this impact related to the attention paid to the recommendation and the friction related towards correcting the mispricing. Thus, they adjusted their test to measure the overnight response and incorporate Nielsen ratings to measure attention. These modifications helped them document interesting relationships between the screen-time on the show and return, total audience and return, and total income of the audience and return. They also found that buy recommendations resulted in a much more pronounced overnight return than sell recommendations.

These observations reinforced research by Barber and Odean (2008) that concluded individual, or retail, investors were much more likely to buy stocks than sell stocks or short stocks after news events. The documented impact of a stock picker with hundreds of thousands of CNBC viewers raised the possibility of other speakers with significant followings to have a similar impact (Engelberg, et al., 2012).

Trading, Twitter, and Trump

President Trump's Twitter represents a unique intersection of audience, frequency, and influence. His authority as President of the United States carries a higher potential for action than a columnist or a stock picker. His sixty-six million strong following on Twitter covers a much larger and more diverse audience than the circulation of the Wall Street Journal or the viewership of CNBC's "Mad Money". The instantaneousness, unpredictability, and frequency of his tweets also differentiate his Twitter from daily shows or columns. Cramer often gives some advanced notice of the companies he features on his daily show; President Trump does not offer the same advanced notice when he questions the decision-making of Fed Chairman Jerome Powell in a series of tweets. Current research explores different industries, time periods, methodologies, and event-inspection periods. This section will detail research surrounding the relationship between President Trump's Twitter, Federal Funds Rate expectations and stock market returns.

Bianchi, Kind, and Kung inspected the relationship between President Trump tweets and the independence of the Federal Reserve (2019). They measured the impact of President Trump tweets criticizing the Fed on tick-by-tick fed funds futures from 5 seconds before and 5 minutes after tweets and found that President Trump tweets, on average, resulted in a negative and statistically significant impact on the fed funds futures. Their results were similar under different event windows from 5 to 60 minutes. They documented that fed funds futures contracts with exposure to more Federal Open Market Committee (FOMC) meetings were impacted more by tweets than contracts with exposure to less FOMC meetings. Fed funds futures contracts with exposure to zero FOMC meetings did not show a statistically significant impact from President Trump tweets. President Trump tweets related to trade also showed a negligible impact on fed funds futures contracts. With their findings, they concluded that market participants did not deem the Federal Reserve completely independent. Other research into the market impact of President Trump's tweets has not been as clear cut.

The first researchers to examine the impact of President Trump's tweets on the stock market covered the time after his election but before he even took office. Born, Myers, and Clark (2017) inspected the relationship between President Trump's tweets from the November 8, 2016 presidential election to his January 20, 2017 inauguration, the returns of ten public companies he mentioned in his tweets over this time period, and the sentiment of his tweets. Their analysis covered fifteen tweets, with all but two occurring outside of trading hours in the United States. They found tweets impacted abnormal returns of companies mentioned over the course of the trading day of the tweets, with positive tweets, on average, exhibiting a larger impact on stock prices than negative tweets. However, they observed that these returns typically dissipated within five days of the tweets and were only statistically significant on the day of the tweets. They documented elevated trading volume the day of tweets and the day following tweets, which they attributed to retail investors (Born, et al., 2017). The dissipation of pricing effects mirrored the market response to Cramer's show documented by the research of Engelberg et. Al. (2012).

Later, researchers covering periods during President Trump's term arrived at similar conclusions. Ajjoub, Walker, and Zhao (2018) conducted research on the impact of

President Trump tweets on the stock market from a different perspective. They segmented by non-media, hybrid, and media companies, filtered tweets mentioning publicly-traded companies into positive, neutral, and negative categories, and covered the period from President Trump's May 26, 2016 GOP nomination to August 30, 2018. Using several different estimation periods from 30 days to 255 days, they found that negative tweets about non-media companies led to the largest abnormal returns and positive tweets resulted in the most volatility for media companies. They attributed the higher impact of positive tweets on returns to President Trump's proclivity to tweet more about negative media coverage than positive media coverage (Ajjoub et al., 2018). They also found that President Trump tweets were significantly more impactful following his election. Similar to the research of Born et al. (2017), they also observed that pricing effects related to President Trump tweets did not persist long term.

Ge, Kurov, and Wolfe (2018) looked at similar questions, exploring the impact of 59 President Trump tweets from November 9, 2016 to July 31, 2017 that mentioned a public company, no matter the time of day relative to trading hours. Reinforcing the findings of Born et al. (2017) and Ajjoub et al. (2018), they found that President Trump tweets statistically significantly impacted company stock prices by an average of more than one percent on the day of the tweet. They also observed elevated trading volume, volatility, and institutional investor attention on the day of tweets. One novel insight they found was that the impacts on stock prices and trading volumes appeared more significant before President Trump's inauguration (Ge et al., 2017) which they reasoned as potentially the result of additional Presidential communications after his inauguration. Also, similar to prior research by Born et al. (2017) and Ajjoub et al. (2018), they observed that the change in price and volume on the first day dissipated over the following five trading days, most likely due to waning investor attention.

The lack of long-term persistence in pricing changes across research into the impact of President Trump's tweets mirrors the findings of Engelberg et al. (2012) on Cramer and suggests that the tweets result in a short-term mispricing. The disparity between the short-term and long-term pricing impacts of these events along with the lack of research inspecting shorter time horizons, makes the ultrashort-term impact of these tweets an interesting, and novel area for further research.

High Frequency Trading and Tweets

In this section, I define HFT and describe its relationship to President Trump's Twitter and markets.

Algorithmic Trading (AT) predates HFT and the differences between the two help define HFT. AT dates back to the 1976 introduction of the first electronic stock market, the National Association of Security Dealers Automated Quotations (NASDAQ), spurring the faster spread of financial information. In the 1990's, the development of the Electronics Communication Network (ECNs) allowed trading of securities outside of regular exchanges, resulting in greater speed and efficiency of trading, lower costs, and fewer manual errors. This facilitated AT, allowing firms and individuals to act on the market with the use of computer algorithms (Agarwal, 2012). AT gained popularity not only because of its technological benefits, but also due to technical factors such as narrowing spreads. In 2001, U.S. stock exchanges began quoting spreads in decimals vs. fractions, resulting in a decrease in minimum spreads, causing traders who profited on spread to seek other options.

A few developments promoted the evolution of AT to HFT: the increased access and volume of information providing more information to act on and regulatory changes from the SEC (Agarwal, 2012). In 2005, the SEC passed the Regulation National Market System, promoting transparency and competition between markets and requiring trade orders to be posted nationally instead of on individual exchanges. This allowed traders to profit on price differences between two different exchanges so long as they could act quickly enough.

On the technological front, an exponential increase in processing power facilitated breakthroughs in hardware and software, resulting in reduced latencies and trading times. These advances in HFT allow high frequency traders to place large numbers of orders in rapid succession, respond to events much faster, and automate this trading (Agarwal, 2012). Currently, there are three types of HFT firms: independent firms, broker-dealer firms, and hedge funds. Independent firms tend to act as market makers, buying and selling orders automatically throughout the day using private money. Broker-dealers tend to have separate HFT desks in addition to their traditional client businesses. Hedge funds generally focus on statistical arbitrage to take advantage of pricing inefficiencies among asset classes.

The backdrop of these developments and the unique dynamics of President Trump's Twitter usage facilitate experiments like NPR's Bot of the United States, a trading bot developed with Tradeworx to trade off of President Trump's Twitter (Goldmark, 2017). The bot used the sentiment of tweets, the companies mentioned in tweets, and other information such as the name of President Trump's daughter to quickly buy stocks and then sell them 30 minutes later in thousands of trades over the course of a year. While this bot failed to turn a profit, it showed the ease, and potential, for proprietary trading firms with quicker more complex bots to trade nearly instantaneously off of President Trump's tweets.

Gap in Literature

Given the extensive research into the impact of news on asset pricing, President Trump's Twitter presents an interesting intersection of status, audience, and interpretation of information. Dougal et al. (2012) demonstrated the potential for a single news column with the right audience to impact broader US equity markets in the form of the DJIA. Engelberg et al. (2012) observed the short-term mispricing a single TV personality can create on individual equities. Born et al. (2017), Ajjoub et al. (2018), and Ge et al. (2018), all documented a similar short-term pricing change and medium-term price change erosion related to President Trump tweets. This erosion typically signals a short-term mispricing of assets (Dougal et al., 2012). The Bot of the United States illustrates the ease of developing trading algorithms to trade off the short-term effect of President Trump's tweets (Goldmark, 2017).

The current literature fails to account for the impact of HFT reducing the time needed to properly incorporate new information into asset prices and ignores the ability of a single speaker to impact entire stock markets rather than individual equities. My research aims to cover these gaps in three distinct ways: zooming in on the ultrashort-term impact of President Trump tweets, expanding the analysis to indexes, and grouping the impact of his tweets by their subjects. With this research, I hope to deepen and advance the discussion on how news moves markets.

METHODOLOGY

To empirically assess whether President Trump tweets affect market pricing or volatility, my thesis methodology focuses on the use of intraday event-study analysis. In an event-study analysis, numerical values for a particular metrics before and after a particular event to gauge the overall impact of that event. In this case, event-study analysis assesses the impact of a tweet on the returns of the SPX and VIX indexes to assess the impact of market pricing and volatility respectively. The SPX index tracks the performance of the S&P 500, a stock market index measuring the stock performance of 500 large companies listed on US stock exchanges. The VIX index measures the market's expectation of 30-day volatility using at-the-money S&P 500 option prices.

For each tweet, I obtained stock SPX and VIX pricing thirty minutes before and after the tweets to measure the impact on pricing and volatility. As mentioned earlier, this particular form of analysis relies on the efficient market hypothesis, particularly that all publicly available information is incorporated into market prices by market participants on each day. By the end of this analysis, I hope to have a better understanding of whether these tweets impact market pricing and volatility and, if so, what impact they have.

In the following section, I detail the sample used for my analysis and its representation across the three categories used for my analysis. I will then discuss the evaluation methods I will use to assess the impact of President Trump tweets. Lastly, I will discuss key limitations associated with the results I obtained and how they affect my analysis and conclusions.

Data Description

My empirical analysis uses three different data sources: Tweets by President Trump, prices on the S&P 500 index, and prices on the VIX index.

Tweets are collected from the personal Twitter account of President Trump (@realDonaldTrump) via TrumpTwitterArchive.com. Each observation contains the text of the tweet, a time-stamp down to the second, the number of retweets, the number of favorites, the device used to tweet, and other factors. The analysis focuses on all tweets and categorizes the President's tweets as related to the Federal Reserve, United States trade, or other.

The tweets were first categorized using the keywords for Fed-related tweets: 'federal reserve', 'interest', 'quantitative', 'rates', 'inflation', 'tightening', 'jay', 'powell', 'fomc'. Trade related tweets were selected using these keywords: 'trade', 'china', 'tariff', 'canada/mexico', 'nafta', 'tpp', 'deal', 'agreement', 'manipulation', 'patent', 'theft', 'deals', 'phase one', 'usmca', 'farmers', 'export', 'import', 'xi jinping'. Tweets related to both trade and the Fed were counted for both. Second, tweets with any of those keywords unrelated to the Federal Reserve or US trade were reclassified to other. In cases of tweets with typos that were later deleted, the initial tweet with the typo was selected and the corrected tweet was thrown out to avoid double counting. The number of retweets and favorites were used to filter for tweets with low engagement that were more likely to contain typos and subsequent corrections. Tweets outside of normal trading hours without requisite data for both the VIX and SPX were thrown out.

Intraday prices for the SPX index and the VIX index were obtained from FirstRate Data. The raw data was cleaned using Python to match the tweets with market data. The time-stamp of each tweet was rounded down and the opening price of the VIX and SPX for that minute, as well as the 30 minutes preceding the tweet and 30 minutes following the tweet were selected. This procedure makes sure the price of the VIX or SPX at minute zero reflects the price before the tweet and minimizes potential variance from tweets coming at the end of a minute versus the beginning in the sample.

The sample period starts on the inauguration of President Trump (January 20, 2017) and ends on the last day for observations of VIX and SPX in the dataset (October 31, 2019). After the application of these selections and filters there were 2,148 total observations with 2,027 falling into other, 99 falling into trade-related, and 28 falling into fed-related (6 were classified as trade-related and fed-related).

Impact Evaluation

The SPX index measures the price of 500 large cap US companies and serves as a reasonable barometer for US equities. The VIX index measures volatility by incorporating the price of at-the-money options contracts on the SPX index that expire within 23 to 37 days and typically moves inversely with the SPX index. While typical event-studies employ estimation periods between six months to a year, my event study employed an estimation window of an hour, similar to research by Bianchi et al. (2019). For each minute in the observation window I calculated the return as:

$$R_n = (P_n - P_{t-30})/P_{t-30}$$

In this equation, R_n is equal to the price at minute n minus the price at the beginning of the window, divided by the price at the beginning of the window. An important assumption of this approach is that no other important events that shift market expectations occur within the time window of the tweet. A short time window was chosen to isolate the observed effects of tweets.

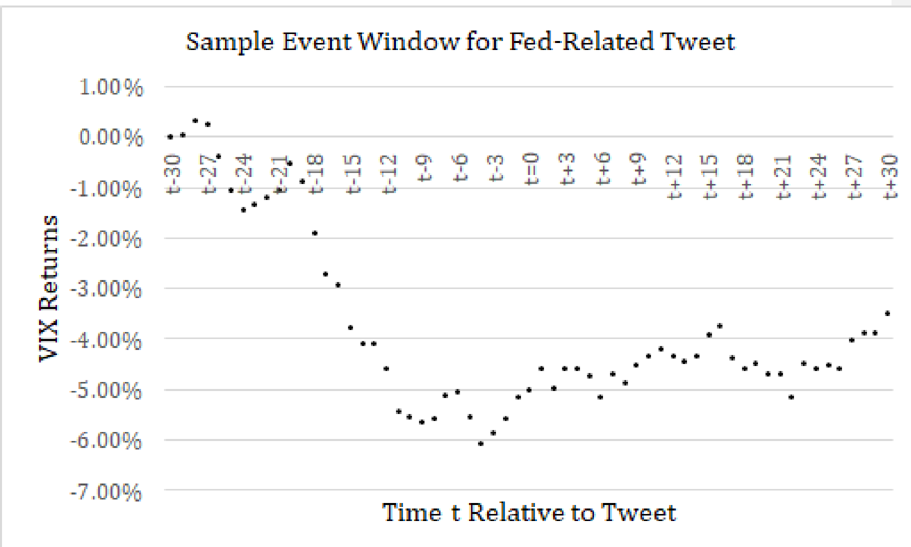

Figure 4.1. Sample Event Window

Limitations

After collecting empirical data and results from this evaluation, it is important to note some potential shortcomings of this approach. First, outside shocks to economic expectations within the estimation of windows of these tweets could influence results if they occur too often within the samples. Leakage of President Trump's tweets before they go out could also diminish the impact when they are tweeted as the market may have already partially or completely incorporated the new information. Use of non-standard language in tweets could also have led to misclassification of tweets into categories, either through omission or false classification. President Trump tweeting as a reaction to outside events that impact pricing and volatility in markets could also lead to a misinterpretation of results, although the shorter event window minimizes this. However, the short event window could result in missing the market response if market participants take more than thirty minutes to incorporate the information in President Trump's tweets. Random noise could also influence results if the groupings of tweets aren't large enough.

RESULTS

In the results section, I provide high-level analysis of four groupings of tweets and their subsequent impacts on market pricing and volatility. Given differing impacts across the groupings, each includes varying commentary. They also include brief discussions of potential factors that may have contributed to the market's reaction.

Overall Impact of Tweets

Looking at the overall impact of President Trump tweets, it does not seem that they statistically significantly impacted market returns or volatility. When President Trump tweets, the stock market as measured by SPX tends to increase over the course of 30 minutes on average. On average, a 1.2 basis point increase in the SPX followed each tweet. While there was a decrease in the stock market as measured by SPX in the first five minutes on average, this pricing impact did not persist over the course of the 30-minute window. This mirrors the results of prior research of Aijoub et. al (2018) and Born et. al (2017) that found the short-term pricing effects of President Trump's tweets on individual equities generally dissipated over a short time span. Given that the entirety of the sampling period came during a bull market when the SPX generally increased it does not seem that President Trump's tweets had a statically significant impact on the stock market as measured by SPX returns. Also, the vast majority (2027) of President Trump's tweets were unrelated to the Federal Reserve or trade in this period so their lack of an impact on market pricing is unsurprising.

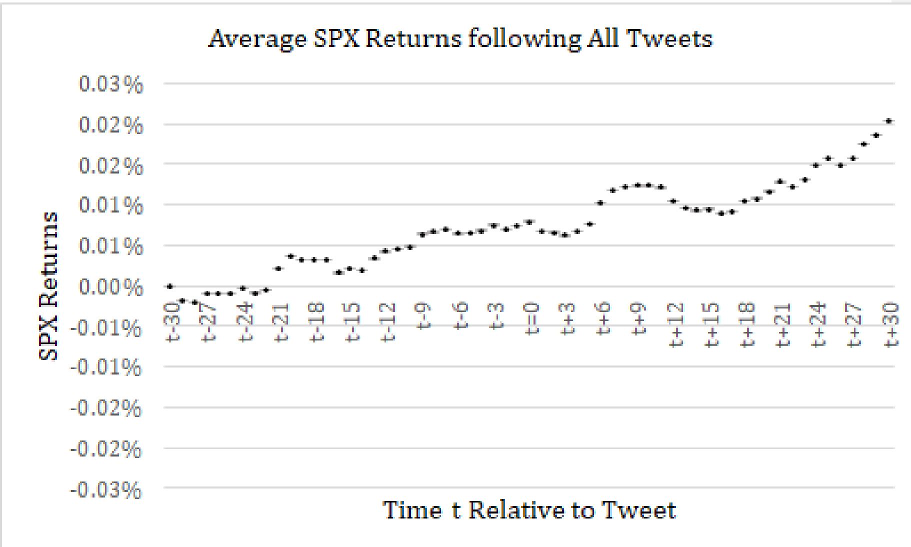

Figure 5.1. Average SPX return following all tweets

The overall impact of President Trump tweets of stock market volatility as measured by VIX generally mirrors the inverse of SPX returns. It does not seem that President Trump's tweets have a statistically significant impact on stock market volatility as measured by VIX returns. On average, a 10 basis point decrease in the VIX followed President Trump tweets by the end of the 30-minute event window. Given that the sampling period occurred entirely during a bull market, the slow decay of the VIX index as the SPX index increases would be expected. While VIX returns have a higher range than SPX returns this is explained by the higher volatility of the index as it tracks the more volatile options of the SPX rather than the underlying index.

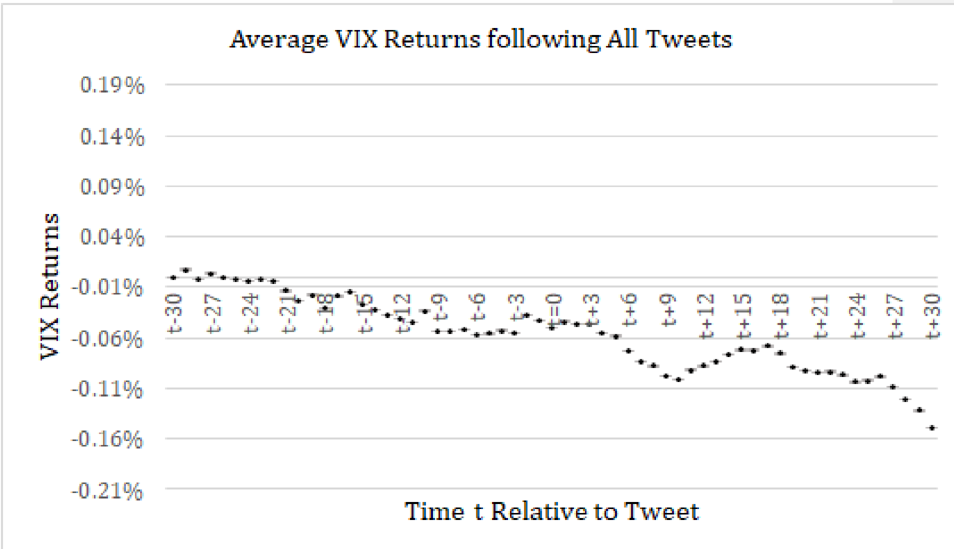

Figure 5.2. Average VIX return following All tweets

While some of President Trump's tweets may have a statistically significant impact on market pricing and volatility, the overwhelming majority do not, resulting in average returns that seem to follow prevailing market trends.

Impact of Fed-Related Tweets

While President Trump's tweets in general did not seem to impact the SPX or VIX, Fed-related tweets had a statistically significant impact on the stock market as measured by SPX returns. While his tweets, on average, resulted in a 1.2 basis point increase in the SPX over the course of the event window, his tweets regarding the Fed resulted in a 2.4 basis point decrease over the course of the event window. Interestingly, the decline in SPX peaks at t+14 at 7.3 basis points on average before the pricing effect erodes over the rest of the event window.

This result is surprising for a number of reasons. Bianchi et al. found that President Trump tweets criticizing the Fed had a statistically significant negative impact on federal funds futures contracts, essentially that the market perceived the Fed as not wholly independent and that President Trump's tweets raised market expectations of rate cuts (2019). Typically rate cuts lead to increased stock market prices, outside of financial services, due to reduced borrowing costs. Given that market participants perceive that President Trump's tweets impact the Fed's decision-making; it is surprising that stock market returns as measured by the SPX declined on average following his tweets. This could mean that market participants value the long-term independence of the Fed from the executive branch more than any short-term positive effects from Fed rate cuts that lower borrowing costs.

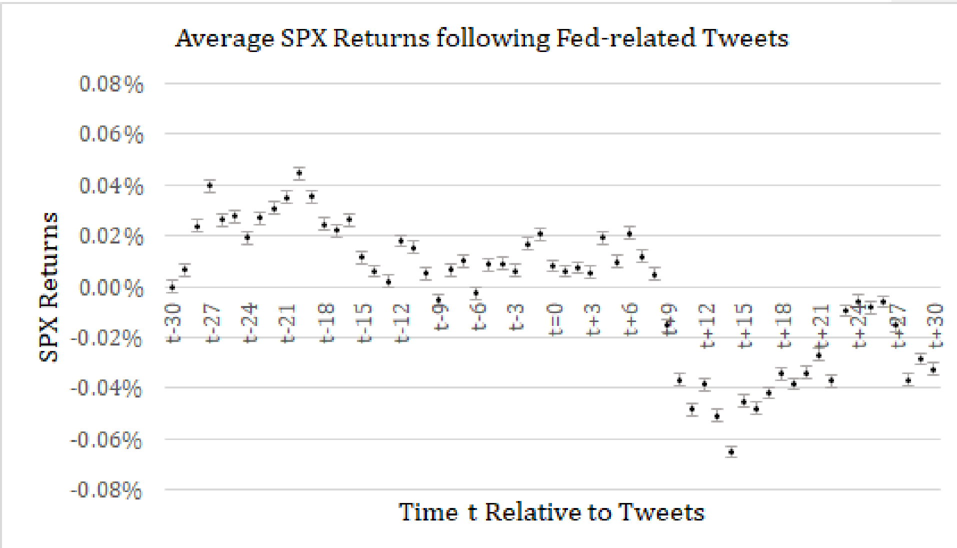

Figure 5.3. Average SPX Returns following Fed-related Tweets

President Trump's tweets had an even more pronounced impact on market volatility as measured by VIX returns. On average, President Trump's tweets resulted in a 42.3 basis point increase in the VIX from t=0 to the end of the event window. Interestingly, VIX returns following Fed-related tweets resemble the inverse of the average VIX returns following all of President Trump's tweets. The peak movement in VIX returns appears in the first ten minutes following the tweet with a leveling out coming after, before a surge at the end of the window. Interestingly, the largest jump in volatility in the event window, as measured by VIX returns, occurs between eight and ten minutes following the tweet. Between t+8 and t+9 there was one positive outlier with a 1.15% cumulative increase in the VIX but there was also one negative outlier with a 1.22% cumulative decrease in the

VIX in between t+8 and t+9, so it is unclear why this jump in volatility as measured by the VIX occurs so much later than t=0.

The elevated volatility as measured by VIX returns persists longer than the pricing effect following tweets which could mean that the immediate pricing impact of President Trump's Fed-related tweets is easier to quantify than the uncertainty they introduce into the market. Another explanation for the surprising results could be market participants responding fastest to firms with the most exposure to interest rate changes, such as banks that typically earn most of their revenue from net-interest income.

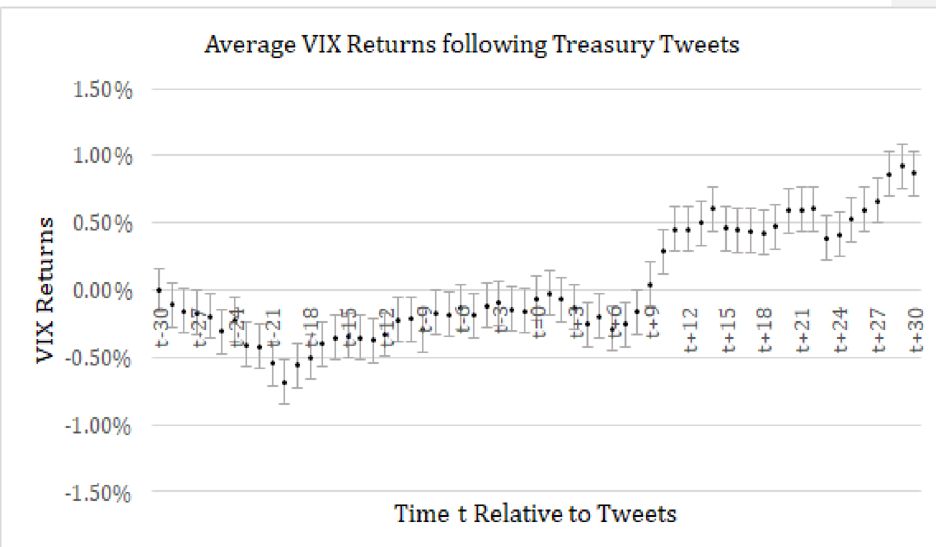

Figure 5.4: Average VIX Return Following Fed-Related Tweets

While market participants do not respond to every President Trump tweet, they seem to respond to tweets concerning the Fed. Despite prior research pointing toward a lack of Fed independence, the market seems to respond negatively to President Trump tweets concerning the Fed, rather than the positive response expected with reduced borrowing costs. Also, the increased volatility following Fed-related tweets persists longer than the pricing effect.

Impact of Trade-related Tweets

Unlike President Trump's average tweets or Fed-related tweets, his tweets regarding trade, on average, did not have a clear trend or impact on market pricing as measured by SPX. From the time of the tweet to the end of the event window, the SPX increased by .4 basis points on average, with choppy movements in between. The lack of a pricing impact is surprising, given the impact that the tariffs and peace talks sometimes discussed in President Trump's tweets could have on the economy. This could be a result of President Trump making most of his tweets with a pronounced impact on market participants' perception of US trade outside of trading hours. Another possible explanation could be the variation in exposure to international trade, especially tariffs, among firms in the S&P 500.

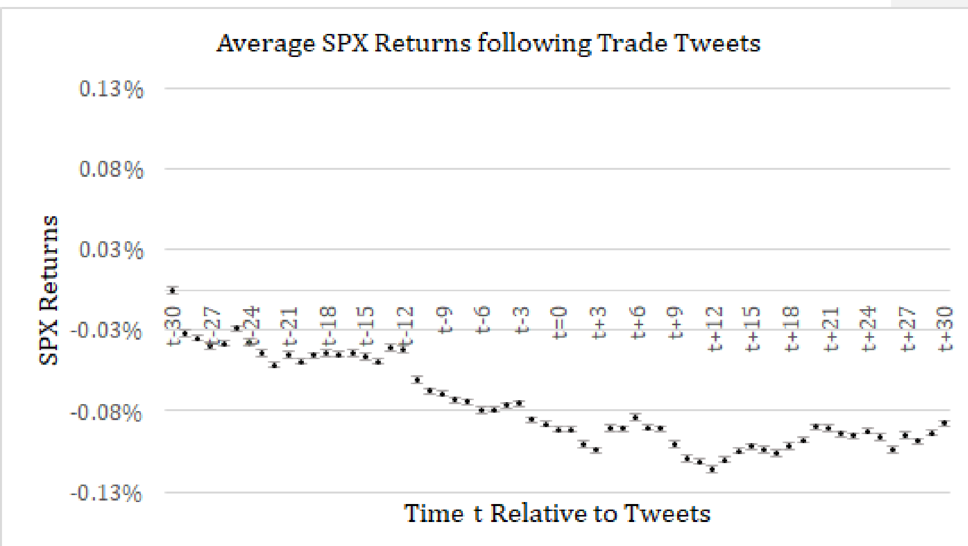

Figure 5.5: Average SPX Returns following Trade-related Tweets

The impact of President Trump's tweets on market volatility as measured by the VIX index were even more surprising than their pricing impact. Typically, the VIX index moves inversely with the SPX index but in this case, on average, the VIX fell starkly while the SPX hardly moved over the event window. According to the Chicago Board Options Exchange, VIX and SPX moved in the same direction over the course of a day slightly over 20% of the time from January 1990 to January 2018 (Rhoads, 2018). However, when the VIX trades below 13 the Chicago Board Options Exchange found that the VIX and SPX moved together nearly 30% of the time (2018). From the time of the tweet to the end of the event window, the VIX declined 41.2 basis points following the average tweet. Relative to the average tweet, this is a much steeper drop in volatility as measured by the VIX index. However, a small jump in volatility as measured by the VIX index followed the first couple minutes after a tweet. One explanation for this is that on average, President Trump tweets about trade following news releases or other events that introduce volatility as measured by VIX returns, into the market.

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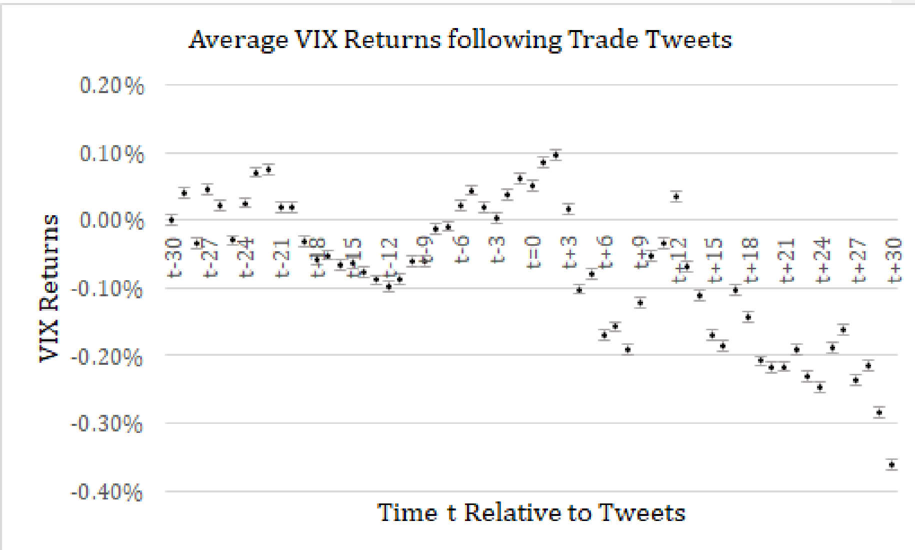

Figure 5.6. Average VIX Return following Trade-Related Tweets

The market reaction to trade-related tweets as measured by the SPX and VIX was unexpected. From the time of tweet to the end of the event window, the average tweet hardly impacted market pricing as measured by SPX while it had a pronounced impact on market volatility as measured by the VIX. While the VIX and the SPX typically moved in tandem, they move in different directions roughly 20% of the time over the course of full trading days. The erosion of volatility without a positive pricing impact could result from President Trump's trade-related tweets clearing up uncertainty around US trade policy without presenting good news for SPX companies. Another possible explanation for the choppy reaction to trade-related tweets is that market participants take different amounts of time to incorporate positive or negative news into asset prices and with the variation in exposure to international trade among S&P 500 firms means the response time, the information presented by tweets was incorporated into S&P 500 firms at different times.

The unclear results from this analysis may warrant further research.

Impact of Other President Trump Tweets

Given that other tweets make up the majority of President Trump's tweets in this sample, it is unsurprising that the average market reaction as measured by SPX returns are similar to all President Trump tweets. On average, a 1.4 basis point increase in the SPX followed tweets over the course of the event window. Given that all of these tweets occurred during a bull market this result is unsurprising.

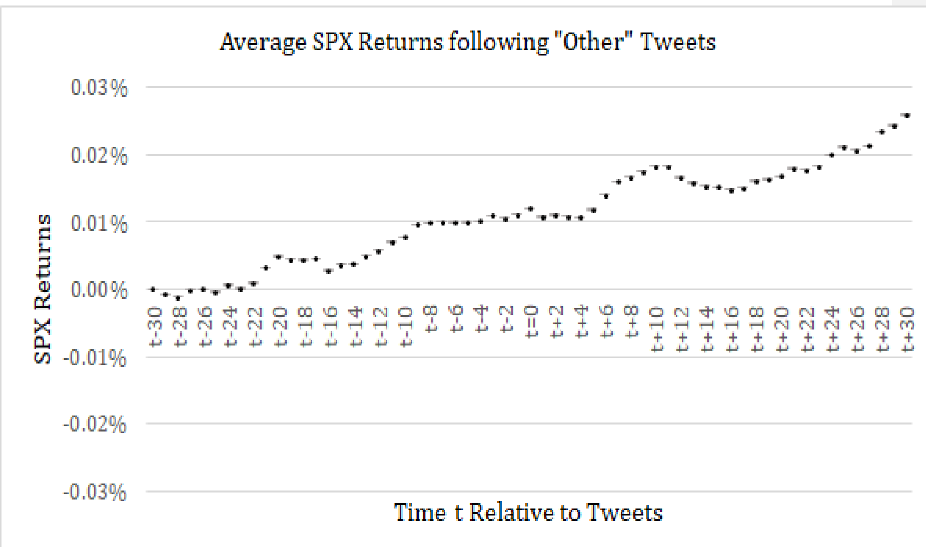

Figure 5.7. Average SPX Returns following other tweets.

The returns of the VIX following other tweets show similarities to VIX returns following all tweets. On average, a 10.4 basis point drop follows the tweet over the course of the event window. Like the VIX returns for all tweets, the average VIX returns for other tweets generally inverse SPX returns.

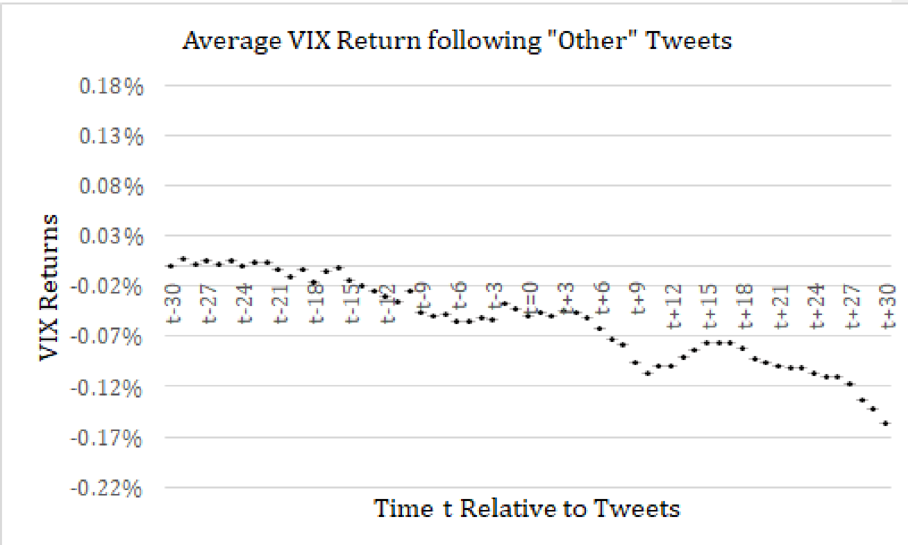

Figure 5.8. Average VIX Returns following Other Tweets

Stock market pricing and volatility following other tweets as measured by SPX and VIX returns seem to primarily mirror the results of all tweets. This makes sense as other tweets make up the bulk of the sample.

CONCLUSION

This section will summarize my results and conclusions while also addressing potential areas for future research.

Recap of Results and Analysis

Through my analysis of President Trump tweets during market hours from his inauguration, January 20, 2017 through October 31, 2019, my research data suggests that his tweets, in general, do not seem to impact stock market pricing or volatility as measured by SPX and VIX returns. Using an hour-long window, returns did not produce consistently significant results to reject the null hypothesis that his tweets do not impact stock market pricing of volatility as measured by SPX and VIX returns.

However, his tweets concerning the Fed did seem to have a statistically significant impact on both market pricing and volatility while his tweets related to trade had a statistically significant impact on market volatility. The impact of tweets related to trade could be explained by market participants taking different amounts of time to price in positive and negative news for firms within the S&P 500. The impact of tweets related to the Fed, coupled with Bianchi et al. research that pointed to a lack of Fed independence, could mean that market participants believe less Fed independence negatively impacts S&P 500 firms (2019).

Future Research

Future analysis could be expanded in a number of ways. This section will cover potential research using sentiment analysis, additional groupings, and the incorporation of futures trading data, as well as a few ways for researchers to take a deeper look into trade-related and Fed-related tweets.

Examining the sentiment of each tweet could help refine results as the pricing and volatility impact of a positive tweet regarding American trade may differ from the impact of a negative tweet. Market participants might also incorporate the impact of negative tweets quicker or slower than the impact of positive tweets. Categorizing tweets by sentiment would allow researchers to document this phenomenon and better observe the time market participants take to respond to tweets. Future research could also incorporate the degree of the sentiment expressed by President Trump's tweets in the form of superlatives, adverbs, and other devices. The impact of tweets in my analysis, especially trade-related tweets, may have been drowned out by equal distributions of positive and negative tweets within the groupings, a limitation that sentiment analysis could alleviate. Going off this, future research could also examine the different variance of returns among groupings, although the different number of tweets in each grouping may limit any potential conclusions from this.

Another way to evaluate the impact of President Trump's tweets would be to incorporate futures trading as a means to gauge market reactions. Given that most of his tweets from his January 2017 inauguration through his October 2019 occurred outside normal trading hours, adding futures data would expand the number of tweets in each grouping significantly. A larger sample size may result in different conclusions for some of the groupings and could also facilitate the addition of more groupings of tweets. Future researchers could add groupings related to his own impeachment hearings, the 2019 government shutdown, Covid-19 or other relevant events occurring during his term. These additional groupings could facilitate the use of alternate measures to evaluate market impact. Future research could also examine the impact of President Trump's tweets on a more granular basis by using trade-by-trade data rather than a minute-by-minute event window.

Given the minimal pricing impact of President Trump's tweets related to trade, future research could take a more refined look into this impact. Grouping S&P 500 firms by their exposure to international trade could give a more nuanced look into the impact of President Trump's tweets related to trade. Researchers could also use a more industrial-heavy index like the Dow Jones Industrial Average. Using industry groupings of S&P 500 firms could also achieve similar results. Researchers could also use exchange rates of currencies used by countries mentioned in President Trump's tweets to gain a more encompassing understanding of the impacts of the tweets.

Similar approaches could be taken to achieve a fuller understanding of the impact of President Trump's tweets related to the Fed. Using fed funds futures as a barometer for market reaction like research by Bianchi et al. is one potential avenue (2019). Future researchers could also incorporate the pricing impact on safe haven commodities such as gold. Grouping S&P 500 firms by industry or exposure to changes in interest rates could also give a more targeted view to analyze the impact. President Trump also continues to mention the Fed in his tweets, so further analysis might reach different conclusions.

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