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A Modern Take on Market Efficiency: The Impact of Trump's Tweets on Financial Markets

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Abstract

We focus on the role of social media as a high-frequency, unfiltered mass information transmission channel and how its use for government communication affects the aggregate stock markets. To measure this effect, we concentrate on one of the most prominent Twitter users, the 45^{th} President of the United States, Donald J. Trump. We analyze around 1,400 of his tweets related to the US economy and classify them by topic and textual sentiment using machine learning algorithms. We investigate whether the tweets contain relevant information for financial markets, i.e. whether they affect market returns, volatility, and trading volumes. Using high-frequency data, we find that Trump's tweets are most often a reaction to pre-existing market trends and therefore do not provide material new information that would influence prices or trading. We show that past market information can help predict Trump's decision to tweet about the economy.

Keywords: Market efficiency, Social media, Twitter, High-frequency event study, Machine learning, ETFs.

JEL classification: G10, G14, C58.

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1 Introduction

Over the last few years, we have seen the influence of social media growing in various walks of life, from the role of targeted Facebook advertising on the outcome of government elections, to the Twitter-fueled Capitol riots of January 2021, or the recent GameStop trading frenzy that started from a Reddit investor forum. This latter event highlights that understanding the impact of social media on financial markets should warrant significant academic and regulatory attention.

In this paper, we focus on the role of social media as a high-frequency, unfiltered mass information transmission channel, and how its use for government communication affects financial markets. We direct our attention to one of the many prominent politicians on Twitter, the 45^{th} President of the United States (POTUS), Donald Trump Jr. After sorting circa 1,400 of his tweets related to the US economy into topics and classifying their textual sentiment by machine learning algorithms, we analyze the aggregate stock market impact of these messages.

Our primary interest is to investigate whether these tweets contain *relevant financial information*, i.e., whether they affect prices, trading volumes or market volatility and how these effects depend on topics and tonality of tweets. We examine high-frequency, minute-level returns and trading volumes of the S&P 500 exchange-traded fund (SPY ETF) and changes in VIX index (Δ VIX). ETFs help us capture market-wide effects, as a well-diversified portfolio is less likely to be driven by idiosyncratic, firm-level events. Moreover, the liquidity and widespread accessibility of ETFs allow both institutional and retail investors to actively trade them.

The key result of this paper is that Trump's tweets are most often a *reaction* to pre-existing market trends, and therefore do not provide material new information that would influence prices or trading. Panel A of Figure 1 illustrates a market trend before Trump's tweets for the example of tweets with negative sentiment about the US economy. This finding confirms that the US stock market is informationally efficient in that it can filter out relevant pricing information from a multitude of diverse voices provided by social media. We present evidence that the Twitter account of the head of the executive branch in the US, who is protected by his presidential immunity and has access to proprietary information that he could "leak" ahead of traditional official channels, is an attention-worthy news source, but the market carefully weighs individual tweets for their information content.

[Figure 1 around here]

A consistent finding across various topics and textual sentiment specifications is that current market prices are more likely driven by past market information rather than Trump's tweets. The exception are tweets about the US-China and US-Mexico Trade Wars, and NAFTA, where Trump has direct involvement in the decision-making or negotiations. Therefore, his opinion on these matters, broadcast in high frequency and without passing through formal government channels and/or news intermediaries, is more likely to contain new information that is relevant for the stock market. The remaining majority of his messages, however, fail to provide content that would lead to price discovery or elicit any other aggregate market reaction.

We use various methods to corroborate our main finding. The high-frequency event studies primarily help to pin down the instantaneous price effect (or lack thereof). In addition, we present matched-sample regressions to control for pre-existing market trends, where matching event windows with non-tweet windows allows us to disentangle the tweets' effect from intraday cyclicality. We also postulate that Trump's tweets do not arrive purely randomly, showing that they are somewhat dependent on past market information. Exploiting this feature, we further show that the timing of tweets is predictable to a certain extent and that tweets, for the most part, do not induce a change in prices or trading. Using stepwise regressions in which we control for a potential relationship of sentiment and past returns, we corroborate our main result that pre-tweet market information is often more relevant than tweet contents and sentiment.

By studying how the executive branch's official communication through social media affects financial markets, we contribute to two main branches of the literature: (i) the effect of social media networks on financial markets, and (ii) how news and government communication is incorporated in financial markets or, more broadly, market efficiency.

The nascent literature on how various forms of social media platforms could deliver information to financial markets is diverse. While some papers focus on investment professionals (Antweiler and Frank, 2004; Bar-Haim et al., 2011) or retail investor message boards (Das and Chen, 2007; Chen et al., 2011), there is an increasing number of studies highlighting the effect of Twitter in revealing investable information (Ranco et al., 2015; Ali, 2018). Our study is closest to those that analyze how Donald Trump's tweets affect the stock prices of individual companies (Born et al., 2017, among others) or different facets of financial markets (Bianchi et al., 2019; Klaus and Koser, 2021; Colonescu, 2018; Filippou et al., 2020). Our paper is complimentary to this strand of literature in that we consider (i) a large number of tweets about the general economy instead of tweets about individual companies, (ii) we provide results for a wide range of tweets across several sub-topics and textual sentiment instead of focusing on a selected number of tweets about a single topic (i.e. mentioning or criticizing monetary policy conduct of the Federal Reserve or tariffs and trade, as in Bianchi et al., 2019 or Filippou et al., 2020); and (iii) we capture market-wide return, volatility and volume effects relevant for a wide range of investors.

Our study also contributes to the literature on official government communication, such as macro announcements or central bank communication, by presenting a complimentary channel (i.e. Twitter) often used by government officials. The financial market impact of the official government communication channels is well established. Andersen et al. (2003b), Kuttner (2001) and Bernanke and Kuttner (2004), among others, study the market effect of macroeconomic announcements, while numerous papers document how central banks, mainly the Federal Reserve's (Fed) communication and potential monetary policy surprises, influence stock returns domestically (Cieslak et al., 2019; Cieslak and

Vissing-Jorgensen, 2020) or internationally (Correa et al., 2020; Cieslak and Schrimpf, 2019). We examine a quasi-official government communication channel, which, despite its different source and nature, still delivers official messages to the electorate and financial investors alike. This is different from traditional official modes of communication that tend not to reach a wide range of investors directly. The extraordinary feature of social media communication is that it eliminates traditional news intermediaries and thereby allows for access to a wide audience directly and instantaneously. We document that some of Trump's tweets have a significant market impact and might affect trading, but the market seems to be able to filter out "true information" from frequent, potentially noisy messages.

The remainder of the manuscript is outlined as follows: Section 2 provides a detailed account of why social media as a quasi-official communication channel warrants attention and how its impact should differ from traditional news sources. Section 3 describes the Twitter and high-frequency ETF data and presents descriptive statistics. In Sections 4 to 7, we describe the multitude of methods that help us quantify the financial market impact of Trump's tweets, namely event studies (Section 4), matched sample regressions (Section 5), Heckman selection model (Section 6), and stepwise regressions (Section 7).[1] Section 8 concludes that we do not find a significant and long-term aggregate impact on financial markets.

2 Measuring the market impact of social media

The market impact of news on financial markets through official communication channels, such as central bank communication, has been thoroughly studied. For instance, a growing literature segment focuses on official government communication channels and their effect on foreign exchange (Almeida et al., 1998; Andersen et al., 2003b), interest

[1]In Online Appendix A, we provide technical details for the machine learning algorithms. Online Appendix B presents examples for tweets along the topic-textual sentiment spectrum and Online Appendix C contains results from additional robustness tests for Sections 4 and 5.

rates (Kuttner, 2001) and stock markets (Bernanke and Kuttner, 2004). Consistent with this notion that official government communication is informative to financial markets, Correa et al. (2020) document that the sentiment of central banks' financial stability reports is also suggestive in predicting banking crises. Moreover, new empirical findings indicate that policymakers take the current state of stock markets into account and that the tonality in which it is discussed is predictive of the ensuing monetary policy course (Cieslak and Vissing-Jorgensen, 2020).

Although these traditional and/or official news channels constitute a primary information source for some investors, others, including retail investors, could learn about information indirectly. One such indirect source could be media or news coverage, such as the Wall Street Journal or on television, i.e. Fox Business or Jim Cramer's Mad Money on CNBC. The presence and tone of news coverage, especially that in television or print media, has been shown to be an important determinant of stock prices (Fang and Peress, 2009; Engelberg and Parsons, 2011; Dougal et al., 2012; Hillert et al., 2014). Alternative sources of information are financial analysts, investment forums, and message boards. For instance, Antweiler and Frank (2004) document that an increase in the number of messages on Yahoo! Finance increases trading volumes and price volatility. Hu and Tripathi (2016) utilize text mining methods to show that investor sentiment measured in investor forums and in related articles from Google Finance both predict future stock returns at the individual firm level, but to a varying extent.

An alternative news channel that appeared and proliferated over the past decade is that of social media. Social media platforms offer a widely accessible and direct news source in real-time. In this context, tweets posted by the POTUS constitute quasi-official government communication that is not passed through traditional information channels or news intermediaries. In other words, Trump's tweets are considered official presidential communication, but come from another source. Moreover, the President's Twitter account fulfills a special dual role: firstly, it is employed to directly, frequently and instantly communicate with the electorate. Secondly, economic messages are broadcast regularly, also targeting investors and financial market participants.

The increasingly pivotal role of social media as an information channel is reflected by the amount of recent studies on the subject. Among the first studies is that of Das and Chen (2007), who measure retail investor sentiment on online stock message boards, and the work by Bollen et al. (2011) that inspects how Twitter mood predicts stock returns. Similarly, Chen et al. (2011) show that social media posts and their comments can help predict future stock returns and company earnings surprises. Jiao et al. (2020) compare the effect of social and news media coverage on stock price volatility and turnover, and present evidence that social networks often repeat news, which some investors interpret as genuinely new information. Behrendt and Schmidt (2018) support the notion of a general relation of Twitter sentiment and stock returns. They report co-movement of intraday price volatility for Dow Jones constituent companies and Twitter sentiment and activity. However, these results are not supported out-of-sample, leading the authors to question the usefulness of Twitter-based stock price predictors, at least in the context of a profitable high-frequency trading strategy. Ranco et al. (2015) dispute that a relation of Twitter sentiment and stock returns on Dow Jones constituent companies holds generally, finding that it can only be established during peaks of Twitter volume.

The closest to our study in the growing literature on the financial market impact of Donald Trump's social media activity are those of Bianchi et al. (2019) and Filippou et al. (2020). Bianchi et al. (2019) document that Donald Trump influences FOMC meeting outcomes through influencing investors' expectations by his pre-FOMC meeting tweets. This is a rather indirect channel, where an official's Twitter activity affects other government or policy decisions. To ensure that we are only measuring the direct financial market impact of government social media communication, we exclude FOMC meeting/press conference days from our sample. Filippou et al. (2020) study the effect of Trump's tweets on the foreign exchange market, and find that the tweets reduce speculative trading. Our focus is on the equity market, where the presence of retail investors and social media followers is likely more prominent than in foreign exchange markets. While they consider similar (although less) tweet topics than our analysis, our approach is distinctly different in two aspects, namely (i) that we specifically study the asymmetric market reaction to both positive and negative tweets within and across topics, and (ii) that our minute-level analysis allows for more precise measurement of the tweet-effect, as opposed to the hourly frequency used in Filippou et al. (2020). Overall, the key difference between this study and others in the literature is that we examine the period preceding the tweets, and show that past market information helps predicting Trump's decision to tweet about the economy, thereby outweighing the average tweet's information content.

Further evidence has been provided that the presence of social media facilitates information acquisition, thereby decreasing its time-associated and monetary costs. If this holds true, material information posted on social media should improve the price efficiency of financial markets, as presented in the seminal work by Fama (1970) and Beaver (1981). Nevertheless, this information channel offers no free lunch, since the multitude of noisy messages has to be filtered and processed at a speed similar to that of their arrival in order to generate profitable trading opportunities, consistent with the idea of Grossman and Stiglitz (1980).

The latter is essentially the focal point of our analysis: Do Donald Trump's unfiltered messages posted at high frequency deliver material, tradable information to financial markets? If so, do they achieve it so consistently across topics and textual sentiment? We answer these questions by analyzing about 1,400 economy-related tweets, separated into four more granular topics, that vary in the extent to which the president is privy to and could potentially leak information ahead of traditional news sources. In addition to studying the effect of tweet frequency, we are also exploring the importance of tweet tonality, as the prior literature on media coverage found textual sentiment to be an important determinant for the subsequent stock price impact (Bollen et al., 2011; Sprenger et al., 2014; Ranco et al., 2015; Nisar and Yeung, 2018).

3 Data and descriptive statistics

This section presents the data and methodology used in our study. The two main data sources that we rely on are Twitter for Donald Trump's tweets and the Trade and Quote (TAQ) database for high-frequency ETF trade data. We also explain how we collect and process the Tweets by means of machine learning algorithms to extract their topical content and textual sentiment used for the analysis.

3.1 Twitter data

We access all of Donald Trump's tweets, from the handle `@realDonaldTrump`, between the date of his election on November 8, 2016 and December 31, 2018 by combining Twitter's own research and development application programming interface (API) and the Trump Twitter Archive (TTA), a comprehensive collection of Donald Trump's tweets maintained by Brendan Brown.[2]

Our focus is on Trump's own tweets, i.e. non-retweets, that are related to the state and the outlook of the US economy. The entire sample between the date of his election in November 2016 and December 31, 2018 comprises 5,526 tweets, before filtering out any tweets by topic or sentiment. Trump is an exceptionally active Twitter user: in our sample period, on average, he publishes 7 tweets a day (excluding retweets). Given the amount of tweets and the resulting topical diversity, we disentangle them along the textual sentiment and topic dimensions to proceed with our analysis. The following sections briefly present the steps taken to filter and sort Trump's tweets. Online Appendix A provides a more detailed review of the machine learning (ML) algorithms used and their application to our data.

[2]Brendan Brown collects all of Trump's tweets in real-time. This collection facilitates downloading tweets within a specific date range, filtered by retweets and original tweets, or selecting certain topics to download.

3.1.1 Topic modeling

In order to specifically analyze the effects of Trump's tweets about the economy on financial markets, we first group the tweets by assigning them to content-based topics. One possible method to assign topic labels would be the use of unsupervised ML algorithms such as Latent Dirichlet Allocation (LDA), where given the number of topics, the algorithm determines their content (see Loughran and McDonald (2016) or Grus (2019), for instance). Russell and Norvig (2016) point out that this method can result in arbitrary topic assignment, which is not suitable for our purposes. Therefore, we implement a semi-supervised topic model (Gallagher et al., 2017). This approach grants us a higher level of control over the resulting topic assignment in that we can provide the algorithm with a list of seed terms. We obtain the list of seed terms directly from Trump's tweets and for the resulting topics, we ultimately verify correct topic assignments by hand.

The outcome of this topic decomposition is depicted in Figure 2. As mentioned above, we use only tweets restricted to economic content for this analysis. The four topics resulting from the decomposition are the following: (1) *Economy, Federal Reserve and Stock Markets*, (2) *(Un-)Employment, Job Creation, American Industries and Production*, (3) the *US-China Trade War* (and later trade agreement), and (4) *US-American and North American Trade Relations*, especially concerning NAFTA and trade or tariffs between the US and Mexico or Canada. Taken together, these four topics make up the category of *Economy Tweets* that helps capturing the average economic tweet effect.[3]

[Figure 2 about here]

After filtering out the non-economic tweets from the full sample of 5,526 tweets, the four final topics of interest assigned by the topic model together amount to 1,399 tweets excluding retweets. Since our topic model allows multiple topic assignments, tweets can

[3]Due to non-overlapping windows, this category comprises less tweets than the sum of individual-topic tweets.

be assigned to more than one topic. Trump also often posts multiple tweets on the same topic (and with the same tonality) in close succession. Since these sequences of tweets practically constitute a single message, we always use the first tweet of such chains and thereby account for potentially overlapping event windows. Consequently, the number of tweets is much larger than the number of events. Panels A and B of Table 1 show the tweet sample composition across topics for all tweets and events, respectively. Figure 3 additionally depicts the monthly average proportion of tweets that are devoted to each of the four topics analyzed over the sample period.

[Table 1 and Figure 3 about here]

At a sample size of 615, most of Trump's tweets with economic content concern the general state of the Economy, (the Fed's) monetary policy, and stock markets (*Economy, Fed and markets* topic). *Employment, industries and production* tweets account for 306 of all *Economy* tweets, and 253 (225) of Trump's economic-content tweets concern international trade and Trade Wars between the US and China (the US and Mexico or NAFTA). As explained above, the number of event tweets in our analysis is lower at 228 (*Economy, Fed and Markets*), 135 (*Employment, Industries and Production*), 78 (*US-China Trade War*) and 88 (*NAFTA/US-Mexico Trade War*). Pooling across topics yields the *Economy* category with a sample of 1,399 (404) tweets before (after) accounting for overlapping windows. We also observe that Trump has become an increasingly prolific Twitter user over time: the total number of *Economy* tweets has almost doubled from 481 in 2017 to 811 in 2018. Figure 3 shows that topics are also seasonal, i.e. they are more or less important to Trump and his followers at different points in time, and might be more or less represented in Trump's tweets.

3.1.2 Sentiment analysis

The prevalent methodology used in the Finance literature to classify textual sentiment is based on financial word dictionaries (see the seminal work of Loughran and McDonald, 2011, 2015, 2020). Since Trump's tweets neither contain highly technical language nor specific finance jargon, this approach is less suitable for our purposes. Consequently, we instead resort to an ensemble machine learning model that consists of several algorithms to classify tweet sentiment. We train this model on 30% of the overall non-retweet Twitter data[4], where the tonality for these tweets in the training data is classified as either neutral, negative or positive by three individuals in order to limit subjectivity in tonality assignment. The overall probability score for the three possible sentiment outcomes (negative, neutral or positive) is obtained by equally weighting the probability scores computed by each single ML algorithm in the ensemble.[5]

[Table 2 and Figures 4 and 5 about here]

Figure 4 and Table 2 show the distribution of sentiment across topics. For all topics, Trump posts positive tweets more often than negative ones. Neutral tweets are hardly ever classified by the ML sentiment model, partly due to the strongly polarized language in Trump's posts, and due to the machine learning classification's difficulty to balance the output proportions for the under-represented outcome labels in the training data.[6]

The descriptive statistics of sentiment across topics displayed in Panel A of Table 2 are based on the probability scores instead of labels: For each tweet, the machine learning algorithm computes the predicted probability to have positive, negative or neutral tonality. Tweets are assigned the tonality for which their predicted probability is highest, and the sentiment scores presented in Table 2 correspond to these predicted probabilities. The *Economy, Fed and Markets*, *Employment, Industries and Production*, *NAFTA/US-Mexico Trade War* and *US-China Trade War* topics have average sentiment

[4]Here, overall Twitter data refers to all of the 16 initial topics identified in Trump's tweets, not only the four with economic content ultimately used in the paper. This approach ensures that the training data is as diverse and unbiased as possible.

[5]Examples of tweets are presented in Table B1 in Online Appendix B to illustrate how topics and sentiment scores are classified by the machine learning algorithms.

[6]Such an under-representation, if present in the training data, tends to be exacerbated in the predicted labels. This does not, however, pose a major issue for the purpose of this analysis, since it is most likely that the tweets with higher sentiment could contain the most relevant information for the aggregate stock market.

scores of 36.54, 60.17, 30.97 and 31.06%, respectively. Sentiment scores also vary over time. The most extreme negative and positive sentiment score values range from -85.37 to 87.36% (for the *Economy, Fed and Markets* topic). Over the sample period, Trump posted a higher number of positive tweets, as displayed in Panel B. While the average sentiment of his tweets was fairly positive overall at about 45% in 2016 and 2017, it greatly reduces by 2018 to 30.58% as President Trump progressively tweets more (Panel C of Table 1).

Figure 5 shows that, in addition to posting more frequently, Trump also contradicts himself more often in terms of textual sentiment. We define sentiment reversal as a sudden change in textual sentiment from one tweet to the next within a topic, i.e., when a positive sentiment tweet is followed by a negative one, or in reverse. Both the increase in tweets posted and the frequency of sentiment reversals suggest that Trump might not offer information relevant for prices, but merely introduces more noise.

3.2 ETFs

To understand the impact of tweets on the equity market, we use the SPY ETF transaction data. SPY was launched by State Street Global Advisors in 1993, and is one of the longest-traded and most liquid ETFs of the world. Tracking the S&P 500 market index through the SPY ETF allows investors, both institutional and retail, to have a well-diversified and tradable exposure to the overall stock market. There is no minimum investment threshold to trading ETFs, which greatly reduces barriers to investing in them. It is also more affordable to invest in the SPY ETF in contrast to directly investing in its constituent companies, as it involves lower trading cost (Ben-David et al., 2018).

These features render ETFs an ideal testing ground to study the market-wide and aggregate social media price impact, for two reasons: Firstly, with an average bid-ask spread of 0.41 basis points over our sample period the SPY ETF is a very liquid instrument. Therefore, it should quickly and precisely reflect new information. Ernst (2021) find that the liquidity of the SPY ETF can reach such desirable levels that it not only contributes to market-wide price discovery, but it also facilitates the price discovery processes of individual stocks. Secondly, to study the impact of social media on financial markets, ETFs are attractive instruments, as they are highly accessible to the average investor and their widespread appeal is likely to extend to social media followers as well. Although, until recently, the academic literature was divided as to whether ETFs could be considered an appropriate vehicle to reflect changes in the underlying assets' fundamentals, the general consensus today is that ETFs facilitate price discovery.[7]

We extract the ETF transaction data from the Trades and Quotes (TAQ) dataset. We construct minute-level volumes by aggregating the trading volume over each minute, and price data by using the latest trade of every minute. Resorting to the last trade of every minute compared to the value-weighted average price (VWAP) is advantageous for our purposes of understanding the effect of information dissemination on prices. VWAP would take the average of all trades within each minute, which means that for tweets occurring in the middle of minutes, stale prices would be used to evaluate market effects.

3.3 Descriptive statistics

Our primary analysis relies on 30-minutes windows before and after each tweet, and similar time windows on other non-tweet days as the reference points. The event study methodology applied in this manuscript is described in the following (Section 4.1).

Table 3 provides summary statistics for the market indicators we use over the 30-minute periods. All variables for the SPY ETF are shown in Panel A. The 30-minute cumulative returns are computed as follows:

$$C\hat{A}R_{i,j(T)}(T_1, T_2) \;=\; \sum_{t\,=\,T_1}^{T_2} R_{it}, \tag{1}$$

where $C\hat{A}R_{i,j(T)}(T_1, T_2)$ stands for cumulative abnormal return for tweet j over the event

[7]For the academic debate on the role of ETFs in price discovery, see Hasbrouck (2003); Yu (2005); Bhattacharya and O'Hara (2018); Ben-David et al. (2018); Glosten et al. (2021), among others.

window from the tweet minute T_1 to minute T_2. R_{it} denotes the return for ETF i at the end of event-window minute t. We construct log-volumes similarly by aggregating minute-level volume data to 30-minute cumulated sums and then reporting the logarithm value. For the calculation of realized volatility over 30-minute periods, we rely on 5-minute returns to reduce the potential of overestimating volatility due to microstructure noise.[8] Panel B shows the summary statistics for the VIX index level and its cumulated changes over 30-minute windows.

[Table 3 and Figure 6 about here]

The box plots in Figure 6 depict the distribution of cumulative returns, split by tweet tonality, across event window lengths. Panel A shows the distribution of positive (left) and negative (right) cumulative returns on the SPY ETF following Trump's tweets. Panel B displays analogous figures for cumulative changes in the VIX index. All Panels present distributions for cumulative returns (changes in the VIX) from the minute when tweets occur until 15, 30, 60, and 120 minutes after. In each panel, the rightmost box plot shows distributions for an event window spanning the tweet minute until end of the day (EOD). We present a more formal test of these figures in Section 4.

4 High-frequency event study

4.1 Methodology

To empirically test whether Trump's Twitter activity has a statistically significant impact on the stock market, measured by changes in the SPY ETF and VIX indices, we conduct a high-frequency event study following Brooks (2019) and compute cumulative returns following Equation 1 above.

[8]For more details and potential solutions to this issue, see Andersen et al. (2003a), Bandi and Russell (2008), and Andersen and Benzoni (2008), among others.

In our high-frequency setting, we do not adjust actual returns by expected returns since expected returns should be very close to zero at the minute-level. At such a short period, any considerable permanent movement should be driven by the market adjusting to new information rather than any risk premium.[9] For each topic and sentiment, we test whether the time-series averages of these tweet-level $C\hat{A}R_{i,j(T)}$ are significantly different from zero using HAC-robust standard errors. This average $C\hat{A}R_{i,j(t)}$, or $AC\hat{A}R_{i(T)}$, estimates the overall market reaction to all of Trump's tweets within the same topic and sentiment.

To test for the speed of the stock market's reaction, we present our results for event windows of differing lengths, as shown in Figure 7. The $AC\hat{A}R_{i(T)}$ tested for statistical significance in the event studies are cumulated over the [0,15], [0,30], [0,60] and [0,120] windows, where [0,T_2] denotes the event window from minute 0, when the tweet is posted, to minute T_2 after the tweet. We also present results from cumulating returns from the tweet minute until the end of the trading day, denoted as [0,EOD] in the tables.[10]

[Figure 7 about here]

We also consider a series of different event window lengths for two reasons: First to assess how fast information gets incorporated into the market, and second, to observe how lasting an impact the tweets have thereon. We work with non-overlapping windows so as not to capture potential market reactions to several tweets within the same event window. For tweets of the same topic and sentiment and a given event window, we therefore use the first tweet based on the identifying assumption that information content might be highest for these tweets.

If tweets contain information relevant to the economy, they should be followed by price discovery in the equity market. For the [0,EOD] event studies, we examine if a tweet elicits a strong and sufficiently persistent market reaction to affect the end of day closing price, and therefore use the maximum-sentiment tweet that occurs within each topic-sentiment

[9] Therefore, $C\hat{A}R_{i,j(T)}$ with an expected return $ER_{it} = 0$ correspond to CR, or cumulative returns.

[10] We record tweet timestamps at the second level, so we set the tweet minutes to the next full minute for all tweets.

specification on any given day. Although we are aware of the caveats of using longer event windows, answering the above questions contributes to our understanding of how high-frequency, direct communication channels, like social media, impact the aggregate financial market. In the following, we refer to these event study results and corresponding $AC\hat{A}R_{i(T)}$ as post-tweet results.

Additionally, we examine whether price trends already manifesting in the market before Trump's tweets might be the driving factor behind potential post-tweet market reactions, by also presenting results for the symmetrical pre-tweet event windows for the [-120,0), [-60,0), [-30,0) and [-15,0) pre-tweet periods. Similarly to the [0,EOD] analysis, we also present results for price movements from the previous-day closing price until the minute before tweets, denoted as ([EOD_{t-1},0)). All of these pre-tweet event windows elapse from the beginning of the event window until one minute before tweets so as not to capture instantaneous market reactions to Trump's tweets, potentially driven by algorithmic trading based on real-time social media trading rules.[11] In our analysis we are excluding tweets that mention single companies as our focus is on market wide effects.

4.2 Event study results

In this section we present the results of the high-frequency event studies for the SPY ETF and the minute-level VIX series. In all tables, we consider the individual tweet topics described in Section 3.1 and the category of *Economy Tweets*, and contrast the market's reaction to tweet tonality by separating positive and negative tweets. This separation is important, as we expect the market to respond differently to how the message is delivered, especially considering the fact that tweets are not pre-scheduled events where a directional drift would be expected. Consequently, averaging the reactions could give a

[11]One example for this would be the US-American technology and marketing company T3, which implemented a trading bot based on Trump's tweets after noticing that companies which are specifically mentioned therein, most often negatively, subsequently experience plummeting stock prices. Based on this observation, T3 has developed the *Trump and Dump Bot* in 2017. The software automatically shorts stocks mentioned in Trump's tweets, realizing significant gains since its inception (https://www.t-3.com/work/the-trump-and-dump-bot-analyze-tweets-short-stocks-save-puppies-all-in-seconds).

biased estimate of how investors process and evaluate the information content potentially conveyed by these tweets.

To determine the market impact of Donald Trump's tweets, we study the market-wide reactions by evaluating the cumulative returns on the SPY ETF (subscript SPY in the tables) right after a tweet's arrival and over various event windows. In this post-tweet window, we evaluate the size, direction and duration of the price effect. In Tables 4 and 5, we present the results for the period from the Q4 2016 to Q4 2018, excluding FOMC conference and announcement days. In the tables, the various $AC\hat{A}R_{i(T)}$ values are tested against zero, where the t-tests are based on Newey-West standard errors. Panels A and B separate the positive and negative-sentiment tweets, respectively.

In Table 4, we find that positive tonality tweets rarely elicit a market reaction, irrespective of the tweet topic or the length of the event window. The exceptions are the tweets on *Economy, Fed and Markets* and *Employment, Industries, Production* topics in a two-hour post-tweet window, where we find an impact smaller than an average 12.763 basis points change that can be measured in comparable non-tweet event windows (not tabulated). This effect is only present in the longer event windows, not the shorter ones, which can either be due to the slow incorporation of information into prices or the presence of confounding events in the observation period. The event study framework, however, does not allow us to disentangle these explanations.

Shifting our focus to negative tweets, the strongest reaction is triggered by the *US-China Trade War* tweets, where it is present for about 30 minutes following the tweet. This effect is most likely driving the corresponding result for the *Economy Tweets* category for the same event window. One would expect the market to react stronger to tweets with the most impactful information, which is likely the case for tweets about trade relations between the US and China, where POTUS takes a leading role in bilateral trade negotiations and therefore has the ability to deliver material information to the market through his tweets, often ahead of traditional communication channels. However, from both positive and negative sentiment directions we can infer that the average tweet effect, if any, is short lived, as none of the topics would shift prices to the extent that would impact the end of day closing prices ([0,EOD]).

[Tables 4 and 5 about here]

To understand any pre-tweet trends in the market, we perform pre-tweet placebo analyses, and report the results in Table 5. Based on evidence from Figure 1 (Panel A), we observe that tweets could often be reaction to pre-existing market trends. Therefore, we investigate whether the market is already moving in a given direction prior to the tweet's arrival, i.e. in the pre-event window. The latter would suggest that Trump is not disseminating new, material information to the market, but either amplifies, or potentially attempts to reverse, ongoing market trends. Across tweet topics and event windows of differing lengths, our results indicate that the SPY ETF might start moving prior to a tweet's arrival. Nevertheless, this analysis does not provide strong and causal evidence that tweets react to pre-existing market trends. To assess this, we need a framework that allows for controlling for both past and contemporaneous information, which we present in Section 5 with our matched sample regression analyses.

Generally, Donald Trump's social media activity could impact the market in two ways: it could either induce price discovery when material information is released by the tweets, or it could increase the uncertainty about the future performance of the stock market. The latter aspect is captured by VIX index. In this study, we use minute-level index values and focus on changes in the VIX index in a setup similar to the previous section. Tables 6 and 7 present the results of post and pre-tweet event studies of the effect (measured in basis points) of tweets on VIX index during the sample period from Q4 2016 to Q4 2018, excluding FOMC announcement days. In the tables, the cumulative changes in the VIX index over various event windows are tested against zero, where the t-tests are based on Newey-West standard errors. Panels A and B separate the positive and negative sentiment tweets, respectively.

[Tables 6 and 7 about here]

The results presented in Panel A of Table 6 indicate that positive-sentiment tweets pooled across topics do not have an immediate effect on the VIX index. However, we find a longer-term price impact on market volatility. We observe that the average tweet effect, captured by *Economy Tweets*, is the strongest with a 32.672 and 102.822 basis point drop in the index value over a two-hour and the end of the trading day event windows, respectively. Similarly, the *Employment, Industries, Production* tweets trigger large drops in the VIX, ranging from 58.624 to 271.833 basis points. *Economy, Fed and Markets* tweets trigger around 38.981 basis points drop in the VIX and the effect stays the same for both longer-term windows. The average change in VIX over a 30-minute non-tweet window is 3.8 basis points, making these effects seem economically large, although we cannot rule out the influence of confounding market events, especially in the absence of a shorter-term effect. In contrast, in Panel B, we observe short-term VIX reactions for the *Economy Tweets* category, the *Economy, Fed and Markets*, and the *US-China Trade War* topics and negative tweet sentiment. These tweets are consistently associated with an increase in VIX, by 21.876 (*Economy Tweets*) to 53.441 (*US-China trade war*) basis points over the first 15 to 30 minutes following the negative tweet on the respective topic.

We explore pre-existing cumulative changes (ACAR in basis points) in VIX in different pre-tweet windows in Panel B of Figure 1 and Table 7. The results of Table 7 Panel A indicate that for the majority of topics, there is no pre-existing drift in the index. In Panel B, we observe that preceding negative-sentiment tweets, volatility often goes down significantly, by about 47.645 basis points on average (*Economy Tweets*) and ranging from −83.162 to −153.607 basis points in the two hours before the tweet. There is also suggestive evidence that market volatility is experiencing a decrease on days when tweets occur, but reverses within the 15 minutes prior to the tweet's arrival. It is possible that the news which were anticipated by the market were revealed, hence the reversal. We observe this pattern for most topics, albeit not statistically significant with the exception of *NAFTA/US-MEX Trade War*.

4.2.1 The effect of changing sentiment

Analyzing the sentiment of the presidential tweets naturally raises the question of how the market reacts to sudden changes in tweet tonality. We observe that although certain topics tend to have a dominant sentiment, there is still variability, as presented in Table 2 and Figure 4. In this section, we focus on these changes in tweet tonality, more specifically, when i) sentiment suddenly changes from one tweet to the next within a topic (sentiment reversal), or ii) when the absolute magnitude in sentiment change is large (sentiment surprise). The corresponding results are reported in Panels A and B of Table 8, respectively.

[Table 8 about here]

Panel A of Table 8 reports the results for sentiment reversal. For most tweet topics, and on average, changing sentiment (in either direction) does not elicit a significant reaction on the SPY ETF, with the exception of tweets about the *Economy, Fed and Markets.* This is pointing in the direction of the findings of Bianchi et al. (2019), who show how Donald Trump's tweets might impede central bank independence by influencing market expectations about monetary policy around FOMC announcements.

In Panel B, we shift our focus to sentiment surprises, which are defined as the residual from an AR(5) process imposed on within-topic sentiment. This analysis considers tweets to exhibit surprising sentiment if their sentiment score is at least one standard deviation larger (smaller) than the average of the distribution proposed by the AR(5) sentiment model. Looking at the effect of large sentiment surprises, we find that the direction of the shift matters: rather consistently, the SPY ETF tends to increase with large positive surprises, except for the *US-China Trade War* tweets, where the SPY ETF price drops by 9.336 basis points. For this specific topic, large negative surprises have a similar, yet smaller effect.

Overall, the results of the event studies suggest that the market filters out tweets that contain potentially material information, and only reacts to those. However, it also suggests that tweets do not arrive fully randomly and that market dynamics preceding tweets play an important role in the subsequent response. Since event studies do not offer a suitable framework to account for these features, in the next sections we implement additional tests, such as the matched-sample regressions (Section 5), and a Heckman-style two-stage model (Section 6) to demonstrate that tweets are predicted by past market movements. Finally, in Section 7 we present a stepwise regression model in order to evaluate whether there is correlated information contained in either sentiment or current market prices that is unaccounted for in past stock market and tweet information.

5 Matched sample regressions

In this section, we follow up on the evidence from previous analysis illustrated in the panels of Figure 1, and the pre-tweet placebo analysis, which both suggest that Trump is more inclined to react to market trends than markets react to to his tweets for the majority of the cases. We conduct regressions of current market information on sentiment dummies, past market information, as well as their interactions. Such a setup allows us to formally examine the potential relation between tweets and returns, realized volatility or trading volumes for the SPY, as well as changes in the VIX, while controlling for the past value of those variables of interest.

We match each event by a counterfactual event window for pre- and post-tweet return (realized volatility, trading volume, change in VIX) randomly sampled from days on which Trump does not tweet about the topic in question. This procedure allows us to estimate the effect of Trump's tweets while directly contrasting it with market conditions in the absence of tweets. The matching-sample pre- and post-tweet return (realized volatility, trading volume, change in VIX) is drawn randomly but from the exact same time of day (minute level) on a day other than the tweet day. This method allows us to separate the effect of tweets from that of intra-day cyclicality.[12]

5.1 Methodology

We perform matched-sample regressions to account for past and contemporaneous information, therefore formally testing whether Trump's tweets are driving, or rather are driven by market dynamics. To this end, we regress post-tweet CAR on the corresponding pre-tweet CAR and tweet sentiment dummies, thereby controlling for market events preceding tweets and tweet sentiment. These within-topic regressions provide evidence as to whether tweets, captured by their sentiment, can explain post-tweet returns, or whether past price information is the determining factor. If pre-tweet returns explain their post-tweet counterparts, then ultimately the tweets do not carry relevant information beyond what is already incorporated in past prices.

In our regressions, we additionally control for time-of-day effects by matching to each pre- and post-tweet window CAR the same-time CAR sampled randomly from another non-tweet day. These counterfactual returns serve as time-matched controls for intraday seasonality and facilitate estimation of the effect of Trump's tweets on changes in SPY ETF and VIX index levels. This methodology is in the spirit of Kirilenko et al. (2017) on the Flash Crash of 2010. The regression results presented in the main body of this paper are based on 30-minute pre- and post-tweet event windows.[13]

We present regression results for each of the four topics and our four variables CAR_{SPY}, ΔRV_{SPY}, $\Delta\ VOL_{SPY}$ and cumulative ΔVIX as follows:

$$\begin{aligned}\hat{V}_t = \beta_0 + \beta_1 \cdot V_{t-1} + \beta_2 \cdot D_+ + \beta_3 \cdot D_- \\ + \beta_4 \cdot V_{t-1} \cdot D_+ + \beta_5 \cdot V_{t-1} \cdot D_-,\end{aligned} \tag{2}$$

[12] Moreover, we remove all *Economy Tweet* days from the counterfactual sample. We do this so as not to capture effects that actually follow from tweets on another topic.

[13] In Online Appendix C, we additionally present results for extended pre-tweet windows of [-120,0)

where V_t denotes the post-tweet return (change) variable of interest and may either be cumulative returns, realized volatility or cumulative change in trading volumes (Δ VOL) for the SPY ETF, or cumulative changes for the VIX index. V_{t-1} denotes the corresponding pre-tweet value, captured by the first lag of the variable. As mentioned above, all pre- and post-tweet returns are matched with randomly sampled same-time counterfactual non-tweet returns. D_+ and D_- are tweet sentiment dummies equal to one if a tweet is positive or negative, respectively. Since we remove the few neutral tweets from the regression data, the intercept, β_0, can be interpreted as the intercept on the variable of interest at non-tweet times for the matched sample.

5.2 Matched sample regression results

Panel A of Table 9 displays the results from regressing 30-minute post-tweet CAR_t for the SPY ETF on 30-minute pre-tweet CAR_{t-1}, dummies indicating whether the respective tweet has positive (D_+) or negative (D_-) textual sentiment, as well as the interaction of the latter with pre-tweet CAR_{t-1}. In all tables, statistical significance is assessed by t-tests using Newey-West standard errors.

In line with the event studies, the only instance where tweet information has a statistically significant influence on CAR_t is for the *US-China Trade War* topic and negative tweets. When Trump tweets negatively about the *US-China Trade War*, CAR_t decreases by 7.475 basis points over the 30 minutes following tweets (statistically significant at the 10% level). The interaction of negative tweets and pre-tweet CAR_{t-1} is also negative and highly statistically significant at the 1% level, suggesting that when a negative-tonality tweet follows a one basis point higher positive return, the current CAR_t drops by 0.311 basis points.

Conversely, this interaction term is associated with a statistically significant increase in post-tweet CAR_t for negative tweets about the *Economy, Fed and Markets*. This positive reaction could be driven by two factors: either by momentum, in which case the previously positive market trend would be more of a driving factor than the negative tweet sentiment, or it might indicate that markets rely more on the already existing trend rather than following tweets, which is consistent with the slow release of information to markets via other informal communication channels (Cieslak and Schrimpf, 2019, for instance).

A similar effect can be found for the overall *Economy* tweet category, for which the interaction of pre-tweet CAR_{t-1} with the negative tweet indicator variable is again positive at 0.318 and is statistically significant at the 1% level. For the *NAFTA/US-Mexico trade* topic, only past return information captured by CAR_{t-1} exhibits a statistically significant and negative influence on post-tweet returns, confirming that Trump's tweets do not convey new information for this topic.

[Table 9 about here]

The overall equity price reactions to Trump's tweets seems limited, which is why we investigate if there are other ways his tweets could influence the market, such as through trading volumes, realized price volatility, or the VIX index, which proxies (forward-looking) uncertainty. Therefore, we present results from regressing changes in trading volumes and realized volatility on the same set of regressors, namely pre-tweet market conditions and tweet sentiment dummies, within each of the topics of interest.

The results for changes in cumulative 30-minute trading volumes are highly consistent across topics, and are displayed in Panel B of Table 9. In all specifications, the influence of pre-tweet volumes as well as their interaction with both positive and negative tweet dummies is highly statistically significant at the 1% level. These positive coefficients on the interaction terms, irrespective of the tweet tonality, suggest that volumes are more affected by past volumes than by Trump's tweets. The tweet examples in Table B1 in Online Appendix B showcase how he advocates *pro* tariffs, especially in the case of US trade relations to Mexico, and *pro* leaving the NAFTA. It is likely that financial markets discount this opinion, considering the potential disadvantages that leaving a trade agreement and imposing restrictive tariffs on major US trade partners could entail.

The matched-sample regression results for the realized volatility of the SPY ETF, reported in Panel C of Table 9, are similar to those for volumes: tweet information is hardly ever an influential factor in determining period t changes in realized volatility over the 30 minutes following Trump's tweets, suggesting these tweets do not contain new information to the market that would translate to price discovery. The only exception are positive tweets about *Employment, Industries and Production*, which are associated with a 1.071 basis point increase in realized volatility. Across topics, we find that due to the persistent nature of realized price volatility, its past value is the only consistently statistically significant explanatory variable.

Table 10 presents corresponding results for cumulative changes in the VIX index. Given that Trump's tweets do not influence returns or trading, they still could affect investor expectations about the future performance of the stock market or uncertainty. Overall, we find that the VIX indeed reacts to Trump's tweets: for all but the *Economy, Fed and Markets* topics, negative tweets are associated with a sizable and statistically significant increase in the VIX, ranging from 40.064 basis points for the pooled *Economy* tweet category to 111.872 basis points for the *Employment, Industries and Production* topic in the 30-minute window following the tweets. These effects are not only economically but also statistically significant at the 5 and 10% levels, respectively. For the *NAFTA/US-MEX trade* topic, positive tweets are also associated with an increase in the VIX index of 66.189 basis points, which suggests that any tweet about this topic significantly increases uncertainty.

[Table 10 about here]

We test the robustness of the regression results. First, we account for the changing relative importance of tweet topics, as shown in Figure 3, by including time fixed effects at the quarterly frequency. The baseline results are robust to the inclusion of quarterly time fixed effects and can be found in Tables C2 and C3 in Online Appendix C. Second, we employ the same matched-sample method as in our baseline regression specifications, but with a longer, 120-minute pre-tweet period. This approach incorporates a longer time period for Trump to react to news, as opposed to the 30-minute benchmark in Tables 9 and 10. These results are qualitatively similar to the benchmark and can be found in Tables C4 and C5 in Online Appendix C.

Taken together with the previously described lack of significant market reactions for the SPY returns, trading volumes and realized volatility, we find that Trump's tweets do not provide information that influences market prices and trading activity. Rather, the increases in forward-looking implied volatility captured by the VIX imply that they introduce short-term noise. If Trump's tweets are not informative but more often a reaction to ongoing market events, however, the past dynamics might forecast when Trump is going to tweet. We explore this possibility in the next section, and additionally control for the non-random tweet arrival in a Heckman-type two-stage model.

6 Heckman Selection Model

A consistent finding across various topics and textual sentiment specifications is that current market prices and trade indicators are more likely driven by past market information rather than Trump's tweets. This section builds on this observation by examining the non-random nature of Trump's tweets and by showing that they are dependent on market information. Exploiting this feature could help us study the return and trading effect of the already anticipated tweets.

6.1 Methodology

In this section we formally test the predictability of Trump's tweets and its effect on the previously showed results by using a model similar to that of the Heckman selection model (Heckman, 1979). In the first stage, we predict the probability that Trump tweets about the *Economy, Fed and Markets*, *Employment, Industries and Production*, or the *US-China* and *US-Mexico* trade wars using observable and high-frequency past stock market information, namely lagged returns of the SPY ETF index and lagged VIX index levels. Then in the second stage, we add the Inverse Mills Ratio derived form the estimated probabilities from the first-step probit regressions to the baseline matched-sample regression specifications. This allows us to control for the potentially non-random occurrence of Trump's tweets.

6.2 Heckman model results

In the first stage of the Heckman model, we predict the probability of Trump publishing a tweet for each 30-minute event window using past stock market information. For parsimony, we use lagged cumulative returns on the SPY ETF and changes VIX levels as predictors, although unreported results indicate that extreme values of these variables also perform well in forecasting a tweet's arrival.[14] We report the results of the analysis in Table 11, where marginal effects calculated at the mean of the respective variables are displayed in percentage points.

[Table 11 about here]

An increase in cumulative returns of the SPY ETF by one basis point in the preceding period is associated with a 0.376, 0.528 and 0.492% increase in probability that Trump will tweet in period t about any of the pooled *Economy* category, the *Economy, Fed and Markets*, or *Employment, Industries and Production*, respectively. While these effects are statistically significant, their economic magnitude is also nontrivial, as they are calculated for 30-minute intervals. Similarly, an increase in cumulative Δ VIX by one basis point before tweets increases the likelihood that Trump will tweet about the respective topic in

[14]While we realize that Trump's decision to tweet most likely follows from a many factors and therefore could be hard to predict accurately and "completely", our model demonstrates that both lagged returns and changes in VIX are *influential predictors* of Trump's tweets. Since these stock market indicators are observable to investors, they could also surmise and therefore anticipate a presidential tweet's arrival.

the following period (next 30 minutes) by 0.043, 0.054 and 0.072% for the *Economy, Fed and Markets*, *Employment, Industries and Production* and *US-China Trade War* topics. The probability that Trump will tweet about any of the four topics in the *Economy* category, displayed in the *Economy* column of Table 11, is increased by 0.038% when lagged Δ VIX increases by one basis point. These results are in line with our previous findings that, for certain topics, Trump reacts more to markets than they do to him. This notion is corroborated especially for the *Economy, Fed and Markets*, *Employment, Industries and Production* and *US-China Trade War* topics. For the *US-China Trade War* and SPY, as well as the *NAFTA/US-Mexico Trade War* topic for both the SPY and the VIX, however, past market prices cannot significantly predict when Trump posts a tweet. In these instances where Trump has authority to influence future political and/or economic outcomes, such as for both of the trade wars, the inability of past market prices to predict tweets about these topics, indicate that his tweets eventually bring material price information to the market.

In the next step, we compute the Inverse Mills Ratio (IMR) and include it in the baseline regression specifications as an additional regressor. This achieves two objectives: Firstly, we account for potentially non-random tweet observations. If Trump's tweets are not random, neither is the sentiment upon which the post-tweet return might depend. In that light, including the IMR can help assess the robustness of our previous results from the benchmark matched-sample regressions to non-random tweet arrival. Secondly, we control for the potential predictability of Trump's tweets to see how this may affect our baseline results. Both objectives serve to further separate instances where markets react to Trump's tweets from those where markets are influenced by their own past information, i.e. lagged returns (or realized volatility or volumes). The results for SPY CAR, trading volumes and realized volatility are in Panels A, B and C of Table 12, respectively. We present analogous results for changes in VIX in Table 13.

[Table 12 about here]

After controlling for tweet predictability, we find that the majority of our baseline regression results remain unchanged. This finding is especially strongly pronounced for the SPY return and Δ VIX regressions. For SPY and cumulative returns, the coefficients on tweet tonality, D_+ and D_-, remain statistically insignificant in all cases, with the exception of the negative tweets about the *US-China Trade War*, where the drop of 7.899 basis points is statistically significant at the 10% level. This decrease is similar in magnitude, 7.475 basis points, for the baseline regressions in Table 9. The interactions of tweet sentiment dummies and past CAR retain their benchmark sign, magnitude and level of statistical significance as well.

Results for changes in volumes for the SPY ETF after controlling for the predictability of Trump's tweets exhibit the same levels of statistical significance and magnitude for the same set of regressors, but with a flipped sign relative to the baseline results presented in Panel B of Table 9. The consistently *negative* and highly significant effect of past volumes on current values across topics is now mirrored by *positive* coefficients of the same sign. Analogously, the previously established *positive* influence of the interactions of past volumes and tweet sign dummies is again highly statistically significant and similar in magnitude, but *negative* across topics. This difference between the benchmark and the selection-corrected specifications suggests that investors account for the anticipated tweets and their effect in their trading behavior.

The results for realized volatility of the SPY ETF are also similar to the baseline. After controlling for tweet predictability, previous realized volatility remains the strongest influencing factor on current values of realized volatility, and retains its consistently positive and highly statistically significant coefficient, ranging from 0.501 (*NAFTA*) to 0.882 (*Economy*) category, all significant at the 1% level. For the pooled category of *Economy* tweets, the interaction term of pre-tweet realized volatility becomes statistically significant at the 10% level and is associated with a decrease in ΔRV in period t by 0.309 for positive tweets.

In the baseline regressions, tweet dummies were statistically insignificant across topics, except for tweets about *Employment, Industries and Production*, where positive tweets led to an increase in realized volatility of 1.071 basis points (statistically significant at the 1% level). After inclusion of the Inverse Mills Ratio, this effect is diminished in magnitude and statistical significance (0.453 basis points, statistically significant at the 10% level). In addition, negative tweets are associated with a 3.321 basis points decrease in realized volatility after accounting for tweet predictability.

[Table 13 about here]

We find that Donald Trump's negative tweets, controlling for tweet predictability via the Inverse Mills Ratio, remain associated with an increase in VIX during the 30-minute post-tweet window for the *Employment, Industries and Production* and both trade war topics (110.893, 94.208 and 77.850 basis points). For the latter Trade War topic (US-Mexico/NAFTA), positive tweets are also associated with an increase in VIX by 63.087 basis points, significant at the 1% level. Consistent with the baseline regression results, we find that negative tweet sentiment is associated with an increase in volatility for all but the *Economy, Fed and Markets* topics. This suggests that negative tweets carry more noise than material information to the market.

7 Stepwise regressions

In the final test for the information content of presidential tweets, we illustrate the role of past information as the common component amongst tweet sentiment and post-tweet returns or ΔVIX, and then test the association between the two after controlling for this past information. This test gives us an indication of whether pre-tweet market information and/or tweet sentiment is more informative in explaining current market conditions.

7.1 Methodology

In order to analyze whether past sentiment (sen_{t-1}) can predict information contained in prices, but not explained by past price information, we additionally conduct a stepwise regression for SPY (CAR) and VIX (cumulative changes), denoted as V_i:

$$\hat{\mathrm{V}_{i,t}} = \beta_0 + \beta_1 \cdot \mathrm{V}_{i,t-1} + \beta_2 \cdot \mathrm{sen}_{t-1} + \varepsilon_{1(i,t)} \tag{3}$$

In a second step, we regress tweet sentiment sen_t on past returns (cumulative changes for VIX):

$$\hat{\mathrm{sen}}_t = \beta_0 + \beta_1 \cdot \mathrm{sen}_{t-1} + \beta_2 \cdot \mathrm{V}_{i,t-1} + \varepsilon_{2(\mathrm{sen},t)} \tag{4}$$

The significance of the coefficient from the last step (β_0), where we regress the residuals from Equation (3) on those from (4), ultimately tells us whether information contained in tweet sentiment can predict past return (cumulative change in VIX) information beyond information already contained in returns (cumulative changes in VIX):

$$\varepsilon_{1\hat{(i,t)}} = \beta_0 \cdot \varepsilon_{2\hat{(\mathrm{sen},t)}} \tag{5}$$

7.2 Stepwise regression results

Table 14 presents the results of the proposed stepwise regressions for SPY (CAR) and VIX (cumulative changes) in Panels A and B respectively.

[Table 14 about here]

The coefficient of interest, β_0 of Equation 5, shows to which extent Trump's tweets contain price-relevant information that cannot be captured by past prices. We see that except for the *US-China Trade War* and both for the SPY ETF and VIX index, none of the coefficients presented in Table 14 indicate that observable past information contained in

Trump's tweets (captured by sentiment), is relevant to explain current market conditions. For the *US-China Trade War* topic, the coefficient of 6.521 for SPY is marginally significant, while the effect is more strongly pronounced for VIX (-62.1513 at 5%).

These findings are consistent with our previous event study and regression results: They corroborate that stock markets differentiate in their reaction to Trump's tweets between topics where he as the President has the power to influence the real economy and government policies, and those where he merely states his opinion, or may be reacting to ongoing market trends. For trade relations with China, the POTUS does have the authority to impose tariffs or negotiate trade deals, whereas he is not able to *directly* influence unemployment figures or the Fed's monetary policy course, for example.

8 Conclusion

In this paper we study the market impact of Donald Trump's Twitter activity by examining a wide range of tweets related to the US economy. After sorting the circa 1,400 tweets into topics and classifying their textual sentiment by machine learning algorithms, we test market impact of these messages. We conduct high-frequency event studies, based on minute-level ETF data on the S&P 500 index and the VIX index, and find that many of the tweets do not elicit an imminent market response, captured either by cumulative returns, trading volumes and the realized volatility of the SPY ETF, or the cumulative changes in the VIX.

The key result of the paper is that Trump himself reacts to pre-existing market trends, which we corroborate by matched sample regressions, as well as by studying the predictability of Trump's tweets. Even after controlling for this tweeting pattern in a Heckman-type two-stage model, we find that current market prices are more likely driven by past market information, rather than his tweets, a finding consistent across various topics and textual sentiment. Although there are tweets that *do have* a short-term market impact, these are mostly related to topics where Trump as the President has a direct involvement in decision making or negotiations, as is the case of the *US-China Trade War*, the stance of the US towards NAFTA, and their relation to North-American trade partners, most prominently Mexico. The remaining majority of his messages about the economy, however, fail to provide content that would lead to price discovery or elicit any other market reaction.

While in this paper we specifically focus on the social media activity of Donald Trump, the phenomenon that we analyze for its potential to impact financial markets extends beyond the influence of any single person, or perhaps even the office that he represents. Since their proliferation in the past decade, social media platforms have begun to provide an unfiltered and direct high-frequency communication channel with both a mass appeal and access. They are therefore undoubtedly going to retain their role as important information outlets for governments, politicians and policymakers alike. To this end, it is imperative that we evaluate the capacity of financial markets to process such frequent and noisy messages in studying their potential market impact.

We find that the US stock market is informationally efficient to the extent that it can clearly separate messages with material information content from the ones without. We show that markets are efficient in considering the Twitter account of the head of the executive branch, who has access to proprietary information and could disclose it through social media, for its value regarding potentially relevant information. However, they also learn over time which topics warrant their attention.

Even though this paper is not to be understood merely as an analysis of Donald Trump himself, his use of social media, especially that of Twitter, provides useful lessons about this novel quasi-official communication channel. Trump is a very active Twitter user, who tweets about a dozen times daily and covers a wide range of topics, thereby providing us with an *extreme case* in terms of the use of this communication tool. Presumably market participants learn to discount the frequency or dilution of the messages, which is why our estimates could be seen as an upper bound of the potential market impact of a very active and prominent user. On the other hand, we should not ignore that as the POTUS, he not only has superior information access and capability to "leak" this information ahead of traditional communication channels, but he enjoys immunity and therefore could actually do so. This special status warrants attention not only to him, but the implied market impact of his messages.

Overall, having studied Donald Trump's Twitter use, we conclude that if his primary objective were to influence financial markets, he had failed to fulfill this goal because his tweets would have had to provide material information for the market to account for them. In other words, the market does not respond to his messages when their content does not go beyond directly observable past price information. On the contrary, it is more likely that Trump's primary aim from the beginning of his political career was to communicate his political agenda and to engage with his voter base and social media following, a goal he successfully accomplished through Twitter until the suspension of his account on January 8, 2021.

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Tables and figures

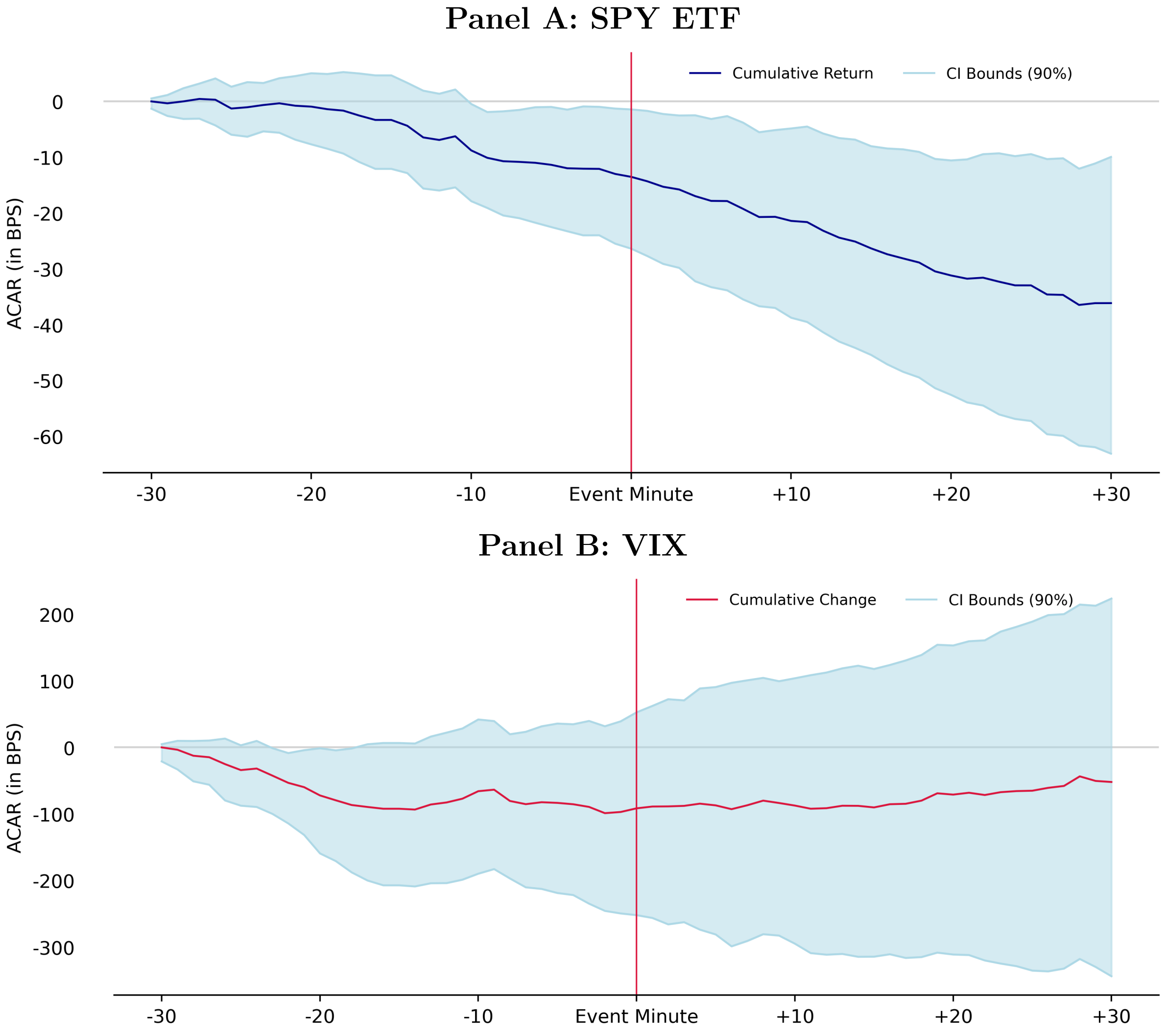

Figure 1 Pre- and post-tweet movements in the SPY ETF and the VIX index

The two panels of the above figure depict the average cumulative returns on the SPY ETF (in Panel A) and the average cumulative changes in the VIX (in Panel B) from 30 minutes prior to 30 minutes after negative tweets about *Employment, Industries and Production.* The figure illustrates that pre-existing market trends are important to consider in the analysis of the potential market impact of Trump's tweets.

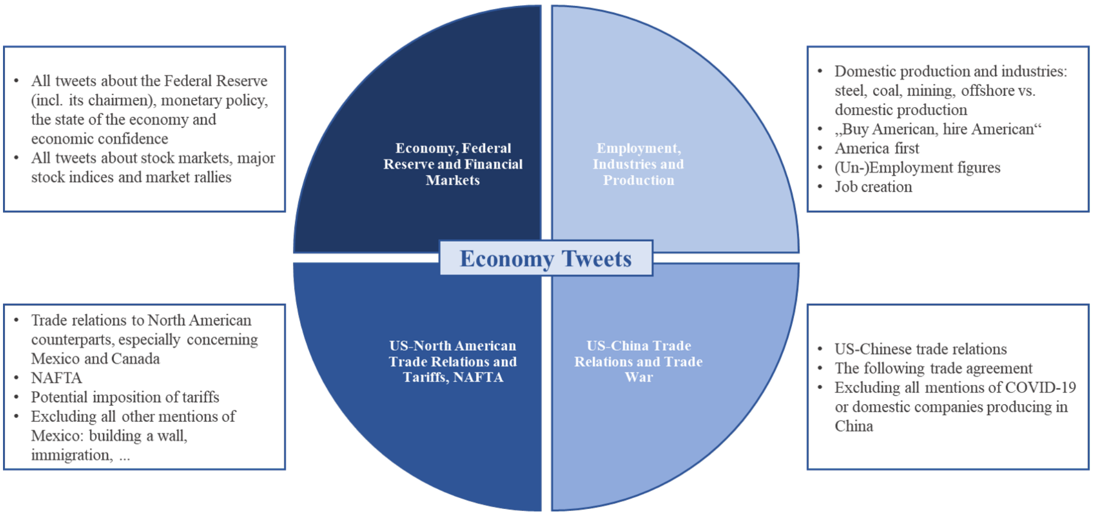

Figure 2 Tweet topics

The above figure depicts the output of the topic modelling ML algorithm. The bubbles list seed terms that correspond to certain topics, based on which the algorithm generates four distinctive tweet topics: (1) *Economy, Fed and markets*, (2) *Employment, Industries and Production*, (3) *US-China Trade War*, and (4) *US-North-American Trade Relations*, or *NAFTA/US-Mexico Trade War* (clockwise from the upper left corner). These topics constitute the category referred to as *Economy Tweets* in this manuscript, a set of all tweets related to the US economy and its international trade relations.

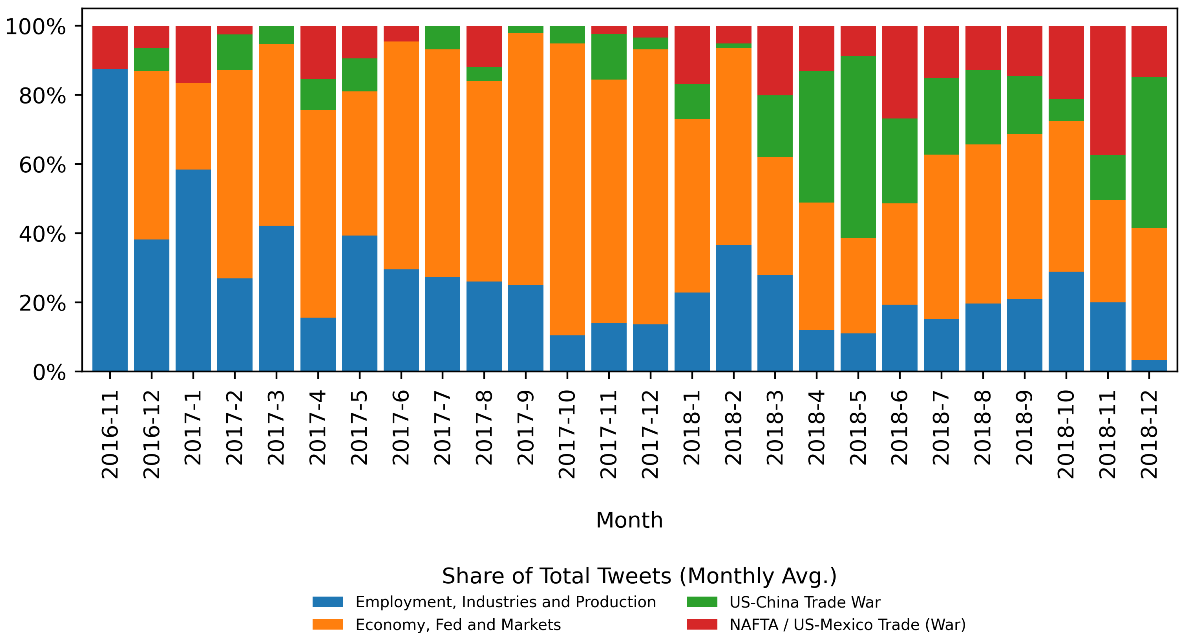

Figure 3 Shares of tweet topics over time

The above figure depicts how the proportion of each of the economy-related topics evolve over time. Each bar represents the full scope of tweets in our sample over a given month, and the colors represent the proportion of the total number of economy-related tweets that Trump posts about one of the four specific topics of interest. The sample spans the period from Q4 2016 to Q4 2018. Tweets are obtained using the Twitter API and from the Trump Twitter Archive.

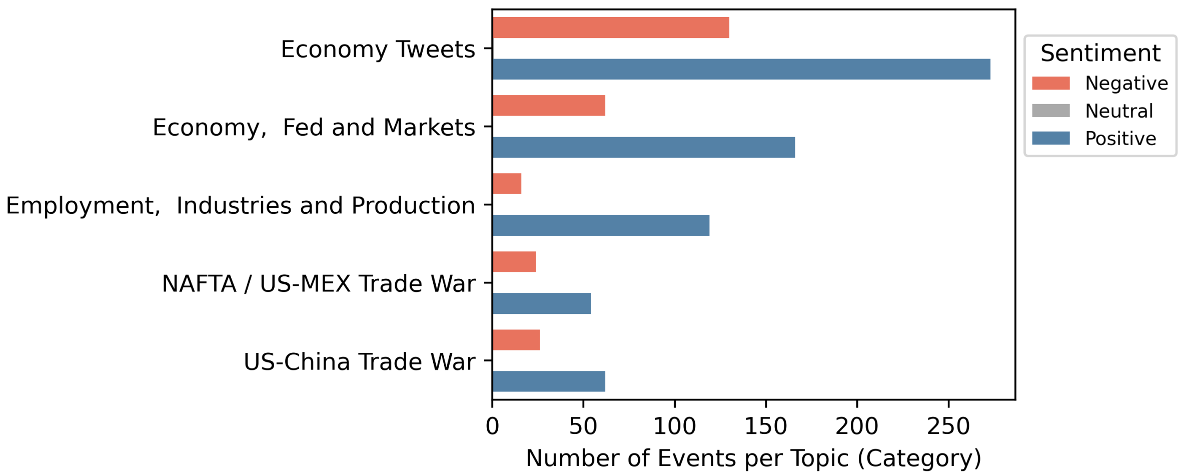

Figure 4 Event distribution along sentiment and tweet topics

The above figure depicts the distribution of textual sentiment over tweet topics, the outcome of the sentiment classification ML algorithm. Red bars represent negative, gray ones neutral, and blue ones positive-sentiment tweets, respectively. Only for the *Economy Tweets* category, there are three neutral tweets in the sample and therefore, the gray neutral-tweet bar is barely discernible. The other topics do not contain neutral tweets. The sample spans the period from Q4 2016 to Q4 2018. Tweets are obtained using the Twitter API and from the Trump Twitter Archive.

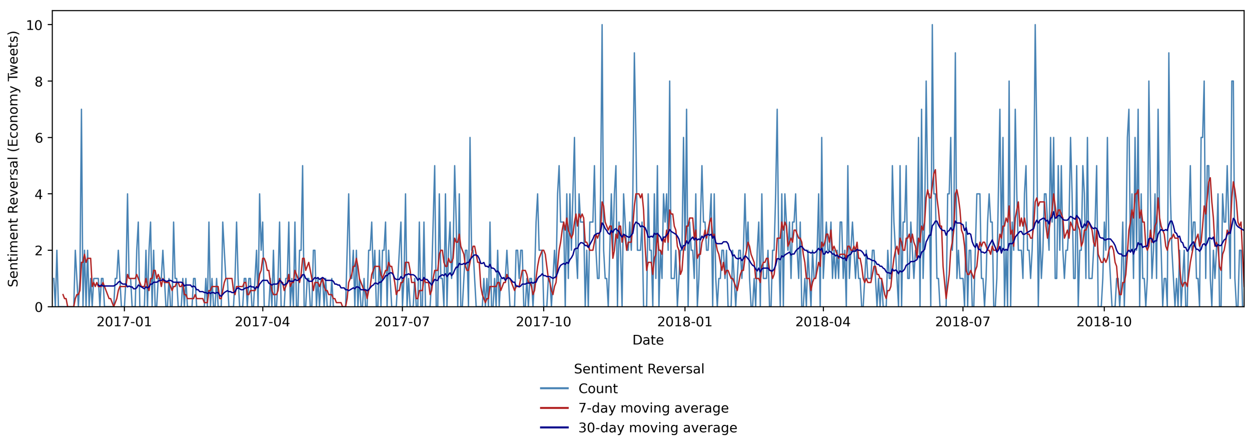

Figure 5 Sentiment reversals

The above figure depicts the time series of sentiment reversals which are defined as a shift in sentiment from one tweet to the next within individual topics. The solid light blue line represents the number of reversals in a day, while the red and dark blue lines show the 7 and 30-day moving average number of daily sentiment reversals, respectively. The sample spans the period from Q4 2016 to Q4 2018. Tweets are obtained using the Twitter API and from the Trump Twitter Archive.

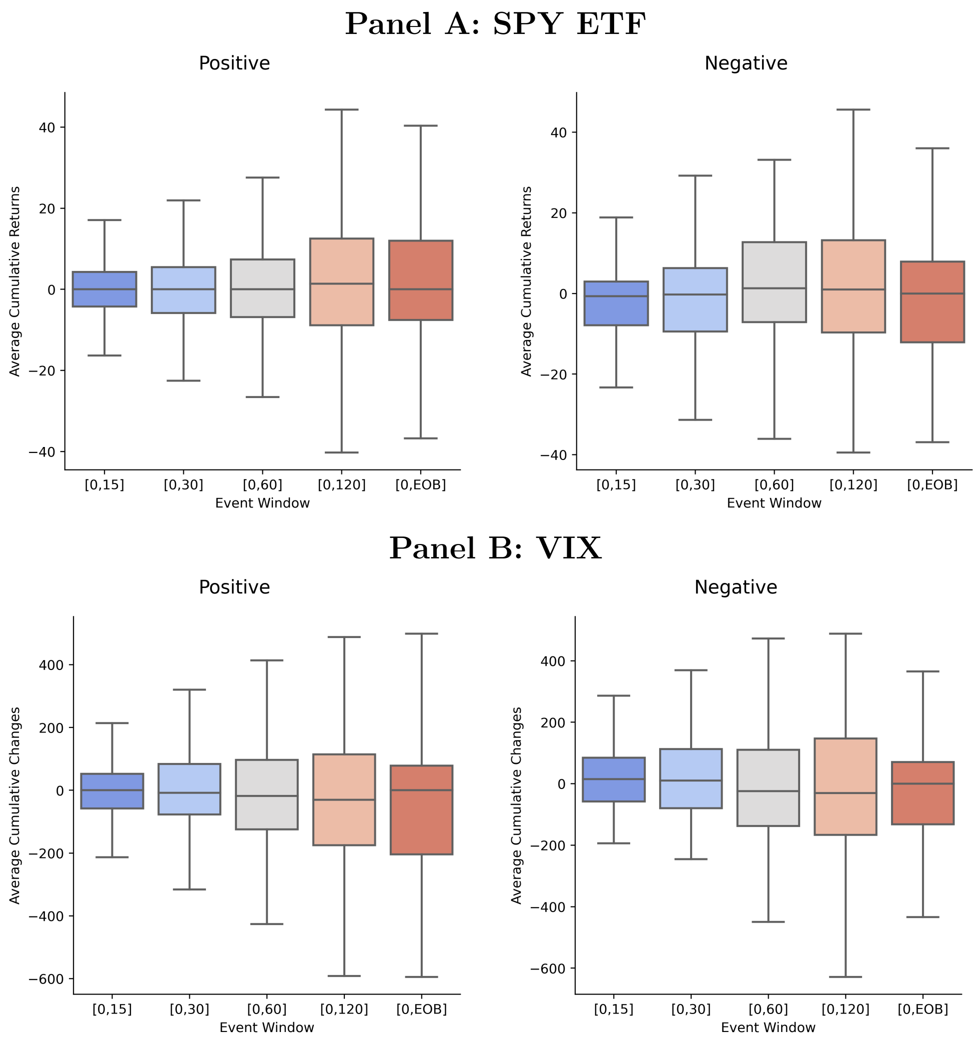

Figure 6 Distribution of CAR and ΔVIX across various event windows

The above figure depicts the distribution of CAR on the SPY ETF and ΔVIX across the event windows in the form of box plots. Panel A presents average cumulative returns for the SPY ETF, split by positive (left panel) and negative (right panel) tweets. Panel B presents the average cumulative changes in the minute-level VIX index, with positive and negative tweets displayed in the left and right panels respectively. The sample spans the period from Q4 2016 to Q4 2018. Tweets are obtained using the Twitter API and from the Trump Twitter Archive. Topics and sentiment scores are assigned based on the machine learning algorithms described in Section 3.1 and Online Appendix A.

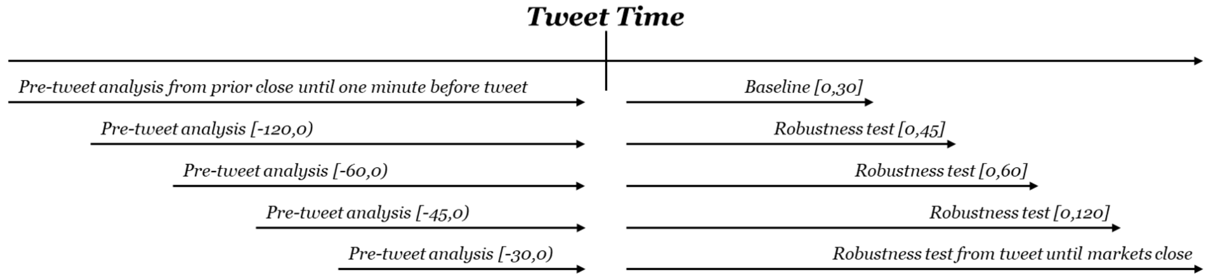

Figure 7 Window lengths for the presented event studies and pre-tweet placebo analyses

The above figure displays the pre- and post-event window lengths we test in our tweet and quasi-placebo event studies. Results for each of the windows depicted above are presented in Section 4.2.

Table 1 Tweet sample decomposition

Sample Period	Economy Tweets	Economy, Fed and Markets	Employment, Industries, Production	US-China Trade War	NAFTA/ US-MEX Trade War
	Panel A: Sample of tweets				
Overall	1,399	615	306	253	225
2016	30	12	14	2	3
2017	481	262	116	29	24
2018	811	341	176	222	198
	Panel B: Sample of event tweets				
Overall	404	228	135	78	88
2016	8	2	2	0	1
2017	155	93	42	10	10
2018	241	133	91	78	67

Note. This table displays the number of tweets in our sample, in full and sampled by year between 2016 and 2018. Panel A shows the complete scope of tweets with economic content, divided by topic and year. Panel B depicts the sample of event tweets, i.e. all tweets within each topic after accounting for non-overlapping event window. Panel B shows the maximum number of tweets used in our event studies and regressions.

Table 2 Tweet summary and sentiments statistics

	Panel A: Sentiment scores by topics				
Topic	Obs.	Min.	Mean	Max.	St.dev.
Economy Tweets	404	-80.009	25.791	80.754	63.562
Economy, Fed and Markets	228	-85.371	36.539	87.361	64.585
Employment, Industries, Production	135	-74.019	60.173	86.861	44.408
NAFTA/ US-MEX Trade War	78	-79.244	30.969	86.858	63.298
US-China Trade War	88	-80.064	31.064	85.900	62.702
	Panel B: Year-by-year sentiment scores				
Year	Obs.	Min.	Mean	Max.	St.dev.
2016	18	-68.640	45.588	81.305	50.654
2017	429	-81.778	45.220	87.361	58.835
2018	878	-85.371	30.582	86.861	63.257

Note: The above table reports the sentiment score summary statistics of the tweets used in this study. Panel A breaks down the sentiment score distribution along topics, while Panel B presents the sentiment scores distribution per year. In Panel A, the observations correspond to the non-overlapping event windows around individual tweets, where the first tweet of chain tweets (tweets in close succession after one another within one topic) are considered, and tweets of other topics as well as retweets are excluded. The sample spans the period from Q4 2016 to Q4 2018, after removal of FOMC press conference and announcement days. Tweets are obtained using the Twitter API and from the Trump Twitter Archive, and the assigned topics and the sentiment scores are assigned based on the machine learning algorithms described in Section 3.1 and Online Appendix A.

Table 3 Market indicators summary statistics

	Panel A: SPY ETF						
Variable	Obs.	Min.	P25	Median	Mean	P75	Max.
Prices ($ US)	211,311	208.479	239.590	258.310	256.615	273.190	293.920
Cumulative Returns (bps)	211,311	-204.545	-6.153	0.672	-0.130	6.845	227.952
Log Volumes	308,499	9.148	14.991	15.644	16.022	17.385	18.892
Realized Volatility (bps)	211,311	0.142	2.463	3.917	5.394	6.596	55.510
	Panel B: High-frequency VIX series						
Variable	Obs.	Min.	P25	Median	Mean	P75	Max.
Index value	211,311	8.910	10.840	12.310	13.839	15.360	49.210
Cumulative change (bps)	211,311	-2241.163	-97.838	-9.078	0.058	85.397	3860.352

Note: The above table reports summary statistics for the SPY ETF and VIX index, in Panels A and B, respectively. The variables in Panel A are minute-level *Price*, as reported in the TAQ database, where the 30-minute *Cumulative return* in basis points is calculated based on Equation 1. *Log Volume* is the natural logarithm of trading volumes, aggregated at the 30-minute level, and *Realized Volatility* is calculated as the 30-minute realized volatility of 5-minute increments, in basis points, as $\mathrm{RV}_{0,30} = \sqrt{\mathrm{CAR}^2_{0,5} + \mathrm{CAR}^2_{6,10} + \mathrm{CAR}^2_{11,15} + \mathrm{CAR}^2_{16,20} + \mathrm{CAR}^2_{21,25} + \mathrm{CAR}^2_{26,30}}$. In Panel B, the *Index value* is the VIX level reported by the data provider, while *Cumulative change* is defined as the change in 30-minute cumulative VIX index changes in basis points. The sample spans the period from Q4 2016 to Q4 2018. The ETF data is obtained from the Trade and Quote database, while the minute-level VIX series is from FirstRateData.com.

Table 4 Event study: SPY ETF returns and tweet tonality

Event Window	Economy Tweets	Economy, Fed and Markets	Employment, Industries, Production	US-China Trade War	NAFTA/ US-MEX Trade War
			Panel A: Positive tweets		
[0,15]	0.083	0.294	0.504	-1.186	-0.825
	(0.11)	(0.38)	(0.46)	(0.99)	(0.55)
	[312]	[175]	[122]	[66]	[54]
[0,30]	-0.088	-1.197	1.228	-0.306	-1.143
	(0.08)	(1.19)	(0.74)	(0.17)	(0.58)
	[299]	[170]	[119]	[64]	[54]
[0,60]	0.522	-0.505	0.968	-0.030	-2.182
	(0.47)	(0.41)	(0.44)	(0.01)	(0.76)
	[286]	[163]	[118]	[64]	[54]
[0,120]	2.166	3.432 **	5.187 **	2.019	-0.972
	(1.45)	(2.00)	(2.09)	(0.48)	(0.28)
	[270]	[158]	[113]	[61]	[53]
[0,EOD]	4.707	0.283	23.558	5.619	-3.940
	(0.92)	(0.11)	(1.49)	(0.93)	(0.56)
	[192]	[113]	[61]	[38]	[34]
			Panel B: Negative tweets		
[0,15]	-2.373 *	-2.683	-3.555 *	-5.734 **	-3.872
	(1.75)	(1.63)	(1.73)	(2.02)	(1.29)
	[159]	[71]	[18]	[30]	[26]
[0,30]	-2.722 *	-0.910	-3.676	-5.979 *	-1.449
	(1.65)	(0.52)	(1.27)	(1.75)	(0.55)
	[149]	[71]	[17]	[30]	[26]
[0,60]	-0.880	1.684	-4.062	-2.013	1.855
	(0.42)	(0.75)	(0.72)	(0.40)	(0.36)
	[148]	[70]	[17]	[30]	[25]
[0,120]	-2.015	1.889	-11.201	2.153	4.441
	(0.68)	(0.42)	(1.24)	(0.23)	(0.45)
	[141]	[69]	[16]	[30]	[25]
[0,EOD]	-5.650	-5.962	-10.658	-5.225	3.932
	(1.20)	(0.77)	(1.30)	(0.57)	(0.44)
	[101]	[57]	[8]	[37]	[37]

Note: The above table presents the results of the high-frequency event studies performed on the SPY ETF returns for various post-event windows. Panel A focuses on the subset of tweets with positive tonality, while Panel B reports the subsample of negative tweets. The sample spans the period from Q4 2016 to Q4 2018. Tweets are obtained using the Twitter API and from the Trump Twitter Archive, while the ETF data is obtained from the Trade and Quote database. Sentiment scores are assigned based on the machine learning algorithms described in Section 3.1.2 and Online Appendix A, whereas the ETF data is aggregated at the minute level following the computation described in Section 3.3. Parentheses report Newey-West standard errors, while the square brackets indicate the number of observations (events) available for the given topic. Statistical significance is denoted by ***, **, * at the 1%, 5% and 10% levels, respectively.

Table 5 Event study: SPY ETF pre-tweet placebo analyses and tweet tonality

Event Window	Economy Tweets	Economy, Fed and Markets	Employment, Industries, Production	US-China Trade War	NAFTA/ US-MEX Trade War
	Panel A: Positive tweets				
[-15,0)	-0.026 (0.05) [318]	0.019 (0.02) [179]	1.035 (1.07) [104]	1.069 (0.83) [67]	-1.261 (0.87) [57]
[-30,0)	-0.125 (0.15) [303]	-0.419 (0.37) [171]	1.809 (1.26) [100]	-0.384 (0.22) [63]	-2.935 * (1.67) [56]
[-60,0)	0.214 (0.15) [286]	0.458 (0.31) [163]	1.568 (0.84) [118]	3.299 (1.00) [64]	2.232 (0.53) [54]
[-120,0)	-3.167 (1.45) [270]	0.444 (0.21) [158]	-0.555 (0.22) [113]	4.316 (0.79) [61]	6.418 (1.23) [53]
[EOD$_{t-1}$,0)	-7.974 (1.21) [190]	-0.891 (0.19) [108]	-23.280 (1.42) [60]	-2.140 (0.16) [41]	15.333 ** (2.22) [38]
	Panel B: Negative tweets				
[-15,0)	0.312 (0.27) [159]	0.625 (0.63) [71]	1.451 (0.92) [38]	-0.859 (0.36) [30]	-2.715 (1.38) [26]
[-30,0)	-0.631 (0.45) [153]	-0.307 (0.18) [71]	0.459 (0.20) [38]	2.430 (0.72) [29]	1.023 (0.22) [26]
[-60,0)	0.167 (0.09) [148]	-0.125 (0.05) [70]	7.107 *** (3.33) [17]	1.293 (0.31) [30]	2.267 (0.61) [25]
[-120,0)	6.382 ** (2.00) [141]	2.745 (0.89) [69]	6.060 (0.86) [16]	7.346 * (1.66) [30]	7.399 ** (2.35) [25]
[EOD$_{t-1}$,0)	1.605 (0.24) [88]	-5.265 (0.57) [48]	19.834 (1.49) [5]	-0.944 (0.06) [38]	-12.634 (0.85) [33]

Note. The above table presents the results of the high-frequency event studies performed on the SPY ETF returns for various pre-event windows. Panel A focuses on the subset of tweets with positive tonality, while Panel B reports the subsample of negative tweets. The sample spans the period from Q4 2016 to Q4 2018. Tweets are obtained using the Twitter API and from the Trump Twitter Archive, while the ETF data is retrieved from the Trade and Quote database. Sentiment scores are assigned based on the machine learning algorithms described in Section 3.1.2 and Online Appendix A, whereas the ETF data is aggregated at the minute level following the computation described in Section 3.3. Parentheses report Newey-West standard errors, while the square brackets indicate the number of observations (events) available for the given topic. Statistical significance is denoted by ***, **, * at the 1%, 5% and 10% levels, respectively.

Table 6 VIX post-tweet event studies

Event Window	Economy Tweets	Economy, Fed and Markets	Employment, Industries, Production	US-China Trade War	NAFTA/ US-MEX Trade War
			Panel A: Positive tweets		
[0,15]	0.155	-4.367	1.576	5.614	9.501
	(0.02)	(0.47)	(0.15)	0.540	0.740
	[312]	[175]	[122]	[66]	[54]
[0,30]	0.307	6.845	-6.244	-7.691	18.629
	(0.03)	(0.47)	(0.410)	(0.480)	(0.930)
	[299]	[170]	[119]	[64]	[54]
[0,60]	-18.774	-6.718	-19.246	-4.287	36.242
	(1.25)	(0.40)	(0.87)	(0.20)	(1.00)
	[286]	[163]	[118]	[64]	[54]
[0,120]	-32.672 *	-36.794 *	-58.624 *	-36.322	10.728
	(1.87)	(1.70)	(1.70)	(1.15)	(0.30)
	[270]	[158]	[113]	[61]	[53]
[0,EOD]	-102.822 **	-38.981	-271.833 *	-65.951	-43.036
	(1.99)	(1.35)	(1.70)	(1.26)	(0.85)
	[192]	[113]	[61]	[38]	[34]
			Panel B: Negative tweets		
[0,15]	21.876 *	26.679 **	19.726	32.487	19.337
	(1.81)	(2.12)	(0.96)	(1.35)	(0.74)
	[159]	[71]	[18]	[30]	[26]
[0,30]	28.366 *	16.758	66.378	53.441 *	19.343
	(1.81)	(0.97)	(1.64)	(1.96)	(0.58)
	[149]	[71]	[17]	[30]	[26]
[0,60]	21.605	1.403	79.074	3.340	-13.364
	(1.01)	(0.07)	(1.05)	(0.0)8	(0.23)
	[148]	[70]	[17]	[30]	[25]
[0,120]	15.596	24.348	139.784	-58.707	-62.117
	(0.55)	(0.86)	(1.38)	(0.89)	(0.84)
	[141]	[69]	[16]	[30]	[25]
[0,EOD]	37.153	60.809	32.313	-47.138	-84.697
	(0.52)	(0.55)	(0.52)	(0.80)	(1.39)
	[101]	[57]	[8]	[37]	[37]

Note. The above table presents the results of the high-frequency event studies performed on the VIX index for various post event windows. Panel A focuses on the subset of tweets with positive tonality, while Panel B reports the subsample of negative tweets. The sample spans the period from Q4 2016 to Q4 2018. Tweets are obtained using the Twitter API and from the Trump Twitter Archive, while the ETF data is retrieved from the Trade and Quote database. Sentiment scores are assigned based on the machine learning algorithms described in Section 3.1.2 and Online Appendix A, whereas the ETF data is aggregated at the minute level following the computation described in Section 3.3. Parentheses report Newey-West standard errors, while the square brackets indicate the number of observations (events) available for the given topic. Statistical significance is denoted by ***, **, * at the 1%, 5% and 10% levels, respectively.

Table 7 VIX pre-tweet placebo event studies

Event Window	Economy Tweets	Economy, Fed and Markets	Employment, Industries, Production	US-China Trade War	NAFTA/ US-MEX Trade War
			Panel A: Positive tweets		
[-15,0)	1.274	1.494	-4.670	-11.496	3.598
	(0.17)	(0.17)	(0.36)	(0.91)	(0.31)
	[318]	[179]	[104]	[67]	[57]
[-30,0)	1.160	7.873	-14.418	3.920	13.918
	(0.10)	(0.61)	(0.66)	(0.19)	(0.74)
	[303]	[171]	[100]	[63]	[56]
[-60,0)	1.309	1.871	-9.544	-20.015	-17.118
	(0.08)	(0.12)	(0.41)	(0.73)	(0.51)
	[286]	[163]	[118]	[64]	[54]
[-120,0)	17.273	-1.104	3.047	-50.061	-60.798
	(0.65)	(0.04)	(0.09)	(1.12)	(1.14)
	[270]	[158]	[113]	[61]	[53]
[EOD$_{t-1}$,0)	111.514	31.307	269.622	44.998	-69.234
	(1.64)	(0.77)	(1.61)	(0.53)	(0.90)
	[190]	[108]	[60]	[41]	[38]
			Panel B: Negative tweets		
[-15,0)	0.508	-16.756	-7.417	27.137	37.952 *
	(0.04)	(1.30)	(0.36)	(1.29)	(1.86)
	[159]	[71]	[38]	[30]	[26]
[-30,0)	3.683	-22.096	-9.946	-18.105	-37.886
	(0.22)	(1.25)	(0.31)	(0.49)	(0.85)
	[153]	[71]	[38]	[29]	[26]
[-60,0)	6.501	-11.054	-121.752 ***	-23.276	-48.805
	(0.35)	(0.34)	(4.00)	(0.49)	(1.29)
	[148]	[70]	[17]	[30]	[25]
[-120,0)	-47.645 *	-83.162 ***	-153.607 ***	-108.011 **	-135.222 ***
	(1.91)	(3.1)1	(3.15)	(2.54)	(4.98)
	[141]	[69]	[16]	[30]	[25]
[EOD$_{t-1}$,0)	-58.994	-22.893	-110.084	-73.655	-62.109
	(1.05)	(0.34)	(0.81)	(0.58)	(0.44)
	[88]	[48]	[5]	[38]	[33]

Note. The above table presents the results of the high-frequency event studies performed on the VIX index for various pre-event windows, following Equation 1. Panel A focuses on the subset of tweets with positive tonality, while Panel B reports the subsample of negative tweets. The sample spans the period from Q4 2016 to Q4 2018. Tweets are obtained using the Twitter API and from the Trump Twitter Archive, while the ETF data is retrieved from the Trade and Quote database. Sentiment scores are assigned based on the machine learning algorithms described in Section 3.1.2 and Online Appendix A, whereas the ETF data is aggregated at the minute level following the computation described in Section 3.3. Parentheses report Newey-West standard errors, while the square brackets indicate the number of observations (events) available for the given topic. Statistical significance is denoted by ***, **, * at the 1%, 5% and 10% levels, respectively.

Table 8 Event studies: the effect of changing sentiment

Sentiment Reversal Direction	Economy Tweets	Economy, Fed and Markets	Employment, Industries and Production	US-China Trade War	NAFTA/ US-MEX Trade War
	Panel A: Sentiment reversal				
Positive after Negative	-0.843	-4.016 **	1.286	-0.439	2.378
	(0.45)	(2.12)	(0.78)	(0.08)	(0.63)
	[88]	[37]	[29]	[18]	[13]
Negative after Positive	-1.120	1.787	-3.206	-5.380	0.217
	(0.68)	(1.10)	(0.76)	(1.54)	(0.08)
	[112]	[54]	[12]	[24]	[20]
	Panel B: Sentiment surprises				
Positive surprises	5.719 ***	6.404	6.357 ***	-9.336 ***	0.932
	(5.63)	(1.58)	(2.74)	(3.11)	(0.37)
	[16]	[15]	[10]	[11]	[18]
Negative surprises	-0.047	0.444	-6.750	-4.462 *	-1.363
	(0.03)	(0.29)	(1.45)	(1.85)	(0.38)
	[91]	[44]	[11]	[16]	[15]

Note. The above table presents the results of the high-frequency event studies performed on the SPY ETF. Panel A focuses on sentiment reversal, defined as a sudden change in tonality, i.e., switching sentiment from one tweet to the next. Panel B presents the results for large sentiment surprises, where a sentiment surprise is modelled as the residual from an AR(5) process, and the analysis considers those surprises that are at least a standard deviation away from the mean of the sentiment surprise distribution. The sample spans the period from Q4 2016 to Q4 2018. Tweets are obtained using the Twitter API and from the Trump Twitter Archive, while the ETF data is retrieved from the Trade and Quote database. Sentiment scores are assigned based on the machine learning algorithms described in Section 3.1.2 and Online Appendix A, whereas the ETF data is aggregated at the minute level following the computation described in Section 3.3. Parentheses report Newey-West standard errors, while the square brackets indicate the number of observations (events) available for the given topic. Statistical significance is denoted by ***, **, * at the 1%, 5% and 10% levels, respectively.

Table 9 Matched sample SPY regressions

	Economy	Economy, Fed and Markets	Employment, Industry and Production	US-China Trade War	NAFTA/ US-MEX Trade
	Panel A: Returns				
Intercept	-2.584***	-3.590***	-0.809	0.321	0.198
	(0.965)	(1.167)	(1.981)	(0.932)	(1.499)
CAR_{t-1}	-0.097***	-0.043	-0.120	-0.098	-0.222***
	(0.031)	(0.079)	(0.076)	(0.082)	(0.069)
D_+	2.090	2.120	2.276	-0.669	-1.702
	(1.433)	(1.632)	(2.791)	(2.228)	(1.810)
D_-	-0.255	3.027	-5.038	-7.475*	-3.071
	(2.219)	(2.151)	(4.070)	(4.068)	(2.942)
$\text{CAR}_{t-1} \cdot D_+$	-0.151	0.118	-0.440	-0.046	-0.067
	(0.207)	(0.176)	(0.334)	(0.177)	(0.094)
$\text{CAR}_{t-1} \cdot D_-$	0.317***	0.382**	0.212	-0.311***	0.154
	(0.121)	(0.178)	(0.278)	(0.102)	(0.162)
$R^2_{Adj.}$	0.025	0.020	0.072	0.034	0.030
N	728	421	242	165	154
	Panel B: ΔVolume				
Intercept	0.104*	0.041	0.089	0.084	0.053
	(0.061)	(0.060)	(0.087)	(0.070)	(0.055)
ΔVOL_{t-1}	-0.537***	-0.479***	-0.603***	-0.500***	-0.402***
	(0.029)	(0.041)	(0.072)	(0.044)	(0.033)
CAR_{t-1}	0.001	0.004	-0.008**	-0.010**	-0.003
	(0.002)	(0.004)	(0.004)	(0.005)	(0.004)
D_+	-0.032	0.034	-0.020	-0.106	-0.126**
	(0.086)	(0.088)	(0.095)	(0.086)	(0.062)
D_-	0.128	0.094	-0.005	0.030	0.110
	(0.104)	(0.084)	(0.176)	(0.118)	(0.100)
$\Delta\text{VOL}_{t-1} \cdot D_+$	1.282***	1.149***	1.321***	1.370***	1.163***
	(0.071)	(0.086)	(0.094)	(0.091)	(0.088)
$\Delta\text{VOL}_{t-1} \cdot D_-$	1.199***	1.273***	1.371***	1.207***	1.033***
	(0.158)	(0.082)	(0.136)	(0.052)	(0.112)
$R^2_{Adj.}$	0.388	0.324	0.423	0.485	0.297
N	726	419	242	162	153
	Panel C: ΔRealized volatility				
Intercept	0.366*	0.089	-0.165	-0.054	0.069
	(0.213)	(0.103)	(0.201)	(0.153)	(0.129)
ΔRV_{t-1}	0.900***	0.679***	0.744***	0.819***	0.504***
	(0.096)	(0.090)	(0.081)	(0.081)	(0.149)
D_+	-0.093	0.213	1.0711***	0.413	-0.2242
	(0.205)	(0.302)	(0.325)	(0.415)	(0.401)
D_-	0.415	0.537	-1.294	0.190	0.467
	(0.410)	(0.482)	(1.139)	(0.766)	(0.662)
$\Delta\text{RV}_{t-1} * D_+$	-0.190	-0.035	-0.151	-0.151	-0.067
	(0.146)	(0.148)	(0.296)	(0.172)	(0.160)
$\Delta\text{RV}_{t-1} * D_-$	-0.159	0.193	0.337	-0.198	0.009
	(0.187)	(0.158)	(0.267)	(0.263)	(0.309)
$R^2_{Adj.}$	0.507	0.514	0.497	0.525	0.269
N	427	297	200	153	142

Note. The above table reports *Returns*, and changes in Trading volume and *Realized volatility* of the SPY ETF, in Panels, A, B and C, respectively. The regressions are based on a matched sample approach, where the post-tweet event window is matched with a random, non-tweet window to separate the effects of the tweets and potential intraday seasonality. The column names indicate the analyzed tweet topic sample. The explanatory variables with the subscript $_{t-1}$ are lagged variables, where the lag corresponds to the 30-minute window preceding the tweet. D_+ and D_- are indicator variables equal to one for positive and negative tweets, respectively, and zero otherwise. The sample spans the period from Q4 2016 to Q4 2018. Tweets are obtained using the Twitter API and from the Trump Twitter Archive, while the ETF data is retrieved from the Trade and Quote database. Sentiment scores are assigned based on the machine learning algorithms described in Section 3.1.2 and Online Appendix A, whereas the ETF data is aggregated at the minute level following the computation described in Section 3.3. Parentheses report Newey-West standard errors. Statistical significance is denoted by ***, **, * at the 1%, 5% and 10% levels, respectively.

Table 10 Matched sample VIX regressions

	Economy	Economy, Fed and Markets	Employment, Industry and Production	US-China Trade (War)	NAFTA/ US-MEX Trade
Intercept	-6.629	2.283	-43.341**	-31.234***	-47.895***
	(6.926)	(10.578)	(18.086)	(9.584)	(15.825)
ΔVIX_{t-1}	-0.012	-0.083	-0.120	-0.053	-0.139
	(0.040)	(0.065)	(0.090)	(0.098)	(0.140)
D_+	9.234	4.823	33.212	21.830	66.189***
	(13.056)	(15.359)	(24.274)	(18.140)	(22.455)
D_-	40.064**	23.531	113.872*	96.062***	81.204**
	(18.724)	(22.191)	(65.781)	(29.778)	(31.345)
$\Delta \text{VIX}_{t-1} \cdot D_+$	-0.171	0.071	-0.206	0.005	-0.002
	(0.170)	(0.148)	(0.227)	(0.169)	(0.186)
$\Delta \text{VIX}_{t-1} \cdot D_-$	0.098	0.257	0.148	-0.122	0.191
	(0.096)	(0.181)	(0.288)	(0.165)	(0.162)
$R^2_{Adj.}$	0.011	-0.006	0.080	0.022	0.024
N	728	421	242	165	154

Note. The above table reports Cumulative changes, denoted as ΔVIX, of the high-frequency VIX series. The regressions are based on a matched sample approach, where the post-tweet event window is matched with a random, non-tweet window to separate the effects of the tweets and potential intraday seasonality. Each column presents results for the indicated topic. The explanatory variables with the subscript $_{t-1}$ are lagged variables, where the lag corresponds to the 30-minute window preceding the tweet. D_+ and D_- are indicator variables equal to one for positive and negative tweets, respectively, and zero otherwise. The sample spans the period from Q4 2016 to Q4 2018. Tweets are obtained using the Twitter API and from the Trump Twitter Archive, while the ETF data is retrieved from the Trade and Quote database. Sentiment scores are assigned based on the machine learning algorithms described in Section 3.1.2 and Online Appendix A, whereas the ETF data is aggregated at the minute level following the computation described in Section 3.3. Parentheses report Newey-West standard errors. Statistical significance is denoted by ***, **, * at the 1%, 5% and 10% levels, respectively.

Table 11 Heckman selection model: first-stage results

Pr(Tweet = 1)	Economy	Economy, Fed and Markets	Employment, Industries and Production	US-China Trade War	NAFTA/ US-Mexico Trade War
$CAR_{t-1}(SPY)$	0.376**	0.528**	0.492*	0.577	0.264
	(2.52)	(2.46)	(1.79)	(1.52)	(0.73)
ΔVIX_{t-1}	0.038**	0.043*	0.054**	0.070*	0.056
	(2.40)	(1.84)	(2.10)	(1.82)	(1.46)
Pseudo R^2	0.006	0.009	0.011	0.013	0.013
N	807	455	269	175	155

Note. This table displays first-stage Heckman selection model results. The figures denote total marginal effects of the displayed variables on the tweet probability in percentage points (e.g. an increase in cumulative returns of the SPY ETF by 1 bp in period *t-1* is associated with a 0.376% increase in probability that Trump will tweet in period *t*). The sample spans the period from Q4 2016 to Q4 2018. Tweets are obtained using the Twitter API and from the Trump Twitter Archive, while the ETF data is retrieved from the Trade and Quote database. Sentiment scores are assigned based on the machine learning algorithms described in Section 3.1.2 and Online Appendix A, whereas the ETF data is aggregated at the minute level following the computation described in Section 3.3. Parentheses report Newey-West standard errors. Statistical significance is denoted by ***, **, * at the 1%, 5% and 10% levels, respectively.

Table 12 Heckman selection model: second-stage results for SPY

	Economy	Economy, Fed and Markets	Employment, Industry and Production	US-China Trade (War)	NAFTA/ US-MEX Trade
			Panel A: Returns		
Intercept	-3.812	12.370	27.729*	7.900	21.974*
	(13.280)	(10.354)	(15.906)	(14.570)	(12.108)
CAR_{t-1}	-0.080*	-0.115	-0.167	-0.111	-0.189**
	(0.046)	(0.090)	(0.105)	(0.100)	(0.094)
D_+	1.802	1.824	0.085	-1.331	-2.285
	(1.428)	(1.756)	(2.264)	(2.412)	(2.641)
D_-	-0.816	2.973	-6.209	-7.899*	-3.116
	(2.094)	(2.614)	(4.166)	(4.573)	(4.331)
$CAR_{t-1} \cdot D_+$	-0.141	0.156	-0.291	0.006	0.006
	(0.177)	(0.155)	(0.268)	(0.256)	(0.133)
$CAR_{t-1} \cdot D_-$	0.295***	0.400**	0.356	-0.298**	0.240
	(0.105)	(0.196)	(0.358)	(0.150)	(0.157)
IMR	2.292	-19.257	-33.027*	-8.790	-26.016**
	(16.342)	(13.379)	(19.399)	(17.401)	(12.858)
R^2	0.018	0.021	0.078	0.028	0.042
	0.027	0.036	0.102	0.067	0.086
N	807	455	269	175	155
			Panel B: ΔVolume		
Intercept	-0.315	0.191	-0.102	0.379	0.052
	(0.835)	(0.744)	(0.577)	(0.450)	(0.430)
ΔVOL_{t-1}	0.715***	0.678***	0.745***	0.832***	0.727***
	(0.075)	(0.093)	(0.064)	(0.039)	(0.073)
CAR_{t-1}	-0.004	-0.001	0.005	0.002	-0.002
	(0.003)	(0.005)	(0.004)	(0.004)	(0.003)
D_+	-0.027	-0.036	-0.046	-0.017	0.078
	(0.080)	(0.083)	(0.085)	(0.158)	(0.137)
D_-	0.112	0.152	0.157	0.083	-0.075
	(0.147)	(0.171)	(0.326)	(0.153)	(0.210)
$\Delta VOL_{t-1} * D_+$	-1.256***	-1.207***	-1.376***	-1.234***	-1.103***
	(0.096)	(0.092)	(0.077)	(0.119)	(0.104)
$\Delta VOL_{t-1} * D_-$	-1.207***	-1.053***	-0.873***	-1.441***	-1.231***
	(0.098)	(0.182)	(0.167)	(0.129)	(0.180)
IMR	0.374	-0.230	0.119	-0.467	-0.049
	(1.023)	(0.918)	(0.699)	(0.544)	(0.514)
R^2	0.345	0.326	0.429	0.485	0.284
	0.351	0.338	0.446	0.509	0.322
N	803	453	267	171	153
			Panel C: ΔRealized volatility		
Intercept	-2.828	1.822	2.286	0.828	5.344**
	(2.355)	(1.821)	(3.567)	(2.718)	(2.560)
ΔRV_{t-1}	0.882***	0.658***	0.713***	0.818***	0.501***
	(0.101)	(0.090)	(0.081)	(0.081)	(0.137)
D_+	-0.102	-0.192	0.458*	0.232	-0.367
	(0.223)	(0.211)	(0.254)	(0.318)	(0.369)
D_-	0.110	0.394	-3.321**	0.192	0.139
	(0.398)	(0.452)	(1.645)	(0.754)	(0.654)
$\Delta RV_{t-1} * D_+$	-0.309*	-0.007	-0.130	-0.149	-0.031
	(0.168)	(0.110)	(0.245)	(0.168)	(0.147)
$\Delta RV_{t-1} * D_-$	-0.047	0.237	0.139	-0.199	0.001
	(0.162)	(0.155)	(0.384)	(0.260)	(0.286)
IMR	3.505	-2.217	-2.813	-1.112	-6.294**
	(2.920)	(2.208)	(4.288)	(3.304)	(3.057)
R^2	0.453	0.497	0.4411	0.511	0.289
	0.461	0.508	0.458	0.532	0.324
N	503	331	227	161	143

Note. The above table displays regression results after inclusion of the Inverse Mills Ratio (IMR) from the Heckman model step 1 (Table 11). Except for the IMR, the regression specifications are the same as in the baseline matched-sample regressions. The sample spans the period from Q4 2016 to Q4 2018. Tweets are obtained using the Twitter API and from the Trump Twitter Archive, while the ETF data is retrieved from the Trade and Quote database. Sentiment scores are assigned based on the machine learning algorithms described in Section 3.1.2 and Online Appendix A, whereas the ETF data is aggregated at the minute level following the computation described in Section 3.3. Parentheses report Newey-West standard errors. Statistical significance is denoted by ***, **, * at the 1%, 5% and 10% levels, respectively.

Table 13 Heckman selection model: second-stage results for VIX

	Economy	Economy, Fed and Markets	Employment, Industry and Production	US-China Trade (War)	NAFTA/ US-MEX Trade
	ΔVIX regressions				
Intercept	62.604	-98.787	-31.833	5.273	223.479
	(83.894)	(97.062)	(82.364)	(107.890)	(209.067)
ΔVIX_{t-1}	-0.010	-0.102	-0.088	-0.036	-0.295**
	(0.037)	(0.075)	(0.089)	(0.097)	(0.144)
D_+	9.348	9.779	32.318	21.629	63.087***
	(13.232)	(18.582)	(20.090)	(15.254)	(23.720)
D_-	38.663**	22.660	110.893*	94.208***	77.850*
	(19.481)	(25.680)	(57.121)	(36.001)	(42.971)
$\Delta VIX_{t-1} * D_+$	-0.190	0.102	-0.226	-0.028	-0.050
	(0.155)	(0.139)	(0.208)	(0.180)	(0.200)
$\Delta VIX_{t-1} * D_-$	0.085	0.264	0.078	-0.150	0.168
	(0.099)	(0.194)	(0.260)	(0.190)	(0.190)
IMR	-84.116	121.569	-8.850	-42.813	-331.978
	(102.761)	(116.489)	(97.554)	(127.751)	(247.486)
R^2	0.012	-0.004	0.072	0.018	0.027
	0.020	0.011	0.096	0.057	0.071
N	807	455	269	175	155

Note. The above table displays regression results after inclusion of the Inverse Mills Ratio (IMR) from the Heckman model step 1 (Table 11). Except for the IMR, the regression specifications are the same as in the baseline matched-sample regressions. The sample spans the period from Q4 2016 to Q4 2018. Tweets are obtained using the Twitter API and from the Trump Twitter Archive, while the ETF data is retrieved from the Trade and Quote database. Sentiment scores are assigned based on the machine learning algorithms described in Section 3.1.2 and Online Appendix A, whereas the ETF data is aggregated at the minute level following the computation described in Section 3.3. Parentheses report Newey-West standard errors. Statistical significance is denoted by ***, **, * at the 1%, 5% and 10% levels, respectively.

Table 14 Stepwise regressions

	Economy	Economy, Fed and Markets	Employment, Industry and Production	US-China Trade (War)	NAFTA/ US-MEX Trade
	Panel A: returns (SPY)				
	Dependent variable: $\varepsilon_{\text{SPY},1}$				
Intercept	0.000	-0.000	0.000	-0.000	0.000
	(0.995)	(1.041)	(1.620)	(2.048)	(1.633)
$\varepsilon_{\text{SPY},2}$	2.058	-0.024	3.189	6.521*	1.680
	(1.637)	(1.816)	(3.696)	(3.471)	(2.880)
$R^2_{Adj.}$	0.003	-0.005	-0.003	0.041	-0.008
N	364	211	121	83	77
	ΔVIX				
	Panel B: Dependent variable: $\varepsilon_{\text{VIX},1}$				
Intercept	-0.000	0.000	-0.000	0.000	0.000
	(10.740)	(12.902)	(14.748)	(17.993)	(19.182)
$\varepsilon_{\text{VIX},2}$	-24.666	-14.994	-39.265	-62.151**	-8.721
	(16.682)	(20.599)	(35.355)	(30.925)	(32.125)
$R^2_{Adj.}$	0.003	-0.002	-0.000	0.034	-0.012
N	364	211	121	83	77

Note. This table shows the stepwise regression results from Equation 5, where residuals from Equation 3 are regressed on those from Equation 4 in order to assess whether the unexplained information contained in the residuals is correlated. The above sample spans Q4 2016 and Q4 2018. Tweets are obtained using the Twitter API and from the Trump Twitter Archive, while the ETF data is retrieved from the Trade and Quote database. Sentiment scores are assigned based on the machine learning algorithms described in Section 3.1.2 and Online Appendix A, whereas the ETF data is aggregated at the minute level following the computation described in Section 3.3. Parentheses report Newey-West standard errors. Statistical significance is denoted by ***, **, * at the 1%, 5% and 10% levels, respectively.

Online Appendix

A Tweet processing with technical details on the machine learning algorithms

We disentangle Donald Trump's tweets along the *textual sentiment*, or polarity, as well as the *topic* dimensions. Both are facilitated by the use of machine learning (ML) algorithms.

A.1 Topic modeling

To model the content of written text, many papers in the literature employ the *Latent Dirichlet Allocation* (LDA) algorithm (Loughran and McDonald, 2016; Grus, 2019). In using this *unsupervised* ML algorithm, merely the desired number of topics can be selected, however not their content. Therefore, LDA can result in somewhat arbitrary topic assignments and demarcations amongst topics (Russell and Norvig, 2016).

Since we want to specifically analyze the potential market impact of Trump's tweets with economic content, we want to be able to guide the topic model in a certain direction. To this end, we use the *CorEx* topic model as a *semi-supervised* alternative (Gallagher et al., 2017). This algorithm allows for providing a list of *seed terms*, which it subsequently uses to assign topic labels. We obtain this list directly from Trump's tweets by assigning all one- to four-word combinations used at least three times by Trump in his tweets (n-grams with $n = \leq 4$) to one or more of 16 topics[15]. This way, it can be ensured that certain topics of interest within Trump's tweets are picked up by the topic model, even if they occur infrequently. For the fours topics of interest for the purpose of this paper, we ultimately verify correct topic assignments by hand (i.e. remove falsely assigned topic labels for each tweet assigned to the *Economy, Fed and Markets*, *Employment, Industries*

[15]Of these 16 initial topics, twelve do not concern economic content and are therefore not further analyzed for the purpose of this analysis.

and Production, *US-China Trade War* or *US-Mexico Trade War / NAFTA* topics).

The four topics we use in this paper contain all potentially market relevant information in Trump's tweets, specifically regarding the four topics: (1) *Economy, Federal Reserve and Stock Markets*, (2) *(Un-)Employment, Job Creation, American Industries and Production*, (3) the *US-China Trade War* (and later trade agreement), and (4) *US-American and North American Trade Relations*, especially concerning NAFTA and trade or tariffs between the US and Mexico or Canada (henceforth *NAFTA/US-Mexico Trade War*). Taken together, these four topics make up the tweet category *Economy Tweets*, which help us proxy the average impact of economic tweets.

A.2 Sentiment analysis

In the previous literature, the prevalent methodology used to classify textual sentiment is based on financial word dictionaries, such as in the seminal work by Loughran and McDonald (2011, 2015). Since Trump neither uses highly technical nor finance-related language in his tweets, the applicability of this approach to our purposes is rather limited. Therefore, we resort to machine learning (ML) models to classify tweet sentiment instead.

We train an ensemble machine learning model on 30 % of the full non-retweet Twitter data, in which we consider all of the 16 initial topics identified in Trump's tweets, not only the four with economic content ultimately used for the analysis paper. This approach ensures that the training data is as diverse and therefore unbiased as possible. The tonality for these tweets is classified as either neutral, negative or positive by three individuals in order to limit subjectivity in tonality assignment. This hand-classified sample is used as the training data for a ML ensemble model consisting of several ML algorithms. The algorithms that we consider to enter our ensemble model are the Naïve Bayes (NB), Support Vector Machine (SVM), Gradient Boosting (GB), Random Forest (RF), k-Nearest Neighbor (k-NN) and Multi-Layer Perceptron (MLP) models (Rao and Srivastava, 2012; Sprenger et al., 2014; Guo et al., 2016; Oliveira et al., 2017).

The overall probability score for the three possible outcomes – *negative*, *neutral* or *positive* sentiment is obtained by equally weighting each single model's probability score. Each of the tested algorithms is evaluated for predictive accuracy using five-fold cross validation (CV) on the training data, and models are only featured in the ensemble if their cross-validated accuracy score in the training data exceeds 70 %. Table A1 shows these CV accuracy figures for each of the potential models in the ensemble. The bottom line shows the average accuracy score across all folds, while the rightmost column depicts the ensemble model CV accuracy scores.

Table A1 Accuracy scores for the machine learning sentiment classification models

	NB	SVM	GB	RF	kNN	MLP	Ensemble
CV Fold 1	73.99	75.30	47.65	67.10	71.15	72.90	75.30
CV Fold 2	75.41	75.19	50.49	66.23	69.62	73.44	75.96
CV Fold 3	76.94	77.05	56.83	69.40	70.71	75.08	77.38
CV Fold 4	73.77	76.07	53.55	66.12	70.27	72.90	75.74
CV Fold 5	75.85	77.49	56.17	68.63	71.15	76.94	77.16
Avg. Accuracy	**75.19**	**76.22**	**52.94**	**67.50**	**70.58**	**74.25**	**76.31**

Note. This table depicts the average accuracy score across all five cross validation folds, and the overall cross-validated accuracy scores for each potential algorithm in the ensemble (bottom row) as well as the ensemble model (rightmost column). Algorithms only enter the final ensemble if their cross-validated accuracy in predicting the training data exceeds 70%. Probability scores for each of the sentiment outcomes – *positive*, *negative* and *neutral* are obtained by equal weighting of the entering algorithms.

[Table A1 about here]

At an average of 76.31 %, the ensemble displays higher CV predictive accuracy than any of the single constituent algorithms. The final algorithms exceeding 70% CV accuracy and therefore voting in the ensemble are NB, SVM, k-NN and MLP. Since the ML ensemble model yields *probability scores* for each of the sentiment outcome classes, we use this score as the sentiment score in our analyses. Each tweet is assigned either a *positive* (1), *neutral* (0), or *negative* (-1) sentiment label if the probability predicted by the ML model for the respective class exceeds that of the remaining two classes.

Using the same training data sample, we can additionally evaluate the performance of a dictionary commonly used to classify sentiment in short texts, e.g. tweets or customer reviews (**V**alence-**A**ware **D**ictionary and s**E**ntiment **R**easoner, VADER, Hutto and Gilbert, 2014). VADER can classify sentiment in the training data only at a much lower accuracy than our ensemble model (56.77 vs. 76.31 %)

Neutral tweets are hardly ever classified by the ML sentiment model for three reasons: firstly, Trump posts more at the extremes than moderate ranges of sentiment, i.e. either very positively, or very negatively, and therefore neutral sentiment is rather underrepresented in his tweets. Secondly, of the tweets that do display rather low sentiment scores, most are retweets or contain only neutrally offered information on when and where to watch certain television interviews, for instance, and are therefore not considered in our analysis. Thirdly, machine learning classification has difficulties correcting for severe *class imbalance*, meaning the under-representation of one of the potential outcome labels in the training data. Such an under-representation, if present in the training data, tends to be exacerbated in the predicted labels. This does not, however, pose a major issue for the purpose of this analysis, since it is most likely that the tweets with more extreme sentiment contain the most relevant information for stock markets, if any.[16]

[16]This assumption is based on the extensive literature on the connection between (social) media sentiment and stock markets.

B Sample tweets

Table B1 Example tweets

Topic	Sentiment	Time posted	Tweet text
Economy, Fed and Markets	Positive	2/16/2017 11:34	Stock market hits new high with longest winning streak in decades. Great level of confidence and optimism - even before tax plan rollout!
Economy, Fed and Markets	Positive	8/4/2017 10:26	Consumer confidence is at a 16 year high....and for good reason. Much more regulation "busting" to come. Working hard on tax cuts & reform!
Economy, Fed and Markets	Positive	9/29/2017 13:39	RECORD HIGH FOR S&P 500!
Economy, Fed and Markets and Employment, Industries and Production	Positive	1/5/2018 11:35	Dow goes from 18,589 on November 9, 2016 to 25,075 today for a new all time Record. Jumped 1000 points in last 5 weeks Record fastest 1000 point move in history. This is all about the Make America Great Again agenda! Jobs Jobs Jobs. Six trillion dollars in value created!
Economy, Fed and Markets and Employment, Industries and Production	Positive	7/2/2017 23:55	Stock Market at all time high unemployment at lowest level in years (wages will start going up) and our base has never been stronger!
Economy, Fed and Markets	Negative	2/24/2018 15:55	The only problem our economy has is the Federal Reserve. They don't have a feel for the Market they don't understand necessary Trade Wars or Strong Dollars or even Democrat Shutdowns over Borders. The Federal Reserve is like a powerful golfer who can't score because he has no touch - he can't putt!
Employment, Industries and Production and NAFTA/US-Mexico Trade War	Positive	1/12/2018 2:49	More great news as a result of historical Tax Cuts and Reform: Fiat Chrysler announces plan to invest more than $1 BILLION in Michigan plant relocating their heavy truck production from Mexico to Michigan adding 2500 new jobs and paying $2000 bonus to United States of America employees!
Employment, Industries and Production	Positive	11/30/2016 3:40	I will be going to Indiana on Thursday to make a major announcement concerning Carrier A.C. staying in Indianapolis. Great deal for workers!
Employment, Industries and Production	Positive	1/3/2017 17:00	Instead of driving jobs and wealth away AMERICA will become the world's great magnet for INNOVATION & JOB CREATION.
Employment, Industries and Production	Negative	2/8/2016 0:41	Chuck Jones who is President of United Steelworkers 1999 has done a terrible job representing workers. No wonder companies flee country!
US-China Trade War and NAFTA/US-Mexico Trade War	Positive	4/20/2017 19:33	We're going to use American steel we're going to use American labor we are going to come first in all deals.
US-China Trade War	Positive	5/3/2018 3:45	Our great financial team is in China trying to negotiate a level playing field on trade! I look forward to being with President Xi in the not too distant future. We will always have a good (great) relationship!
US-China Trade War	Negative	4/4/2018 11:22	We are not in a trade war with China that war was lost many years ago by the foolish or incompetent people who represented the United States of America Now we have a Trade Deficit of $500 Billion a year with Intellectual Property Theft of another $300 Billion. We cannot let this continue!
NAFTA/US-Mexico Trade War	Negative	1/27/2017 13:19	Mexico has taken advantage of the United States of America for long enough. Massive trade deficits & little help on the very weak border must change NOW!
NAFTA/US-Mexico Trade War	Negative	9/1/2018 15:00	There is no political necessity to keep Canada in the new NAFTA deal. If we don't make a fair deal for the United States of America after decade of abuse Canada will be out. Congress should not interfere with these negotiations or I will simply terminate NAFTA entirely & we will be far better off..

C Additional tables and analyses

Table C1 Variable definitions

Sentiment reversal	Sentiment reversal is a change in tonality, i.e., switching sentiment from one tweet to the next.
Sentiment surprise	A sentiment surprise is modelled as the residual from an AR(5) process imposed on the sentiment scores of tweets within a topic. For the analysis, we consider those surprises that are at least a standard deviation away from the mean of the sentiment surprise distribution, i.e. "extreme" swings in sentiment.
Sentiment dummies	D_+ and D_- are indicator variables equal to one for positive and negative tweets, respectively, and zero otherwise.
CR, CAR or cumulative return	CAR is defined as the minute-level abnormal return with expected return of 0, that is then cumulated over the given event window. Based on the same principle, we calculate cumulative changes for the VIX index.
Trading volume	Trading volume is aggregated across all transactions from the tweet (event) minute to the next. We then construct 30-minute log-volume by aggregating the 1-minute volumes and then reporting the logarithm value.
Cumulative volumes	The above minute-level volumes are aggregated at the 30 (120) minute level. For the sake of simplicity, we refer to cumulative 30 (120) minute volumes as volumes or VOL in the paper.
Δ VOL or Δ volume	In the regressions, we use the change in 30-minute (120-minute) cumulative log-volumes.
Realized volatility (RV)	Realized volatility is computed as the square root of the squared sum of cumulative returns over each five-minute block within each event window, e.g. for the [0,30] baseline event window: $RV_{0,30} = \sqrt{CAR^2_{0,5} + CAR^2_{6,10} + CAR^2_{11,15} + CAR^2_{16,20} + CAR^2_{21,25} + CAR^2_{26,30}}$.
Δ RV	Analogously to Δ VOL, Δ RV denotes changes in realized volatility from one 30 (120)-minute window to the next. Following the logic of computing returns, we use *changes* in RV in our analyses.

Table C2 Matched sample SPY regressions with quarter FE

	Economy	Economy, Fed and Markets	Employment, Industry and Production	US-China Trade (War)	NAFTA/ US-MEX Trade
			Panel A: Returns		
Intercept	4.3073	8.1784*	-4.3401*	9.0171***	5.4087***
	(3.6812)	(4.6259)	(2.3594)	(2.5991)	(1.9851)
CAR_{t-1}	-0.1017***	-0.0625	-0.1395*	-0.1018	-0.2406***
	(0.0329)	(0.0852)	(0.0812)	(0.0934)	(0.0847)
D_+	2.0141	2.0598	2.1603	-0.7139	-2.0873
	(1.6914)	(2.0480)	(2.9620)	(2.2418)	(2.5269)
D_-	-0.0976	3.2448	-4.1953	-7.9000*	-4.0234
	(2.1411)	(2.6841)	(4.7726)	(4.2042)	(4.7466)
$\text{CAR}_{t-1} \cdot D_+$	-0.1429	0.1262	-0.4167	-0.0667	-0.0320
	(0.2187)	(0.1771)	(0.3655)	(0.2013)	(0.1138)
$\text{CAR}_{t-1} \cdot D_-$	0.3317***	0.4145**	0.1549	-0.2909*	0.2220
	(0.1114)	(0.2017)	(0.3213)	(0.1551)	(0.2075)
Quarter FE	Yes	Yes	Yes	Yes	Yes
$R^2_{Adj.}$	0.0186	0.0183	0.0547	0.0088	0.0362
N	728	421	242	165	154
			Panel B: ΔVolume		
Intercept	-1.7855***	-0.2909	-1.2481*	0.2303	-1.0147
	(0.5672)	(0.6272)	(0.6412)	(0.6734)	(1.2759)
ΔVOL_{t-1}	0.8575***	0.9485***	0.8786***	0.9458***	0.9855***
	(0.0367)	(0.0454)	(0.0541)	(0.0491)	(0.0445)
CAR_{t-1}	0.0045	0.0030	-0.0013	0.0000	0.0018
	(0.0047)	(0.0058)	(0.0076)	(0.0062)	(0.0069)
D_+	2.1673***	1.1264**	1.8142***	1.0729*	0.5640
	(0.3852)	(0.5380)	(0.6461)	(0.5602)	(0.6884)
D_-	2.2457***	1.2126**	1.0672	1.1395	0.7426
	(0.5048)	(0.5893)	(0.9041)	(0.6987)	(0.4759)
$\Delta\text{VOL}_{t-1} \cdot D_+$	0.0714	-0.0088	0.0643	0.0029	-0.0496
	(0.0434)	(0.0518)	(0.0620)	(0.0621)	(0.0435)
$\Delta\text{VOL}_{t-1} \cdot D_-$	0.0606	-0.0399	0.1024	-0.0566	-0.0324
	(0.0442)	(0.0562)	(0.1199)	(0.0538)	(0.0571)
Quarter FE	Yes	Yes	Yes	Yes	Yes
$R^2_{Adj.}$	0.9627	0.9612	0.9606	0.9735	0.9802
N	726	419	242	162	153
			Panel C: ΔRealized volatility		
Intercept	-0.5891*	2.0113***	-0.3317	1.0770	0.1500
	(0.3077)	(0.3312)	(0.3824)	(0.9447)	(0.2469)
ΔRV_{t-1}	0.3216***	0.3069***	0.3193	0.4448***	0.0326
	(0.0738)	(0.0619)	(0.2157)	(0.1120)	(0.1320)
D_-	0.3848	0.0106	-0.6340	-0.4863	0.7446
	(0.2914)	(0.3908)	(0.7644)	(0.8948)	(0.7243)
D_+	0.4558**	-0.5621*	0.6491	0.4956	-0.3140
	(0.2108)	(0.2956)	(0.5120)	(0.5861)	(0.4854)
$\Delta\text{RV}_{t-1} \cdot D_+$	-0.0080	0.3019*	0.3739	0.1464	0.3372**
	(0.1394)	(0.1756)	(0.3184)	(0.1519)	(0.1466)
$\Delta\text{RV}_{t-1} \cdot D_-$	0.2823	0.5084***	0.2797	0.2911	0.5604***
	(0.1936)	(0.1350)	(0.2265)	(0.2573)	(0.2098)
Quarter FE	Yes	Yes	Yes	Yes	Yes
$R^2_{Adj.}$	0.1750	0.3186	0.2312	0.2759	0.1417
N	571	332	218	153	138

Note. The above table reports *Returns*, and changes in Trading volume and *Realized volatility* of the SPY ETF, in Panels A, B and C, respectively. The regressions are based on a matched sample approach, where the post-tweet event window is matched with a random, non-tweet window to separate the effects of the tweets and potential intraday seasonality. Each column presents results for the indicated topic. The explanatory variables with the subscript $_{t-1}$ are lagged variables, where the lag corresponds to the 30-minute window preceding the tweet. D_+ and D_- are indicator variables equal to one for positive and negative tweets, respectively, and zero otherwise. The sample spans the period from Q4 2016 to Q4 2018. Tweets are obtained using the Twitter API and from the Trump Twitter Archive, while the ETF data is retrieved from the Trade and Quote database. Sentiment scores are assigned based on the machine learning algorithms described in Section 3.1.2 and Online Appendix A, whereas the ETF data is aggregated at the minute level following the computation described in Section 3.3. Parentheses report Newey-West standard errors. Statistical significance is denoted by ***, **, * at the 1%, 5% and 10% levels, respectively.

Table C3 Matched sample VIX regressions with quarter FE

	Economy	Economy, Fed and Markets	Employment, Industry and Production	US-China Trade (War)	NAFTA/ US-MEX Trade
Intercept	-81.0781***	-112.9189***	-13.5961	-186.3954	-122.9943***
	(14.2412)	(25.8461)	(24.3167)	(146.7061)	(31.2783)
ΔVIX$t-1$	-0.0146	-0.1062	-0.1567*	-0.0535	-0.1811*
	(0.0407)	(0.0746)	(0.0942)	(0.1137)	(0.1062)
D_+	9.6129	5.4896	35.7767	21.8553	68.6157***
	(15.1890)	(20.1323)	(24.2126)	(15.8502)	(23.4718)
D_-	39.9982**	23.3727	108.8758**	102.3618***	89.3634**
	(19.2144)	(26.4423)	(54.7224)	(34.4230)	(44.4654)
$\Delta\text{VIX}_{t-1} \cdot D_+$	-0.1678	0.0884	-0.1666	-0.0233	0.0661
	(0.1679)	(0.1403)	(0.2213)	(0.1679)	(0.1945)
$\Delta\text{VIX}_{t-1} \cdot D_-$	0.1054	0.3136	0.1295	-0.0918	0.2679
	(0.0947)	(0.1994)	(0.2636)	(0.1988)	(0.1647)
Quarter FE	Yes	Yes	Yes	Yes	Yes
$R^2_{Adj.}$	0.0042	-0.0087	0.0738	0.0122	0.0285
N	728	421	242	165	154

Note. The above table reports Cumulative changes, denoted as ΔVIX of the high-frequency VIX series. The regressions are based on a matched sample approach, where the post-tweet event window is matched with a random, non-tweet window to separate the effects of the tweets and potential intraday seasonality. Each column presents results for the indicated topic. The explanatory variables with the subscript $_{t-1}$ are lagged variables, where the lag corresponds to the 30-minute window preceding the tweet. D_+ and D_- are indicator variables equal to one for positive and negative tweets, respectively, and zero otherwise. The sample spans the period from Q4 2016 to Q4 2018. Tweets are obtained using the Twitter API and from the Trump Twitter Archive, while the ETF data is retrieved from the Trade and Quote database. Sentiment scores are assigned based on the machine learning algorithms described in Section 3.1.2 and Online Appendix A, whereas the ETF data is aggregated at the minute level following the computation described in Section 3.3. Parentheses report Newey-West standard errors. Statistical significance is denoted by ***, **, * at the 1%, 5% and 10% levels, respectively.

Table C4 Matched sample SPY regressions with 120-minute pre-event window

	Economy	Economy, Fed and Markets	Employment, Industry and Production	US-China Trade (War)	NAFTA/ US-MEX Trade
	Panel A: Returns				
Intercept	1.1409	1.6450	0.1573	2.7778*	0.6746
	(1.0984)	(1.5944)	(1.7744)	(1.6557)	(1.0107)
CAR_{t-1}	0.1492**	-0.0400	-0.0280	-0.0167	0.0718
	(0.0640)	(0.0734)	(0.0577)	(0.0565)	(0.0810)
D_{+}	-1.4405	-2.9188*	1.5466	-3.3805	-2.6450
	(1.6550)	(1.7288)	(3.2188)	(2.9128)	(1.9096)
D_{-}	-5.4047*	-2.2238	-6.4154	-10.0608**	-3.5393
	(3.0388)	(2.5418)	(4.2218)	(4.7333)	(2.9933)
$\text{CAR}_{t-1} \cdot D_{+}$	-0.0230	0.1019	-0.2136	0.1716	-0.0124
	(0.1023)	(0.1313)	(0.1653)	(0.1261)	(0.0781)
$\text{CAR}_{t-1} \cdot D_{-}$	-0.1125	0.1347	0.0444	-0.0504	-0.1076
	(0.0717)	(0.1097)	(0.1385)	(0.0955)	(0.1622)
$R^2_{Adj.}$	0.0469	-0.0004	0.0879	0.0498	-0.0128
N	436	290	186	136	133
	Panel B: ΔVolume				
Intercept	0.6711***	0.9371***	0.0615	0.3941*	0.4399***
	(0.1187)	(0.1658)	(0.0431)	(0.2198)	(0.1325)
ΔVOL_{t-1}	0.4651***	0.3092	0.8139***	-0.1082	-0.9840***
	(0.1454)	(0.1881)	(0.0357)	(0.2224)	(0.1552)
CAR_{t-1}	-0.0014	-0.0047	-0.0045**	0.0056	-0.0058**
	(0.0018)	(0.0032)	(0.0023)	(0.0066)	(0.0029)
D_{+}	-0.4557***	-0.7416***	0.0726	-0.2829	-0.3558**
	(0.1651)	(0.1957)	(0.0687)	(0.2909)	(0.1717)
D_{-}	-0.5210***	-0.7813***	-0.2878	-0.0897	-0.2548
	(0.1487)	(0.1977)	(0.1755)	(0.3253)	(0.1661)
$\Delta\text{VOL}_{t-1} * D_{+}$	-0.3823	-0.1478	-0.6603***	-0.0863	0.8255**
	(0.3084)	(0.3330)	(0.1780)	(0.6150)	(0.4138)
$\Delta\text{VOL}_{t-1} * D_{-}$	-0.1313	-0.0873	0.1816	0.5546	2.3659***
	(0.3417)	(0.3296)	(0.1585)	(0.9356)	(0.2368)
$R^2_{Adj.}$	0.1254	0.1363	0.4617	0.0107	0.3266
N	435	289	185	135	132
	Panel C: ΔRealized volatility				
Intercept	0.2737*	0.0158	0.0765	0.0820	0.0004
	(0.1477)	(0.1147)	(0.2249)	(0.1615)	(0.1177)
ΔRV_{t-1}	0.9859***	0.6311***	0.8055***	1.0179***	0.8154***
	(0.0927)	(0.0833)	(0.1102)	(0.0794)	(0.1082)
D_{+}	0.3991	0.5099**	0.4902	0.0655	-0.4032
	(0.2434)	(0.2549)	(0.3651)	(0.4724)	(0.3443)
D_{-}	0.4807	0.0752	-0.3383	0.8469	1.0352
	(0.4862)	(0.4428)	(0.9746)	(0.7603)	(0.7425)
$\Delta\text{RV}_{t-1} \cdot D_{+}$	-0.0581	0.2675*	0.3365	-0.0046	0.0132
	(0.1549)	(0.1499)	(0.2043)	(0.2281)	(0.1404)
$\Delta\text{RV}_{t-1} \cdot D_{-}$	-0.1859	0.5278***	0.7979***	-0.0833	0.0005
	(0.3361)	(0.1877)	(0.2839)	(0.3453)	(0.4994)
$R^2_{Adj.}$	0.6115	0.4965	0.5917	0.6278	0.4730
N	426	297	200	153	142

Note. The above table reports *Returns*, and changes in Trading volume and *Realized volatility* of the SPY ETF, in Panels, A, B and C, respectively. The regressions are based on a matched sample approach, where the post-tweet event window is matched with a random, non-tweet window to separate the effects of the tweets and potential intraday seasonality. Each column presents results for the indicated topic. The explanatory variables with the subscript $_{t-1}$ are lagged variables, where the lag corresponds to the 30-minute window preceding the tweet. D_{+} and D_{-} are indicator variables equal to one for positive and negative tweets, respectively, and zero otherwise. The sample spans the period from Q4 2016 to Q4 2018. Tweets are obtained using the Twitter API and from the Trump Twitter Archive, while the ETF data is retrieved from the Trade and Quote database. Sentiment scores are assigned based on the machine learning algorithms described in Section 3.1.2 and Online Appendix A, whereas the ETF data is aggregated at the minute level following the computation described in Section 3.3. Parentheses report Newey-West standard errors. Statistical significance is denoted by ***, **, * at the 1%, 5% and 10% levels, respectively.

Table C5 Matched sample VIX regressions with 120-minute pre-event window

	Economy	Economy, Fed and Markets	Employment, Industry and Production	US-China Trade (War)	NAFTA/ US-MEX Trade
Intercept	-18.3615	-13.8287	-10.0547	-25.4204	-31.4958**
	(11.7785)	(13.2143)	(24.4252)	(19.1487)	(13.3840)
ΔVIX$_{t-1}$	-0.0205	-0.0663	-0.1150	-0.0234	-0.0019
	(0.0401)	(0.0521)	(0.1067)	(0.0335)	(0.0466)
D$_{+}$	18.2279	12.7758	-3.4042	5.5685	62.2025**
	(20.1473)	(16.5945)	(33.1944)	(20.7867)	(25.9008)
D$_{-}$	64.2554**	38.2893	114.7799	111.6588**	108.3337*
	(29.7551)	(28.3114)	(84.6563)	(54.7480)	(63.5634)
ΔVIX$_{t-1}$ $\cdot D_{+}$	0.1161	0.1518	-0.0208	0.0851	0.1309
	(0.0819)	(0.1112)	(0.1629)	(0.0792)	(0.0983)
ΔVIX$_{t-1}$ $\cdot D_{-}$	0.1009	0.0964	0.3058	0.1866	0.2942
	(0.0685)	(0.1162)	(0.3021)	(0.1729)	(0.2976)
$R^2_{Adj.}$	0.0151	-0.0023	0.0684	0.0220	0.0334
N	439	289	186	136	133

Note. The above table reports Cumulative changes, denoted as ΔVIX of the high-frequency VIX series. The regressions are based on a matched sample approach, where the post-tweet event window is matched with a random, non-tweet window to separate the effects of the tweets and potential intraday seasonality. Each column represents results for the indicated topic. The explanatory variables with the subscript $_{t-1}$ are lagged variables, where the lag corresponds to the 120-minute window preceding the tweet. D_{+} and D_{-} are indicator variables equal to one for positive and negative tweets, respectively, and zero otherwise. The sample spans the period from Q4 2016 to Q4 2018. Tweets are obtained using the Twitter API and from the Trump Twitter Archive, while the ETF data is retrieved from the Trade and Quote database. Sentiment scores are assigned based on the machine learning algorithms described in Section 3.1.2 and Online Appendix A, whereas the ETF data is aggregated at the minute level following the computation described in Section 3.3. Parentheses report Newey-West standard errors. Statistical significance is denoted by ***, **, * at the 1%, 5% and 10% levels, respectively.

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