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Sustainable Architecture for Finance in Europe

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Abstract

We propose the "President reacts to news" channel of stock returns by studying
the financial market impact of the Twitter account of the 45th president of the
United States, Donald Trump. We use machine learning algorithms to classify topic
and textual sentiment of 1,400 economy-related tweets to investigate whether they
contain relevant information for financial markets. Analyzing high-frequency data,
we find that after controlling for past market movements, most tweets are reactive
and predictable, rather than novel and informative. The exceptions are tweet topics
where the president has direct policy authority and his negative sentiment could
adversely affect economic outcomes.

Keywords: Government communication, Social media, Twitter, Machine learning,
ETFs.

JEL classification: G10, G14, C58.

1 Introduction

Investment practitioners, policy makers, and academics share a consensus that public announcements made by government agencies such as the Bureau of Labor Statistics (BLS), the Bureau of Economic Analysis (BEA), or bodies of the Federal Reserve System or Board (Fed) are a valuable news source and can elicit an aggregate stock market reaction.[1] What is less clear, however, is the mechanism through which investors process and incorporate this information into asset prices. While some studies claim that macroeconomic announcements help revise investor expectations, others suggest that policy-competent institutions do not aim to provide information, but that they themselves react to economic news instead – a channel coined "Fed reacts to news" by Bauer and Swanson (2020).[2]

In this paper, we study the head of the executive branch of the government, the president of the United States (POTUS), and whether his direct communication triggers a stock market impact comparable to that of monetary policy makers. The president, alongside with Congress, has an exclusive policy competence when it comes to bilaterally or internationally negotiated commercial policy, most importantly in the domain of trade deals and tariffs. We argue that this authority over commercial policy is *complementary* to that held by the Federal Reserve Board and the Federal Open Market Committee (FOMC) over monetary policy and that its potential market impact therefore warrants similar academic scrutiny. To study this effect, we direct our attention to the 45th POTUS, Donald J. Trump, and his social media activity on Twitter. After sorting circa 1,400 of his tweets related to the US economy into topics and classifying their textual sentiment by machine learning (ML) algorithms, we analyze the aggregate stock market impact of these messages.

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[1]A prominent example from the macro-finance literature is the Fed's market impact around FOMC meeting days, looking into the stock market reaction leading up to and around the Fed's meetings (Bernanke and Kuttner, 2005; Lucca and Moench, 2015; Cieslak and Schrimpf, 2019; Cieslak and Vissing-Jorgensen, 2021, among others.).

[2]For evidence on how macroeconomic announcements induce investors to revise their expectations, see, for instance, Campbell et al. (2012) and Nakamura and Steinsson (2018) on the "Fed information effect."

Our primary objective is to investigate whether these tweets contain *relevant financial information*, by affecting prices, trading volumes, or market volatility, or whether they are merely a *reaction* to pre-existing market trends, and thus do not lead to a market response. Studying Trump's Twitter posts provides a unique setting for addressing these questions, since he is the first president to openly share his thoughts on social media on both a wide range of issues and in an unfiltered and almost real-time manner, thereby granting us the opportunity to quantify the effect of (high-frequency) presidential communication. We examine high-frequency, minute-level returns and trading volumes of the S&P 500 exchange-traded fund (SPY ETF) and changes in the VIX index (ΔVIX). The use of ETFs helps 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 for active trading both by institutional and retail investors.

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. 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. On occasion, however, the president's tweets do reveal information about his opinion and/or preferences on topics in which he has the direct authority and power to influence policy outcomes. The future outlook implied by preferences revealed in this way *could* eventually induce price discovery and trigger stock trading.

The mechanism behind these effects is best understood from Figure 1, which presents the typical timeline of events: Following the arrival of economic news, the market incorporates relevant information. Next, observing both the news and the subsequent market reaction, Trump's tweet arrives, which could potentially lead to the market adjusting its initial reaction. This potential channel of how economic news could be incorporated into asset prices highlights the necessity to account for pre-tweet market conditions when studying the potential impact of Trump's tweets, as we propose in this study.

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[Insert Figure 1 around here]

This result, consistent with the latest findings of the macro-finance literature on the FOMC announcements (Bauer and Swanson, 2020), gives rise to the "Trump reacts to news" effect, as opposed to the alternative "Trump information" effect. The latter would imply that the president, protected by presidential immunity, has (access to) material and superior information that he could disclose on Twitter ahead of traditional communication channels, and that might be relevant to stock pricing. Although this rationale could explain the anecdotal evidence on Trump's market impact, as indicated in Figure 1, it overlooks that Trump's tweets are preceded by the arrival of economic news and a subsequent market reaction. Considering the alternative "Trump reacts to news" framework that we propose in this study allows us to control for this *omitted information* and explains why the majority of tweets are reactive and therefore predictable by past market information, at least to a certain extent. Moreover, this mechanism can also account for the topical heterogeneity of Trump's tweet impact: When tweets by the president serve as a revelation of his preferences, the impact will be dominant in cases where he has authority (i.e., decision-making power) and his actions directly affect economic policy outcomes. This evidence is corroborated by our finding of occasional, albeit predominantly negative, effects of tweets about the US-China and US-Mexico Trade Wars, and NAFTA. Intriguingly, this framework also provides a potential explanation for the other existing studies on the overall market impact of Trump's tweets (see Bianchi et al. [2019] for Fed-related tweets, and Filippou et al. [2020] for foreign exchange implication).[3]

We use various methods to corroborate our main finding. First, matched-sample regressions allow us to directly control for pre-existing market trends; matching event windows with non-tweet windows sampled from the same time on non-tweet days allows us to disentangle the tweets' effect from intraday cyclicality. We also postulate that

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[3]The president's potential effect on financial markets is not limited to their Twitter communication. Wagner et al. (2018) and Child et al. (2021) analyze the effect of Donald Trump's election on company stocks.

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Trump's tweets do not arrive purely randomly, showing that they are somewhat dependent on past market information. Second, 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. Last, using stepwise regressions to account for the potential relationship of sentiment and past returns, we corroborate our main result that, after accounting for the effect of pre-tweet market information on tweet sentiment scores, sentiment residuals do not explain post-tweet market movements.

By studying how official communication by the executive branch through social media affects financial markets, we contribute to two main branches of the literature: (i) how news and government communication are incorporated in financial markets and stock prices, and (ii) the effect of social media networks on financial markets.

Our study contributes to the growing literature on official government communication, such as macro announcements or central bank communication, by presenting a complementary channel (i.e., Twitter) increasingly used by government officials. The financial market impact of other official government communication channels is well established. Andersen, Bollerslev, Diebold, and Vega (2003b), Flannery and Protopapadakis (2015), Kuttner (2001), and Bernanke and Kuttner (2005), among others, study the market effect of macroeconomic announcements, while numerous papers document how central banks, mainly the Fed's communications and potential monetary policy surprises, influence stock returns domestically (Cieslak et al., 2019; Cieslak and Vissing-Jorgensen, 2021; Gómez-Cram and Grotteria, 2021) or internationally (Correa et al., 2020; Cieslak and Schrimpf, 2019). We examine an official government communication channel, even if that communication is conveyed through an unusual medium, 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

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instantaneously. We document that some topically specific Trump tweets have a significant market impact and might affect trading. However, the majority of these messages are reactive and therefore predictable using past market information.

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 (Bar-Haim et al., 2011) or retail investor message boards (Antweiler and Frank, 2004; Das and Chen, 2007; Chen et al., 2011), an increasing number of studies highlight 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 complementary to this strand of literature in that (i) we consider a large number of tweets about the general economy instead of fewer or even single 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., criticizing the monetary policy conduct of the Federal Reserve or tariffs and trade, as in Bianchi et al. [2019] or Filippou et al. [2020], respectively), (iii) we capture market-wide return, volatility, and volume effects relevant for a wide range of investors, and (iv) we provide a conceptual framework that explains which tweets are likely to evoke a market reaction.

The remainder of this paper is outlined as follows: Section 2 provides a detailed literature review. Section 3 describes the Twitter and high-frequency ETF data and presents descriptive statistics. In Sections 4 to 6, we describe the multitude of methods that help us quantify the financial market impact of Trump's tweets, namely matched-sample regressions (Section 4), Heckman selection models (Section 5), and stepwise regressions (Section 6). Section 7 concludes.[4]

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[4]In Online Appendix A, we provide further technical details for the ML algorithms. Online Appendix B lists examples of tweets along the topic-textual sentiment spectrum, while Online Appendix C presents various specifications of high-frequency event studies. Finally, Online Appendix D contains results from additional robustness tests.

2 Related literature

This section provides a detailed overview of the two large yet diverse strands of the literature to which our study contributes. First, the market impact of direct presidential messaging is rather similar to that of central bank communication and (surprise) monetary announcements; both are extensively studied phenomena in the macro-finance literature. The comparability of the mechanisms behind these announcements to our setting allows us to approach presidential communication by using a similar theoretical framework. Secondly, we contribute to studies focusing on social media as an alternative news channel for investors and to the segment of such studies specifically centered around Trump's Twitter activity.

Direct and unfiltered presidential communication via social media is a relatively new phenomenon that warrants thorough investigation, especially, as the president has a direct policy authority in the commercial (trade) domain, quite comparable to that of the Fed in the monetary policy domain, and could affect financial markets. Due to this parallel and because of the novelty of the use of various social media outlets by government entities, we look for a familiar and better studied benchmark, namely that of central banks. Monetary policy communication by central banks, such as the FOMC or the European Central Bank (ECB), and their effect on financial markets has been the subject of academic interest for decades.[5]

Although information asymmetry has been a focus of the theoretical academic debate on models that aim to understand central bank monetary policy since the 1970s, empirical work arguing for its relevance emerged only about three decades later (Sargent and Wallace, 1975; Barro, 1976; Barro and Gordon, 1983, are examples of these theoretical models). By showing that increases in the Fed funds rate predict long-term US treasury rates, Romer and Romer (2000) present an additional case of information

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[5]The effect of news on financial markets is not limited to equity markets and is well documented for other asset classes as well (see, for instance, Almeida et al. (1998) and Andersen, Bollerslev, Diebold, and Vega (2003b) for effects on the foreign exchange market).

asymmetry consistent with the notion of the "Fed information effect"; namely, how the Fed's access to information superior to that of commercial forecasters translates into improved inflation projections. Kuttner (2001) and Gürkaynak et al. (2005) propose forward-looking measures to identify monetary policy surprises coming from central bank communications. Building on these measures, Bernanke and Kuttner (2005) show that the stock market experiences an upswing after expansionary monetary policy surprises, which is accompanied by a decrease in federal funds futures prices. Using the Campbell and Ammer (1993) decomposition of stock returns, they provide further evidence that their findings are not driven by expectations of future inflation.

By contrast, Faust et al. (2004) find that monetary policy announcements do not improve private sector forecasts of upcoming macroeconomic data releases, including CPI and GDP. Similarly, Campbell et al. (2012) fail to support the notion that Fed announcements contain significant information about inflation. Nevertheless, they show that monetary policy tightening is followed by a downward revision of the Blue Chip unemployment forecast, an effect attributable to the information conveyed by the Fed to the private sector. Using changes in the high-frequency federal funds futures rate, Nakamura and Steinsson (2018) show that Blue Chip GDP forecasts are revised upwards after a tightening of monetary policy, a phenomenon that is explicable by the Fed information effect.[6]

Most comparable, in both in methodology and rationale, to our study is the work of Bauer and Swanson (2020), who resolve the discrepancies posed by the mixed evidence on the market impact of FOMC announcements. They show that the market reaction to news arriving prior to FOMC announcements is an omitted variable, and incorporating that news flips the sign of revisions that were previously attributed to monetary policy surprises. More specifically, a tightening in monetary policy will be followed by a downward revision in Blue Chip GDP forecast after controlling for the news *before* FOMC announcements. This is consistent with their proposed "Fed responds to news"

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[6] Correa et al. (2020) focus on the role of central banks' financial stability reports, showing that the sentiment expressed in those documents is suggestive in predicting banking crises.

channel, which also explains the Fed information effect proposed by earlier studies.[7] The mechanism proposed by Bauer and Swanson (2020) in the context of FOMC announcements is directly applicable to our setting and to study the two-way interaction between presidential tweets and financial markets, as opposed to the simpler view that tweets affect markets.. This framework not only explains the significant tweet reaction found in other studies (see, for instance, Bianchi et al., 2019; Filippou et al., 2020) but also well accommodates our key empirical observation that Trump's tweets are reactive; that is, they are predictable by past market information rather than affecting subsequent market trends.

Although the traditional and/or official news channels constitute a primary information source for some investors, many investors, including retail investors, can learn information indirectly. One such indirect source is 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 of 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).

Financial analysis and investment forums and stock message boards constitute alternative sources of information for financial markets (Antweiler and Frank, 2004; Das and Chen, 2007; Hu and Tripathi, 2016). An additional news channel, increasing in importance, is social media: Hirshleifer (2020) points out that the social transmission of news can shape economic thinking and behavior in many aspects.[8] In their novel role as news outlets for companies and politicians, social media platforms offer a widely accessible and *direct*

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[7]Their finding is in line with Cieslak and Vissing-Jorgensen (2021), who show that policymakers pay attention to the stock market before announcements, since the market itself affects the announcement outcome.

[8]The increasingly important role of social media as an information channel is reflected by the sheer number of recent studies. Among the first to study their impact on markets are Bollen et al. (2011), who inspect how Twitter moods predict 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. Behrendt and Schmidt (2018) support the notion of a general relation of Twitter sentiment and stock returns, while 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.

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source of information where messages are communicated in real time. Tweets posted by the president constitute official government communication that is not passed through traditional information channels or news intermediaries. Moreover, the president's Twitter account fulfills a special dual role: First, it enables direct, frequent, and instant communication with the electorate. Second, (economic) messages targeting specifically investors and financial market participants are also regularly disseminated.

The closest parallels 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 by conditioning investors through his pre-FOMC meeting tweets. This is a rather indirect channel, where the Twitter activity of a government entity affects other government or policy decisions.[9] Filippou et al. (2020), on the other hand, study the effect of Trump's tweets on the foreign exchange market and find that the tweets reduce speculative trading. Both studies suggest that Trump's tweets directly impact financial markets, similar to the "Fed information effect" of the macro-finance literature discussed above. Our focus lies, however, on the equity market, and while they consider similar (although fewer) tweet topics, our approach can be distinguished in three aspects. First, we specifically study the asymmetric market reaction to both positive and negative tweets within *and* across topics. Second, 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). Third and most importantly, we take into account pre-tweet market movements and show that Trump tweets are largely reactive to pre-existing market trends. We confirm this in different empirical settings, including placebo tests.

This last aspect is the key difference between our study and all previous examples from the literature on the topic. In fact, by including the period preceding the tweets in our analysis, we show that controlling for past market information is important to

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[9]To ensure that we are only measuring the (potential) direct financial market impact of government social media communication, we exclude meeting and press conference days of the FOMC and BLS announcement days from our sample.

disentangle the financial market impact of Trump's messages from movements following past economic news. This "Trump reacts to news channel," analogous to the "Fed reacts to news channel" proposed by Bauer and Swanson (2020), not only helps predict Trump's decisions to tweet about the economy but can also explain the topical and sentiment-based heterogeneity found in the market impact of his social media posts.

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 ML algorithms to extract their topical content and textual sentiment for the analysis.[10] The section concludes by presenting descriptive statistics.

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.[11] To ensure that we are only capturing the direct financial market impact of Trump's communication on Twitter, we exclude FOMC meeting and press

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[10]The Twitter data collection, preparation, and sorting is based on extended data and augmented versions of the Python codes and ML algorithms presented in Kormanyos, 2020. The unpublished thesis can be made available upon request.

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

conference days from our sample.[12]

Our focus is on Trump's own tweets (i.e., non-retweets) that are related to the state and 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 was an exceptionally active Twitter user: in our sample period, on average, he published seven tweets a day (excluding retweets). Given this volume and the topical diversity, we disentangle the tweets 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 ML algorithms used and their application to our data.

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 categories. One possible method for assigning topic labels would be the use of unsupervised ML algorithms such as Latent Dirichlet Allocation, 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, with topics either too broadly or too narrowly defined, and, is thus not suitable for our purposes. Therefore, we implement a semi-supervised topic model (Gallagher et al., 2017), which 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 this list of seed terms directly from Trump's tweets; for the resulting topics, we ultimately verify correct topic assignments by hand.

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[12]In further untabulated robustness analyses, we additionally remove dates from the tweet day sample on which the Bureau of Labor Statistics (BLS) announces macro news pertaining to economic (confidence), production, consumption or unemployment figures. All of our results for the SPY ETF cumulative returns, trade volumes, and realized volatility, along with changes in the VIX presented herein are robust to this adjustment.

The outcome of this topic decomposition is depicted in Figure 2. As mentioned above, we use only tweets containing economic content for this analysis. The four topics resulting from the decomposition are: (1) *Economy, Fed, and Stock Markets*, (2) *(Un-)Employment, Job Creation, American Industries, and Production*, (3) the *US-China Trade War* (and later trade agreement), and (4) *North American Trade Relations*, especially concerning NAFTA and trade or tariffs between the US and Mexico or Canada.[13,14] In addition, we pool these four topics, which then make up the category of *Economy Tweets* that helps capture the *average* economic tweet effect. Table B1 in Appendix B provides illustrative examples of positive and negative-sentiment tweets for each of these topics.

[Insert Figure 2 here]

After filtering out non-economic tweets, the four final topics of interest assigned by the topic model total 1,399 tweets, excluding retweets. Since our topic model allows multiple topic assignments, tweets can be assigned to more than one topic. Trump also often posted multiple tweets on the same topic (and with persistent tonality) in close succession. Since these sequences of tweets practically constitute a single message, we always use the first tweet of such series 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 tabulate the tweet sample composition across topics for all sample tweets and events used in the final analysis, respectively. Figure 3 additionally depicts the monthly average proportion of tweets for each topic analyzed over the sample period.

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[13]In the remainder of the paper, we abbreviate topics (1) through (4) with the following: *Economy, Fed, and Markets*, *Employment, Industries, and Production*, *US-China Trade War*, and *NAFTA/US-Mexico Trade War*.

[14]On December 22, 2017, Donald Trump signed the Tax Cuts and Jobs Act (TCJA) into law, a tax reform that resulted in a decrease in individual income tax rates mainly for higher income brackets and implemented lower flat corporate and estate tax rates. In our sample, tweets pertaining to the planning, passing and signing of this act can be found both in the *Economy, Fed, and Markets* and *Employment, Industries, and Production* topics, depending on the perceived impact of the TCJA on financial markets, and employees and job creation, respectively. In untabulated robustness tests, we filter out these tweets from the aforementioned topics and treat them as an additional topic called *Tax Reform* in the analysis. After removal of these tweets, the main results remain unchanged, while the effects found for the *Tax Reform* topic are statistically insignificant.

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The final sample of event tweets considered in this analysis comprises 228, 135, 88, and 78 tweets for the (1) *Economy, Fed, and Markets*, (2) *Employment, Industries, and Production*, (3) *US-China Trade War* and (4) *NAFTA/US-Mexico Trade War* topics, respectively. The number of tweets considered in the pooled *Economy* category is 404.[15] In this pooled category, Trump posted 3.64 tweets per week on average that are considered in our event sample; or, put differently, at least one economy-related tweet every two days.

[Insert Table 1 here]

At a sample size of 615, most of Trump's economy-related tweets 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 became an increasingly prolific Twitter user over time: The total number of *Economy* tweets almost doubled from 481 (155) in 2017 to 811 (241) in 2018. Figure 3 shows that certain topics were more or less important to Trump and his followers at different points in time..

[Insert Figure 3 here]

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[15]It is important to note that the total number of pooled *Economy* tweets is lower than the sum of tweets considered in each of the four topics individually. There are two reasons: First, since tweets can belong to multiple topics, pooling them in the Economy tweets category will yield fewer overall tweets since duplicates are counted only once. Second, we account for non-overlapping event windows.

3.1.2 Sentiment analysis

The prevalent methodology to classify textual sentiment in financial economics is based on financial word dictionaries (see the seminal work of Loughran and McDonald (2011, 2015, 2020)). Since Trump's tweets contain neither highly technical language nor specific finance jargon, this approach is less suitable for our purposes. Consequently, we resort to an ensemble ML model that consists of several algorithms to classify tweet sentiment. We train this model on 30% of all the non-retweet Twitter data, 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.[16,17]   The overall probability score for the three possible sentiment outcomes is obtained by equally weighting the probability scores computed by each ML algorithm in the final ensemble model that is used to classify tweet sentiment.[18]

[Insert Table 2 and Figure 4 here]

Figure 4 and Panel A of Table 2 show the distribution of sentiment across topics. For all topics, Trump posted 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 partly due to the ML classification's difficulty in balancing the output proportions of the under-represented outcome labels in the training data.[19]

The descriptive statistics of sentiment across topics displayed in Panel A of Table 2 are based on probability scores instead of labels: For each tweet, the ML algorithm predicts the probability of positive, negative or neutral tonality. Tweets are assigned the tonality

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[16]Here, "all Twitter data" refers to all of the roughly 5,500 Trump tweets, with including a wider range of topics to ensured that the training data is as diverse and unbiased as possible.

[17]In the rare cases where the three human-assigned tweet sentiment labels in the training set were not unanimous, we selected the sentiment label suggested by a majority vote.

[18]The ensemble consists of six distinct ML algorithms, that vote on the predicted labels with equal weights if their cross-validated predictive accuracy in each iteration exceeds 70%.

[19]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 scores (higher in absolute values) could more reliably reveal Trump's preferences on economy topics.

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 scores of 36.539, 60.173, 31.064, and 30.969%, respectively. Sentiment scores also vary by topic. The most extreme negative and positive sentiment score values range from -85.371 to 87.361% (for the *Economy, Fed, and Markets* topic). Over the sample period, Trump posted, on average, more positive tweets than negative ones, as displayed in Panel B of Table 2. While the average sentiment of his tweets was very positive overall at 45.932% in 2016, it was already lower (but still far above zero) at 35.372% in 2017, and dropped even further to 18.961% by 2018, as President Trump progressively tweeted more frequently and negatively.[20]

3.2 ETFs

To understand the impact of tweets on the equity market, we use transaction data of the SPY ETF. SPY was launched by State Street Global Advisors in 1993 and is one of the longest-traded and most liquid ETFs in 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, which greatly reduces barriers to investment for ETFs. It is also more affordable to invest in the SPY ETF than directly investing in its constituent companies, as it involves lower trading costs (Ben-David et al., 2018).

ETFs (SPY specifically) provide an ideal laboratory to study the market-wide and aggregate price impact of high-frequency presidential communications. First, the SPY ETF is a highly liquid instrument, with an average bid-ask spread of 0.41 basis points over

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[20]Figure C2 in Appendix C shows that, in addition to posting more frequently, Trump also contradicted 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 vice versa. Both the increase in tweets posted and the frequency of sentiment reversals suggest that Trump might not have offered information relevant for prices but merely introduced more noise.

our sample period. Therefore, it should quickly and precisely reflect new information: Ernst (2021) finds that the liquidity of the SPY ETF can reach such desirable levels that it not only contributes to market-wide price discovery but also facilitates the price discovery processes of individual stocks. Second, to study the impact of presidential social media posts 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.

We extract the ETF transaction data from the TAQ database. We construct minute-level volumes by aggregating the trading volume over each minute and price data by using the last trade of every minute. Resorting to the last trade of each minute instead of using value-weighted average prices (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 would correspond to using stale prices to evaluate market effects for tweets that occur in the middle of these minutes.

3.3 Descriptive statistics

Our primary analysis relies on 30-minute windows before and after each tweet and similar time windows on non-tweet days as reference points. Table 3 provides summary statistics for the market indicators we use over the 30-minute periods. Summary statistics for the SPY ETF are tabulated in Panel A. Panel B shows the summary statistics for the VIX index level and its cumulative changes over 30-minute windows.

We compute 30-minute cumulative returns 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 ETF or the VIX

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index i and tweet j over the event window T from tweet minute T_1 to minute $T_2 = 30$.[21] R_{it} denotes the return for ETF or index i at the end of event-window minute t. We similarly construct log volumes by aggregating minute-level volume data to 30-minute cumulative sums before taking logarithms. For the calculation of realized volatility over 30-minute periods, we rely on 5-minute returns to limit the possibility of overestimating volatility due to microstructure noise.[22]

[Insert Table 3 here]

The box plots in Figure 5 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 index) 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 the end of the trading day (EOD). We present a more formal test of these figures in the form of high-frequency event studies in Appendix C.

[Insert Figure 5 here]

3.4 The distribution of returns around tweets

Studying the impact of Trump's tweets raise the question whether the days on which he tweets were different from the days when he did not. To answer this question, we analyze

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[21]We assume expected returns over 30-minute windows to be sufficiently close to zero so that $C\hat{A}R_{i,j(T)}(T1,T2) = CR_{i,j(T)}(T1,T2) - \hat{E}R_{i,j(T)}(T1,T2) = CR_{i,j(T)}(T1,T2)$ is defined as the 30-minute cumulative abnormal return with an expected return $\hat{E}R_{i,j(T)}(T1,T2)$ of zero, in which case the cumulative abnormal returns CAR equal cumulative returns CR. Nonetheless, we use the term cumulative abnormal returns, abbreviated as CAR, in the remainder of this paper for the sake of consistency with the prevalent notation used in the literature.

[22]For more details and a potential solution to this issue, see Andersen, Bollerslev, Diebold, and Labys (2003a), Bandi and Russell (2008), and Andersen and Benzoni (2008), among others.

return distributions separated along three dimensions in Tables 4, 5, and 6: In each of the three tables, Panel A displays the p-values from Kolmogorov-Smirnov (KS) tests of the return distribution around each of the four tweet topics, split by sentiment, and for the pooled sample of *Economy* tweets. Panels B and C of each table depict the histograms overlaid with the estimated kernel density functions for the latter tweet category, split by tweet sentiment. Statistical significance in Panel A of Tables 4, 5, and 6 would suggest that the examined return series are likely drawn from the same distribution. Furthermore, Table 4 displays these p-values for pre-tweet CAR_{t-1}, the independent variable in our regressions (Section 4), and the matched counterfactual returns at the same time of day from days when Trump did not tweet. Analogously, Table 5 shows these figures for post-tweet CAR_t, or the dependent variable in the regressions presented in Section 4. Finally, Table 6 displays analogous test results and histograms for pre- vs. post-tweet returns on tweet days.

[Insert Tables 4 and 5 here]

None of the pre-tweet returns, except for the *Employment, Industries, and Production* topic, seem to be drawn from the same distribution as the matched-sample returns, which suggests that days on which Trump tweeted about the economy were statistically different from those when he did not (Table 4). The same holds for post-tweet returns (Table 5), where the only exceptions are the positive and negative tweets about *Employment, Industries, and Production*, but along with tweets about the *US-China Trade War* and positive tweets about *NAFTA/US-Mexico Trade War*. In both cases, the differences in tweet and counterfactual return distributions is also evident in the histograms displayed in Panels B and C.

[Insert Table 6 here]

Finally, the KS null hypothesis that returns before and after tweets follow the same distribution can be rejected for all topics and polarities, with the exception of negative

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tweets about *Employment, Industries, and Production*, which suggests that returns after tweets are structurally different from those before tweets (Table 6). Whether this difference in pre- and post-tweet return distributions originates from the tweets themselves or rather market trends that were manifest before the tweets, some of which might have driven Trump's decision to tweet in the first place, needs to be tested in a more formal setting. Keeping in mind that pre-tweet returns are already different from non-tweet day returns *before* Trump tweets, it appears crucial to control for pre-tweet market conditions when analyzing the potential market impact of his social media posts: To this end, we present parsimonious regressions in Section 4 that allow us to control for these usually omitted pre-tweet market conditions.

4   Matched-sample regressions

In this section, we present the results for our main regressions of current market information on sentiment indicators and past market information, along with their interactions. Our methodological setup allows us to formally examine the potential relation between tweets and returns. Furthermore, to test whether tweets are followed by increased trading activity, we examine the relation between tweets and trading volume. Finally, we develop empirical tests based on changes in realized volatility and the VIX to examine whether tweets are followed by an incorporation of new information, while controlling for past values of these variables of interest.

We match each event by a counterfactual event window for pre- and post-tweet cumulative returns (CAR), or changes in realized volatility (ΔRV), trading volumes (ΔVOL), and the VIX index (ΔVIX), randomly sampled from days on which Trump did not tweet about any of the four main topics.[23] This procedure allows us to estimate the effect of Trump's tweets while directly contrasting it with market conditions in the absence of

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[23]We remove all single-topic and pooled *Economy* tweet days from the sample, from which we then draw matched counterfactual event windows. We do this so as not to capture effects that might follow from tweets not connect to our topic of interest.

tweets. The matching-sample pre- and post-tweet cumulative returns (ΔRV, ΔVOL, ΔVIX) are drawn randomly but from the exact same time of day (minute level) on a day other than the tweet day. This allows us to separate the effect of tweets from that of intra-day cyclicality, by differencing the tweet and non-tweet counterfactual returns in our analysis.

4.1 Methodology

We perform matched-sample regressions to account for past and contemporaneous information, thus formally testing whether Trump's tweets were driving market dynamics more than past market conditions. To this end, we regress post-tweet CAR_t on the corresponding pre-tweet CAR_{t-1} and tweet sentiment dummies, thereby controlling for both market events and sentiment preceding the tweets. These within-topic regressions provide evidence as to whether tweets, more specifically their sentiment, can explain post-tweet cumulative returns or whether past price information is the determining factor. If pre-tweet cumulative returns explain their post-tweet counterparts, then ultimately the tweets do not carry relevant information to a larger extent than what is already incorporated in past prices. We perform similar tests using trading volume to see whether we find any abnormal trades that could be attributed to the tweets. As additional indicators for the potential incorporation of information in the market following the tweets, we also look for any change in realized volatility and the VIX, controlling for past movements.

In our empirical setting, we account for time-of-day effects by matching to each pre- and post-tweet window CAR, ΔRV, ΔVOL, and ΔVIX the same-time CAR sampled randomly from a non-tweet day. These counterfactual returns serve as time-matched controls for intraday seasonality and facilitate an estimation of the actual effect of Trump's tweets on changes in SPY ETF and VIX index levels. This approach is inspired by the methodology presented in 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.[24]

Our approach thus minimizes the potential influence of intraday seasonality on the results. Since trading activity and liquidity are expected to be lower outside trading hours, we additionally remove tweets posted before 9:30 AM ET or after 4:00 PM ET from the sample to avoid potentially biasing the results downward. Fortunately, we do not restrict the tweet sample excessively through this step: As illustrated by Figure 6, which shows the distribution of tweets over the time of day, Trump posted the vast majority of his tweets during trading hours. Given the trade-off between losing out-of-trading-hour tweets versus working with stale prices in those event windows, we opt for tweet exclusion, thereby minimizing any bias related to delayed market reactions to late-night tweeting. Taking both facts together, tweets posted when markets are open are likely to capture the potential market impact of Trump's tweets most accurately and in a timely manner.

[Insert Figure 6 here]

We present regression results for each of the four topics: (1) *Economy, Fed, and Markets*, (2) *Employment, Industries, and Production*, (3) *US-China Trade War* and (4) *NAFTA/US-Mexico Trade War* and for the pooled *Economy Tweets* category. We analyze the potential impact of Trump's tweets on our four variables of interest (CAR, ΔRV, ΔVOL for the SPY ETF and cumulative ΔVIX), as follows:

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

where V_t denotes the post-tweet variable of interest from tweet minute 0 until 30 minutes after and may stand cumulative returns (CAR), realized volatility (ΔRV) with the cumulative change in trading volumes (ΔVOL) for the SPY ETF, or cumulative changes

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[24]In Online Appendix D, we present results for extended pre-tweet windows of [-120,0).

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for the VIX index (ΔVIX). The lagged variable V_{t-1} captures the pre-tweet number from minutes [-30,0) before tweets. As noted above, all pre- and post-tweet cumulative returns are matched with randomly sampled same-time counterfactual non-tweet cumulative returns. D_+ and D_- are tweet sentiment dummies equal to one if tweet sentiment is positive or negative, respectively.[25] Following the removal of neutral-sentiment tweets, the intercept β_0 can therefore be interpreted as the intercept on the variable of interest at non-tweet times for the matched sample. In the cumulative volume regressions, we additionally include past cumulative returns on the SPY ETF based on evidence from the nascent literature that volumes are most likely affected by both past trades and past changes in prices (as in Hasbrouck 1991a, 1991b). In the interest of parsimony, however, we do not include CAR_{t-1} in the realized-volatility regressions.

4.2   Difference in market conditions around tweets and matched samples

Before presenting our benchmark results from the matched sample analysis, we examine whether the returns of tweet and counterfactual subsamples differ in their distributions and whether tweet returns are different before and after tweets. This enables us to compare the distributions between subsamples, which is especially imperative in the absence of a clear baseline level of a tweet reaction. This way, we can show whether tweets alter this distribution. We perform this analysis separately for positive and negative tweet sentiment so as not to average out potentially opposing effects in a pooled setting. The visual representation of this analysis is depicted in Figures 7 and 8, which show the distribution of the difference between tweet and sampled counterfactual 30-minute cumulative returns on the SPY ETF for 30-minute intervals over the 120 minutes leading up to and following tweets.

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[25]As explained in Section 3.1.2, neutral tweets are rarely classified by the ML sentiment model due to the low number of neutral tweets in the training data which itself arises from the strongly polarized language in Trump's posts. Based on our assumption that tweets with more extreme positive or negative sentiment carry higher potential informational content than (more) neutral tweets, we remove neutral tweets from our sample completely.

[Insert Figures 7 and 8 here]

Examining the distributional difference between tweet and counterfactual returns provides the first descriptive evidence of our main result; namely, that Trump may have been more reactive to markets than they were to his tweets. What remains an empirical question, however, is whether market conditions on days when he tweeted were different from those when he did not, especially *before* he decided to tweet. Values larger than zero in Figures 7 and 8 indicate that tweet returns for the time interval depicted on the x-axis are, on average, larger than matched-sample figures. For positive tweets about the *Economy, Fed, and Markets*, returns were already larger on days when Trump tweeted compared to those when he did not. For positive tweets about the remaining *Employment, Industries, and Production* and both trade war topics, cumulative returns for up to two hours before tweets are larger than counterfactuals, but over the hour before tweets and for 90 minutes after, they are lower. We observe a similar pattern for the post-tweet pooled *Economy Tweets* category, which might suggest that when markets experienced a decline, Trump might have tweeted something positive about the economy, with the intention if reversing market sentiment. We formally test this notion in the first step of the Heckman selection model presented in Section 5.

For negative tweets about the *Economy, Fed, and Markets*, the differences are generally larger leading up to and following tweets, which indicates that Trump posted negative tweets about this topic more often after markets experienced higher returns than otherwise. This pattern is suggestive evidence that Trump's decision to tweet was likely not random and depended on pre-tweet market conditions. For the *Employment, Industries, and Production* and both trade war topics, the return difference is more strongly pronounced for negative than for positive tweets (i.e., it differs more strongly from zero), but the direction in this difference is less clear, showing a mixed picture.

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4.3 Results

In this subsection, we report the results of the regression described in Eq. (2). Panel A of Table 7 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 Tables 7 and 8, statistical significance is assessed by t-tests using HAC-robust standard errors.

As the table shows, the only instance where tweet information has a statistically significant influence on CAR_t is for the negative tweets about the *US-China Trade War*. When Trump tweeted negatively about the *US-China Trade War*, CAR_t decreased by 7.475 basis points over the 30 minutes following tweets (statistically significant at the 10% level). For an increase in pre-tweet CAR_{t-1} by one standard deviation, or 17.033 basis points, this figure corresponds to a decrease in current CAR_t by 127.322 basis points over the 30 minutes following tweets (see Table 3 for descriptive statistics). 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 percent (one standard deviation) higher positive return, the current CAR_t drops by 0.311 (5.297) 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 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 (see, for instance, Cieslak and Schrimpf, 2019).

We observe a similar effect 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 0.317, or 5.416 basis points for a one standard deviation increase in CAR_{t-1}, and is statistically significant at the 1% level. For the *NAFTA/US-Mexico Trade War* topic, only past return information captured by CAR_{t-1} is statistically significant and has a negative influence on post-tweet cumulative returns, confirming that Trump's tweets did not convey new information for this topic.

[Insert Table 7 here]

Overall, the reactions of equity prices to Trump's tweets seem limited, which is why we investigate whether there might be other ways in which his tweets could have influenced 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 of the SPY ETF on the same set of regressors. The results for changes in cumulative 30-minute trading volumes are highly consistent across topics and are displayed in Panel B of Table 7.

In Panel B of Table 7, for all specifications, the influence of pre-tweet volumes and their interactions with both positive and negative tweet dummies are highly statistically significant at the 1% level. These positive coefficients on the interaction terms, irrespective of tweet tonality, suggest that volumes were more affected by past volumes than by Trump's tweets. The tweet examples in Table B1 in Online Appendix B showcase how President Trump advocated *for* tariffs, especially in the case of US trade relations with Mexico, or *for* leaving NAFTA. It is likely that financial markets either discounted this opinion, considering the potential disadvantages that leaving a trade agreement and imposing restrictive tariffs on major US trade partners could entail, or their expectations regarding Trump's preferences on this topic were in line with the tweet content (and this did not need to be updated).

The matched-sample regression results for the realized volatility of the SPY ETF, reported in Panel C of Table 7, are similar to those for volumes: Tweet information is hardly ever an influential factor in determining period t changes in realized volatility

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over the 30 minutes following Trump's tweets. This suggests that these tweets did not contain information that was new to the market, either at its face value or regarding Trump's preferences, and would thus translate into price discovery. The only exception is positive tweets about *Employment, Industries, and Production*, which are associated with a very slight increase in realized volatility of 1.071 basis point. Across topics, we find that while the tweets rarely have an affect, the realized volatility past value is a consistently statistically significant explanatory variable, due to the persistent nature of realized volatility.

Although Trump's tweets did not influence cumulative returns or trading, they could still have affected investor expectations about the future performance of the stock market or uncertainty. To this end, Table 8 presents corresponding results for cumulative changes in the VIX index. Overall, we find that the VIX index did indeed react to Trump's tweets: For all but the *Economy, Fed, and Markets* topics, negative-sentiment 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 large but also statistically significant at the 5% and 10% levels, respectively. For the *NAFTA/US-Mexico Trade War* topic, positive-sentiment 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 increased uncertainty.

[Insert Table 8 here]

We test the robustness of the regression results in several ways. First, we account for the changing relative importance of tweet topics, as shown in Figure 3, by including time fixed effects at the quarterly level. The baseline results are robust to the inclusion of quarterly time fixed effects and can be found in Tables D2 and D3 in Online Appendix D. 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 7 and 8. These results are qualitatively similar to the benchmark and can be found in Tables D4 and D5 in Online Appendix D. In further untabulated robustness tests, we additionally exclude macroeconomic news announcement days of the BLS from the sample and, finally, treat the 2017 TCJA tax reform as an additional topic and remove the corresponding tweets from the four main topics analyzed in this paper. Our results remain unchanged after both the removal of BLS dates and the adjustment of tweets for the 2017 tax reform, suggesting that in cases where we do find significant responses to Trump's tweets, they were driven neither by macroeconomic news nor by the tax reform.

Taken together with the previously described lack of significant market reactions for cumulative returns on the SPY ETF, trading volumes, and realized volatility, we find that Trump's tweets, on average, do not provide information that influences market prices and trading activity. Rather, the increases in forward-looking implied volatility captured by the VIX suggest 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 have offered indications of when Trump was going to tweet. We explore this possibility in the next section and in addition subsequently control for this non-random arrival of tweets in a Heckman-type two-stage model.

5 Heckman Selection Model

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

5.1 Methodology

In this section, we formally test the predictability of Trump's tweets and its effect on the previously presented results by using a model similar to 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 two trade war topics using observable and high-frequency past stock market information; lagged cumulative returns of the SPY ETF index and lagged VIX index levels. In the second stage, we add the inverse Mills ratio (IMR), based on the estimated tweet probabilities from the first-stage probit regressions, to the baseline matched-sample regression specifications. This allows us to control for the likely non-random occurrence of Trump's messages, and to corroborate that the "Trump reacts to news" mechanism drove the sporadic impact of economy-related tweets.

5.2 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. In the interest of parsimony and comparability to the set of predictors used in the main regressions, we use lagged cumulative returns on the SPY ETF and changes in VIX levels as predictors.[26] While we realize that Trump's decision to tweet most likely followed from a multitude of factors not limited to those we include in this step and therefore could be hard to predict accurately and "completely," our model serves mainly to demonstrate that both lagged cumulative returns and changes in VIX are *influential predictors* of Trump's tweets, even if they are not able to predict the tweets fully on their own. Since investors can observe these stock market indicators, they could also have surmised and therefore anticipated the arrival of a presidential tweet, in hopes of those tweets revealing information about Trump's preferences on a given topic. We report the results of the

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[26]Untabulated results indicate that extreme values of these variables, such as top quartiles of the return or volatility distribution, perform even better in forecasting a tweet's arrival.

analysis in Table 9, where marginal effects calculated at the mean of the respective variables are displayed in percentage points.

[Insert Table 9 here]

Table 9 suggests that an increase in cumulative returns of the SPY ETF by 10 basis points (one standard deviation of 17.033 basis points) in the preceding period is associated with a 3.76% (6.404%), 5.28% (8.993%), and 4.92% (8.380%) increase in probability that Trump would tweet in period t about any of the pooled *Economy, Economy, Fed, and Markets*, and *Employment, Industries, and Production* topics, respectively. The magnitude of these effects is not only statistically significant but also economically nontrivial, as they are calculated for 30-minute intervals.

Similarly, an increase in cumulative ΔVIX by 10 basis points (one standard deviation of 200.603 basis points) before tweets statistically significantly increased the likelihood that Trump would tweet about the relevant topic within the following 30 minutes by 0.43% (8.626%), 0.54% (10.833%), and 0.72% (14.443%) for the *Economy, Fed, and Markets, Employment, Industries, and Production*, and *US-China Trade War* topics. The probability that Trump would tweet about any of the four topics in the *Economy* category, displayed in the *Economy* column of Table 9, increases by 0.38% (7.623%) when lagged ΔVIX increases by 10 basis points (one standard deviation).

These results are in line with our previous findings that, for certain topics, Trump reacted more to markets than investors did to him. This notion is corroborated especially for the pooled *Economy* category and the *Economy, Fed, and Markets* and *Employment, Industries, and Production* topics for both SPY ETF and VIX and, in the case of VIX, also for the *US-China Trade War* topic. For the *US-China Trade War* (SPY ETF) and the *NAFTA/US-Mexico Trade War* topic (both SPY ETF and VIX), however, past market prices cannot significantly predict when Trump would post a tweet. In the case of both trade wars, Trump had the policy authority to influence future political and economic outcomes. The associated inability of past market prices to predict tweets about these

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topics indicates that in such instances, Trump's tweets actually either brought material price information to the market or revealed his opinion and/or preferences about potential future policy outcomes.

In the second stage of the Heckman model, we compute the IMR from the first-stage results presented above and add them to the baseline regression specifications as an additional regressor. This serves three objectives: First, we control for potential selection bias stemming from non-random tweet arrival. If Trump's tweets were not random, then neither was 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. Second, we control for the potential predictability of Trump's tweets to assess how it may affect our baseline results. Both objectives serve to further separate instances where markets reacted to Trump's tweets from those where markets were influenced more strongly by past information, such as lagged cumulative returns, realized volatility or volumes, or news that arrived prior to the tweets. Third, we investigate whether Trump played a role in amplifying past market performance.

The results for SPY ETF CAR, trading volumes and realized volatility are displayed in Panels A, B, and C of Table 10, respectively. We present analogous results for cumulative changes in VIX in Table 11.

[Insert Tables 10 and 11 here]

After controlling for tweet predictability, we find that the majority of our baseline regression results remain unchanged. This provides strong support for the "Trump reacts to news" mechanism, where the majority of the tweets were indeed expected by market participants, and only triggered a market reaction on topics where Trump has presidential policy authority. The robustness of our baseline results is especially pronounced for the SPY ETF return and ΔVIX regressions. For CAR on the SPY ETF, the coefficients on tweet tonality, D_+ and D_-, remain statistically insignificant in all cases, with the

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exception of 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 to the 7.475 basis points we find in the baseline regressions presented in Table 7. The interaction terms of tweet sentiment dummies and past CAR retain their benchmark sign, magnitude, and level of statistical significance as well, confirming the amplification effect that tweets had on cumulative returns.

The 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 7. 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 sentiment dummies is again highly statistically significant and similar in magnitude, but *negative* across topics. This difference between the benchmark and selection-corrected specifications suggests that investors accounted for the probability of a tweet and its 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.[27]

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 IMR, this effect is diminished in magnitude and statistical significance (0.458 basis points, statistically significant at the 10% level). In

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[27]This effect ranges from 0.501 (*NAFTA/US-Mexico Trade War*) to 0.882 basis points (*Economy* category), all significant at the 1% level, which corresponds to increases of 2.306 and 4.060 basis points, respectively, for a one standard deviation increase in pre-tweet ΔRV by 4.603 basis points. 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 basis points for positive tweets.

addition, negative tweets are associated with a 3.321 basis points decrease in realized volatility after accounting for tweet predictability.

Finally, in Table 11, we find that Donald Trump's negative tweets, controlling for tweet predictability by inclusion of the IMR, 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, respectively). Positive tweets about the *NAFTA/US-Mexico Trade War* are also associated with an increase in VIX by 63.087 basis points (significant at the 1% level). Consistent with our baseline regression results, we find that negative tweet sentiment is associated with an increase in volatility for all but the *Economy, Fed, and Markets* topic. Taken together, this suggests that negative-tonality tweets carried more noise than material information to the market.

6 Stepwise regressions

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

6.1 Methodology

In order to analyze whether past sentiment (sen_{t-1}) can predict information contained in prices, that is not explained by past price information, we conduct a stepwise regression for cumulative returns on the SPY ETF and the cumulative changes in ΔVIX, denoted as V_i:

$$\hat{\text{V}}_{i,t} = \alpha_0 + \alpha_1 \cdot \text{V}_{i,t-1} + \alpha_2 \cdot \text{sen}_{t-1} + \varepsilon_{1(i,t)} \tag{3}$$

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

$$\hat{sen}_t = \beta_0 + \beta_1 \cdot sen_{t-1} + \beta_2 \cdot V_{i,t-1} + \varepsilon_{2(sen,t)} \qquad (4)$$

The significance of the coefficient from the last step (γ_0), where we regress the residuals from Eq. (3) on those from (4), ultimately tells us whether information contained in tweet sentiment can predict information content for past cumulative returns (cumulative changes in the VIX) *beyond* the information already contained in past cumulative returns (cumulative changes in VIX):

$$\hat{\varepsilon}_{1(i,t)} = \gamma_0 \cdot \hat{\varepsilon}_{2(sen,t)} \qquad (5)$$

6.2 Stepwise regression results

Panels A and B of Table 12 present the results of the proposed stepwise regressions for SPY ETF CAR and ΔVIX, respectively.

[Insert Table 12 here]

The coefficient of interest, γ_0 in Eq. 5, shows the extent to which Trump's tweets contain price-relevant information that cannot be captured by past prices. We see that except for the *US-China Trade War*, none of the coefficients presented in Table 12 indicates 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. The effect is even more strongly pronounced for the VIX index (-62.151 at 5%).

These findings are consistent with our previous results: They corroborate that stock markets differentiate in their reaction to Trump's tweets between topics where (i) he, as

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the president, had the power to influence the real economy and government policies, and where his tweets *could* thus have provided additional information, and those where (ii) he merely stated his opinion or may have been reacting to ongoing market trends or news preceding those trends but could not have materially impacted economic outcomes.

7 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 roughly 1,400 tweets into topics and classifying their textual sentiment by machine learning algorithms, we test the market impact of these high-frequency messages. In our analyses, we account for pre-tweet market conditions, including news preceding Trump's tweets, based on minute-level ETF data on the S&P 500 and VIX indices, 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 cumulative changes in the VIX.

The key result of the paper is that Trump himself reacted to pre-existing market trends, which we corroborate by matched-sample regressions, as well as by studying the predictability of his tweets. Even after controlling for this tweeting pattern in a Heckman-type two-stage model, we find that market prices were more likely driven by past market information than by Trump's tweets, a finding consistent across various topics and textual sentiment. This finding gives rise to our proposed *"Trump reacts to news"* channel of stock returns, in which the tweets are predominantly informative about Trump's opinion or preferences regarding certain topics. In fact, we find the tweets that did have a short-term market impact are mostly related to topics where Trump as the president has direct authority over decision making or negotiations, as is the case for the *US-China Trade War*, the stance of the US towards NAFTA, and its relationship with North-American trade partners, most prominently Mexico. In these instances, the tweets

reveal Trump's attitude towards the topic in question, which consequently could result in market participants adjusting their initial reaction to the news that potentially triggered the tweet. The remaining majority of the president's messages about the economy, however, do not provide information 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 behind any office, no matter how ostensibly powerful. Since their proliferation in the past decade, social media platforms have begun to serve as an unfiltered and direct high-frequency communication channel with both mass appeal and nearly universal access. These different social media platforms 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, especially when these messages are broadcast by the head of the executive branch of any major country's government. Even though this paper is not to be understood merely as an analysis of Donald Trump himself, his use of social media, especially Twitter, provides useful lessons about this novel government communication channel.

Trump was a much more active Twitter user than both his predecessors or his successor, Joe Biden. In contrast to them, he tweeted about a dozen times daily and covered a wide range of topics, providing us with an *extreme case* in terms of the use of this communication tool. Moreover, he only infrequently resorted to the official presidential Twitter account `@POTUS`, which is carefully vetted and managed by staff. Rather, his opinions of and intentions for tax, economic, and commercial policy were discussed on his private account `@realDonaldTrump`, often quite spontaneously and without careful consideration (see, for instance, the infamous "covfefe" incident[28]). Nevertheless,

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[28]The incident refers to a likely misspelling of the word *coverage* in a tweet which Trump posted in 2017, has since been deleted, and read "Despite the constant negative press covfefe".

these intentions proved to translate into real reforms and negotiations with potential repercussions for the wider economy and are therefore informative about Trump's choice to exert his power: Before signing the 2017 Tax Cuts and Jobs Act into effect and throughout the trade negotiations and subsequent deal between the US and China following the trade war, Trump often discussed both issues on Twitter.

Moreover, it is crucial to acknowledge that as the president, Trump not only had superior information access and a unique ability to "leak" this information ahead of traditional communication channels, but he enjoyed immunity and therefore could actually do so. This special status warrants attention not only to him, but also to the implied market impact of his messages. In response to less extreme instances of government communication, the market impact is thus expected to be similar but presumably less pronounced. We therefore argue that analyzing the market impact of Donald Trump's tweets provides an *upper bound* estimate of the potential market impact of government communication (via social media), especially because he was a very active and prominent user. This is important to note, since policymakers, governing bodies of other economies, and news outlets often voiced concern over Trump's outspoken use of Twitter regarding decisions of (inter-)national economic importance. If our market impact estimates provide an upper bound and we rarely find significant market-wide effects for topics where Trump does not have policy authority, this evidence should be reassuring and applicable to evaluate the potentially detrimental market effects of other leaders, present or future, who might behave and communicate similarly to President Trump.[29]

Overall, having studied Donald Trump's Twitter use, we conclude that if his primary objective was to influence financial markets, he had failed to fulfill this goal, since his tweets would have had to consistently provide material information in order for the market to account for them. In other words, the market did not respond to his messages when their content did not go beyond directly observable past price information. On the

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[29]Although anecdotal evidence and some prior research documents significant "Trump effects" for single stocks (**?**), our results show that this impact, on average, does not extend to and persist at the market-wide level. Even for topics where the president can implement direct intervention, such effects are short-lived.

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 seems to have successfully accomplished through Twitter until the suspension of his account on January 8, 2021.

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Tables and figures
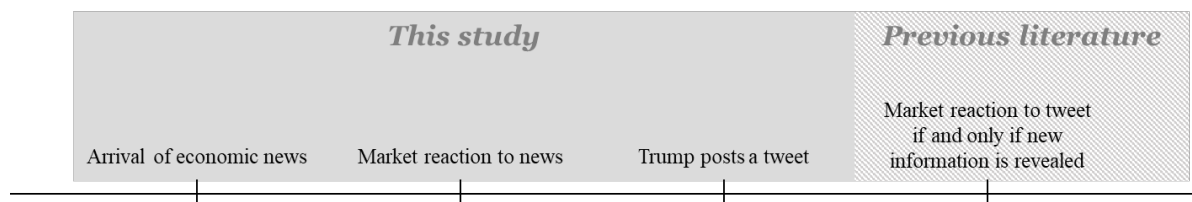
Figure 1 Timeline of information arrival

This figure depicts the stylized sequence of events for a typical scenario during which Trump posted a tweet on his Twitter account. First, economic news arrived, either from government agencies, like the BLS or BEA, or branches of the Federal Reserve System, that constitute price-relevant news for market participants. Preceding the arrival of a tweet from Trump's Twitter account, markets would observe this information and incorporate it into prices. Trump, in turn, after observing the news himself, the subsequent market reaction, or both, would post a tweet. Following Trump's tweet, the market *could* adjust its initial reaction to the news, depending on the informativeness of the tweet. A novel feature of this setup, relative to prior empirical work studying the market impact of Trump's social media activity covering only the section of the timeline highlighted in gray, is that we also consider events *preceding the tweet's arrival* (solid darker gray section). Observing solely the gray section would suggests that *most* of Trump's tweets were informative, which would prompt a "Trump information effect", while adding the previously omitted red section can accommodate the topical heterogeneity of the tweet impact – a novel "Trump reacts to news" effect.
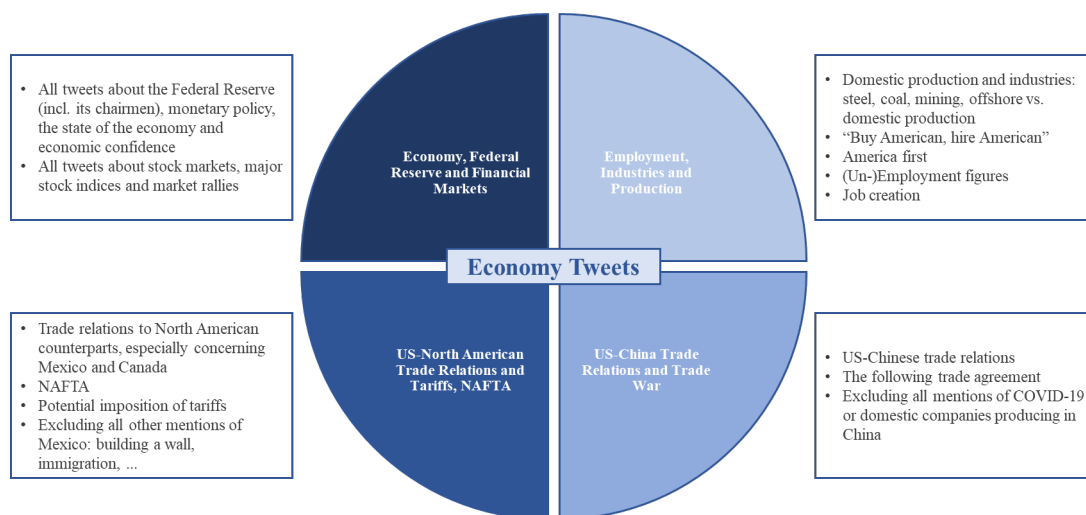
Figure 2 Tweet topics

The above figure depicts the output of the topic modeling 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) *NAFTA/US-Mexico Trade War* (clockwise from the upper left corner). These topics constitute the category referred to as *Economy tweets* in this paper, a set of all tweets related to the US economy and its international trade relations.

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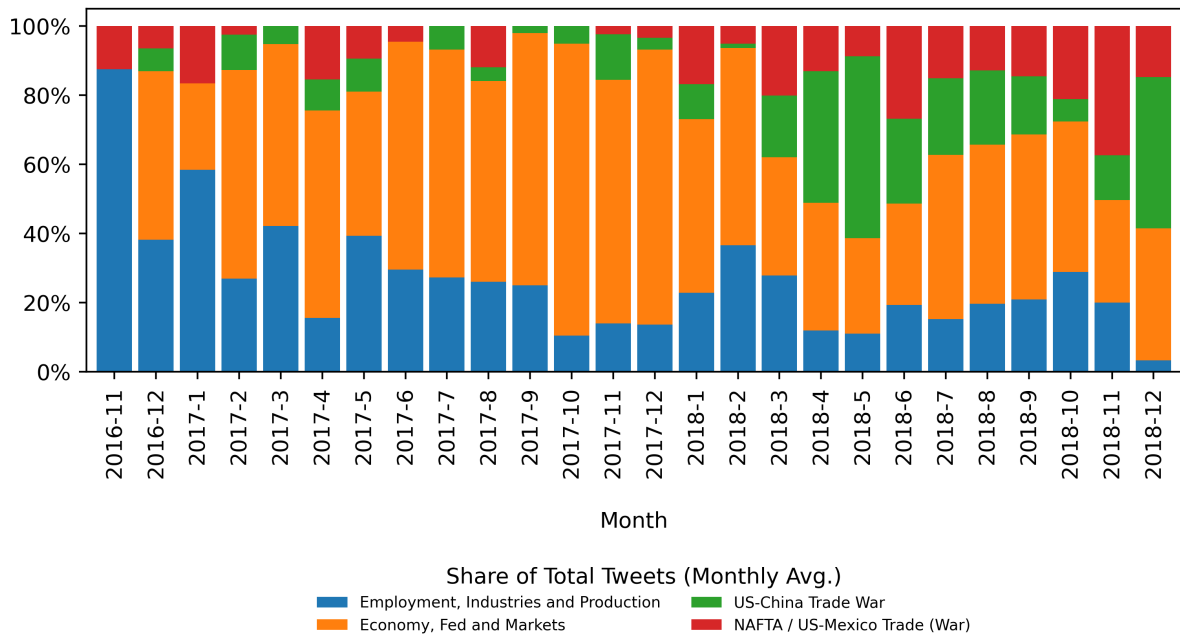
Figure 3 Shares of tweet topics over time

The above figure depicts how the proportions of economy-related topics evolved over time. Each bar represents the full scope of tweets in our sample over a given month, while the colors show the proportion of the total number of economy-related tweets that Trump posted about one of the four specific topics of interest. The sample spans the period from Q4 2016 to Q4 2018. Tweets were obtained using the Twitter API and from the Trump Twitter Archive.
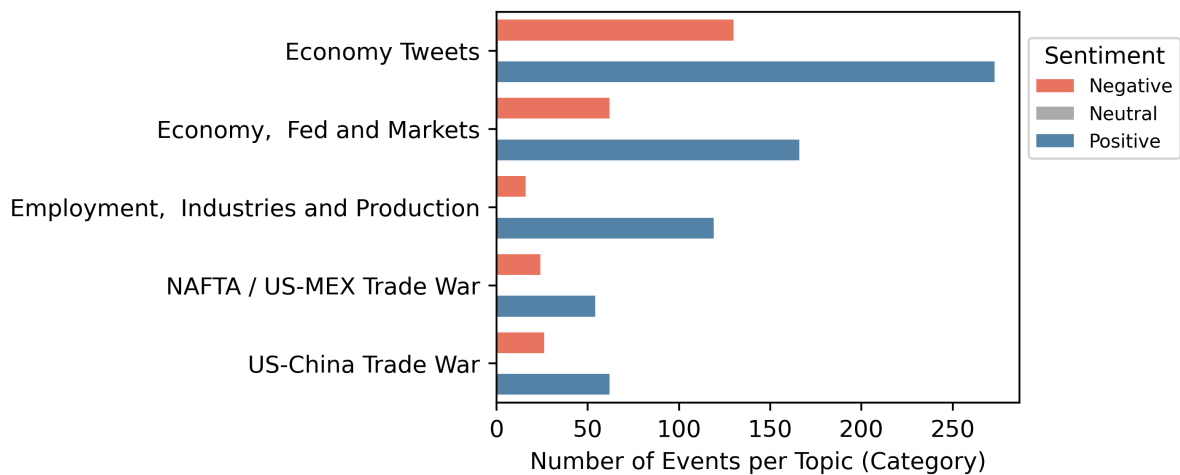
Figure 4 Event distribution along sentiment and tweet topics

The above figure depicts the distribution of textual sentiment of tweet topics and is the outcome of the sentiment classification ML algorithm. Red bars represent negative, gray ones neutral, and blue ones positive tweets. For the pooled *Economy tweets* category, there are three neutral tweets in the sample, so 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 were obtained using the Twitter API and from the Trump Twitter Archive.

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Panel A: SPY ETF

Panel B: VIX
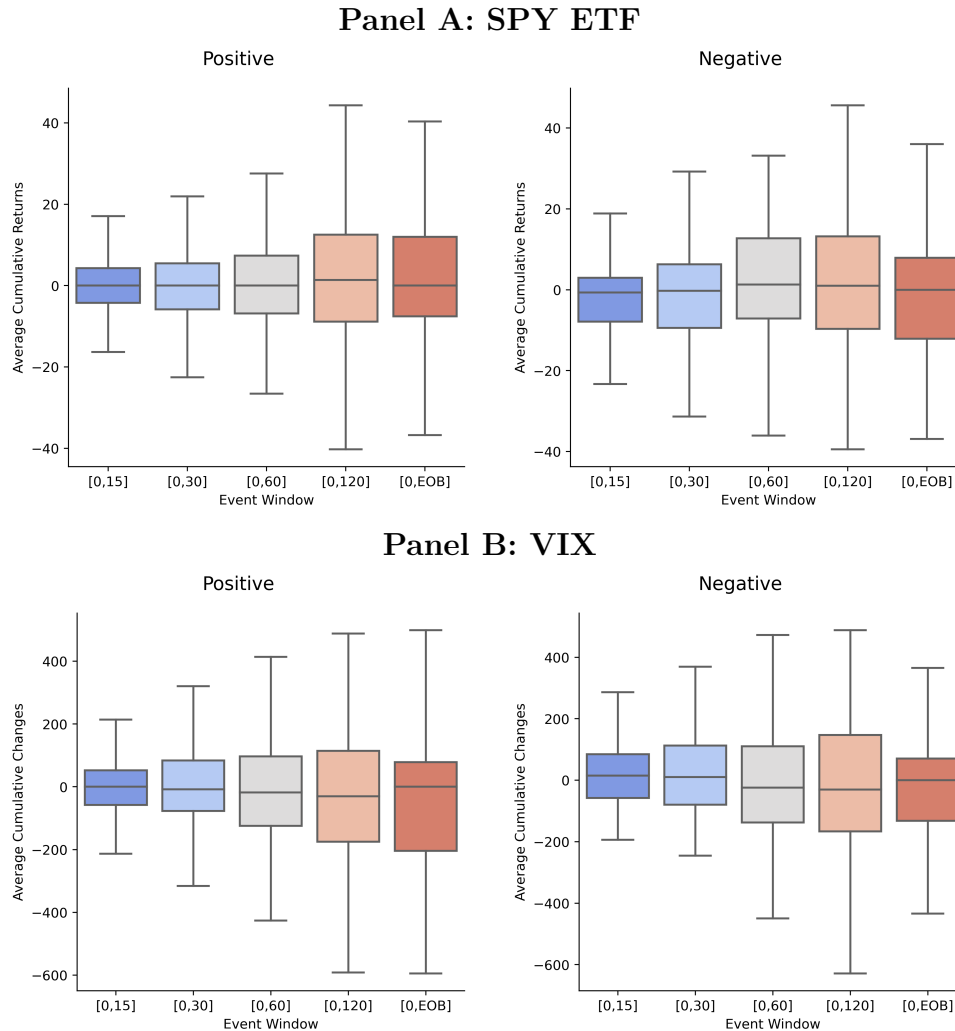
Figure 5 Distribution of CAR on the SPY ETF and ΔVIX across various event windows

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, divided into 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 were obtained using the Twitter API and from the Trump Twitter Archive.

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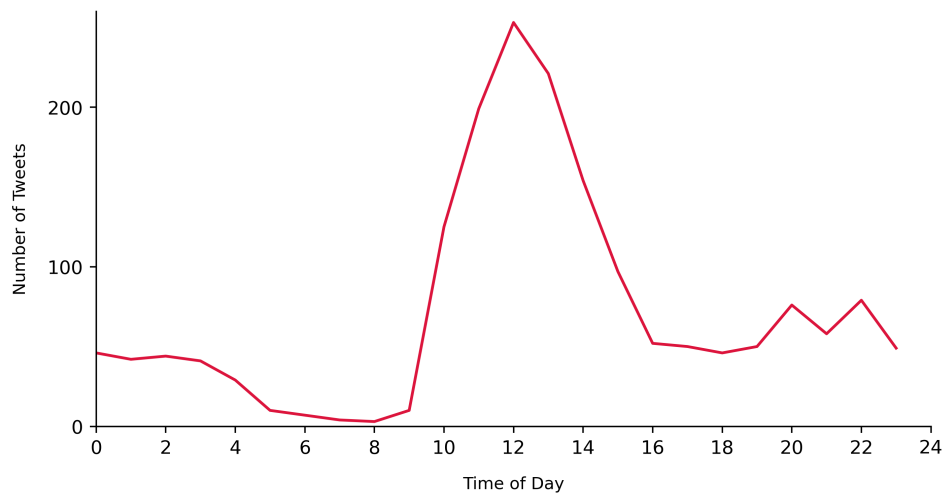
Figure 6 Frequency of tweets by time of day

The above figure shows the number of tweets Trump posted at each hour of the day over our sample period of Q4 2016 of Q4 2018. The majority of tweets were posted during trading hours.
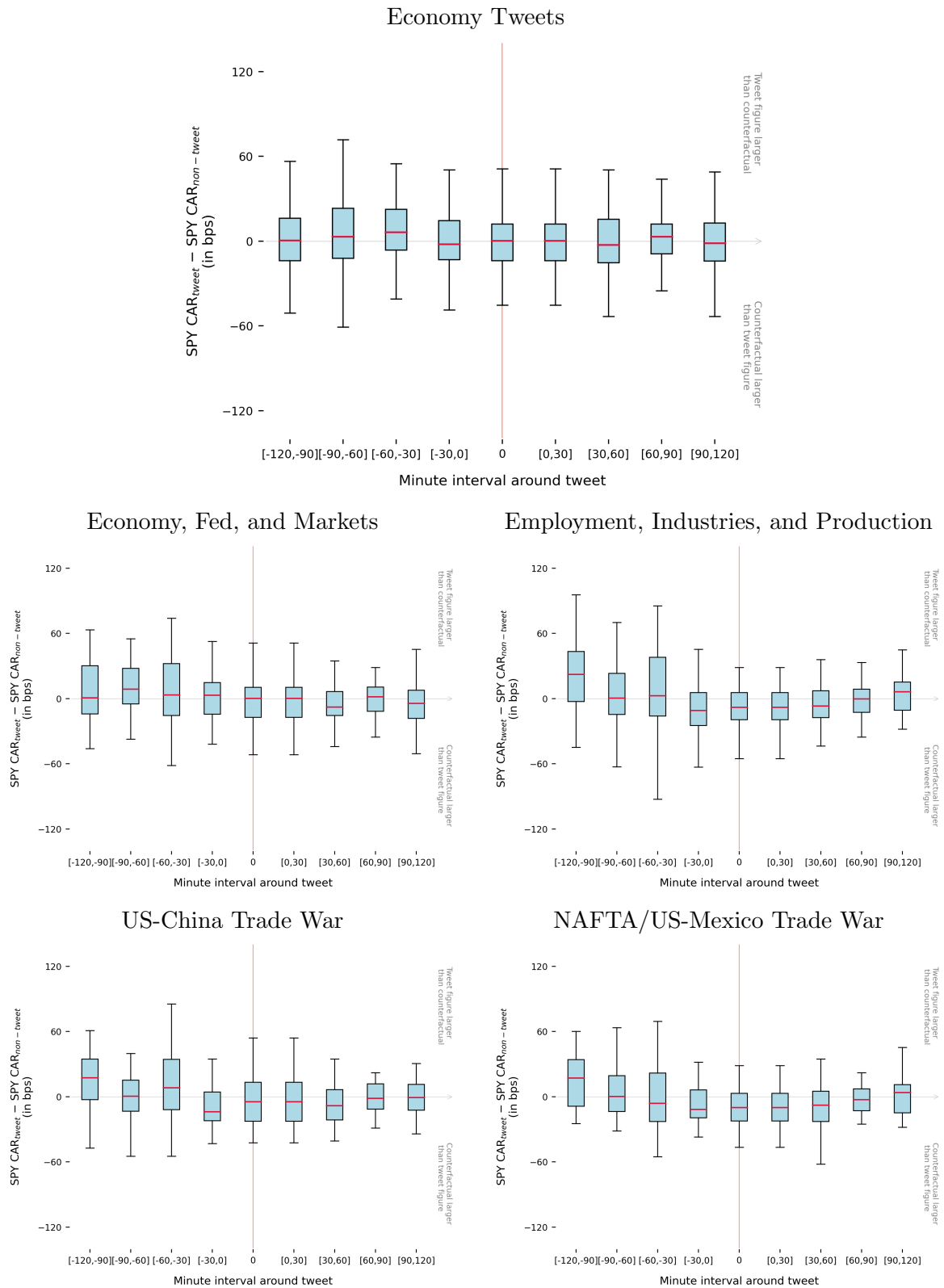
Figure 7 Differences between cumulative tweet and matched non-tweet returns around positive tweets

The above figure depicts differences between the cumulative tweet and counterfactual non-tweet returns across topics for positive-sentiment tweets. The upper panel presents all *Economy tweets*, while the lower panels focus on individual topics. The figures zoom in on the returns differentials across different 30-minute windows around the tweet arrival. The sample spans the period from Q4 2016 to Q4 2018. Tweets were obtained using the Twitter API and from the Trump Twitter Archive, while the ETF data was obtained from the TAQ database.

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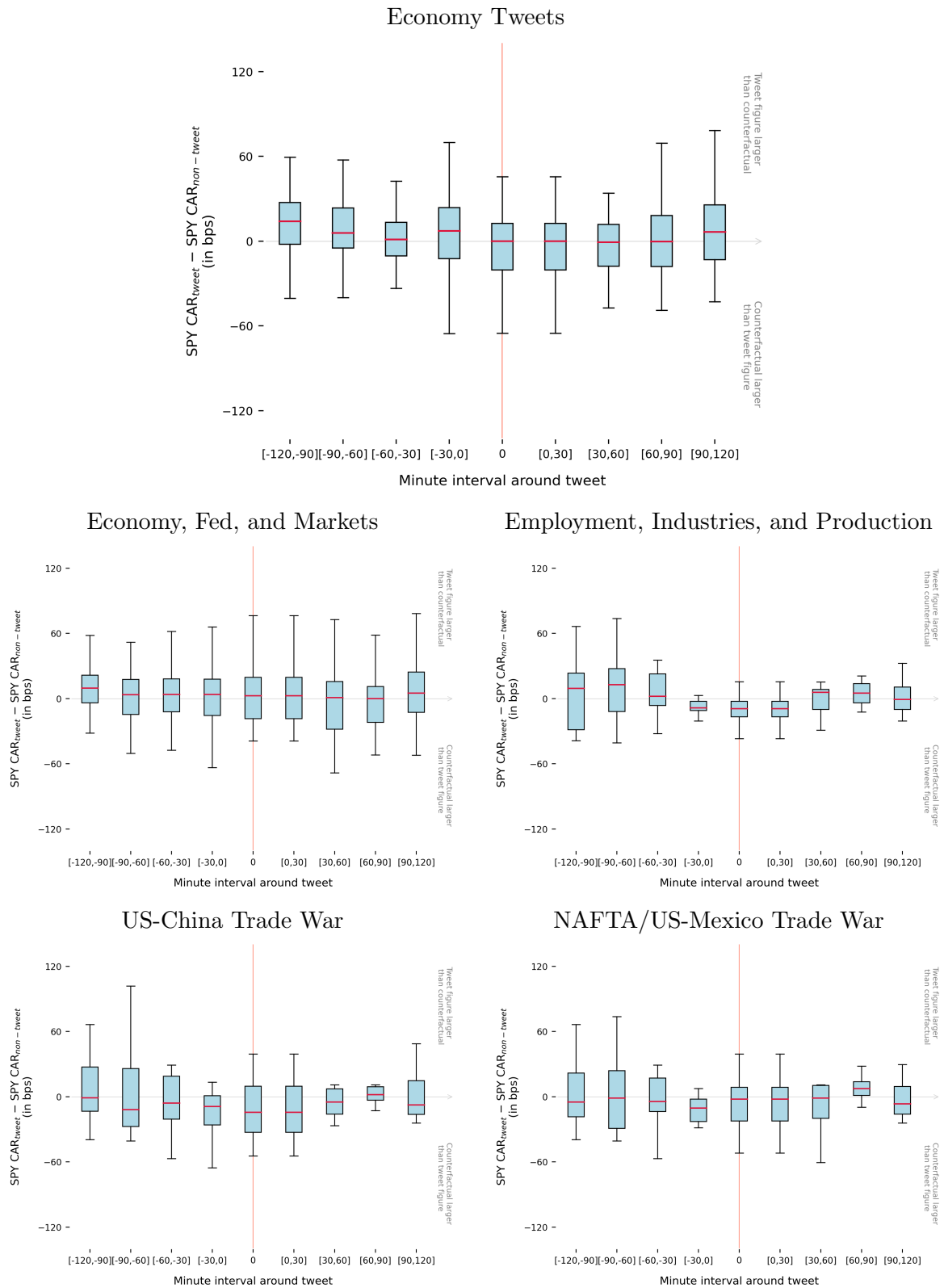
Figure 8 Differences between cumulative tweet and matched non-tweet returns around negative tweets

The above figure depicts differences between the cumulative tweet and counterfactual non-tweet returns across topics for negative-sentiment tweets. The upper panel presents all *Economy tweets*, while the lower panels focus on individual topics. The figures zoom in on the returns differentials across different 30-minute windows around the tweet arrival. The sample spans the period from Q4 2016 to Q4 2018. Tweets were obtained using the Twitter API and from the Trump Twitter Archive, while the ETF data was obtained from the TAQ database.

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Table 1 Tweet sample decomposition

Sample Period	Economy Tweets	Economy, Fed, & Markets	Employment, Industries, & Production	US-China Trade War	NAFTA/ US-Mexico Trade War
Panel A: Number of tweets before adjustment					
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 tabulates the total number of tweets with economic content, divided by topic and year. Panel B tabulates the sample of event tweets, i.e. all tweets within each topic after accounting for non-overlapping event windows.

Table 2 Event tweet summary and sentiments statistics

	Panel A: Statistics by topics					
	Number of tweets		Sentiment scores			
Topic	Obs.	Weekly Avg.	Min.	Mean	Max.	Std.dev.
Economy Tweets	404	3.640	-80.009	25.791	80.754	63.562
Economy, Fed, and Markets	228	2.111	-85.371	36.539	87.361	64.585
Employment, Industries and Production	135	1.239	-74.019	60.173	86.861	44.408
US-China Trade War	88	0.898	-80.064	31.064	85.900	62.702
NAFTA/ US-Mexico Trade War	78	0.729	-79.244	30.969	86.858	63.298
	Panel B: Statistics by year					
	Number of tweets		Sentiment scores			
Year	Obs.	Weekly Avg.	Min.	Mean	Max.	Std.dev.
2016	8	1.167	-68.640	45.932	77.540	48.197
2017	155	2.981	-78.978	35.372	80.754	60.377
2018	241	4.635	-80.009	18.961	80.522	65.249

Note: The above table reports the sentiment score summary statistics of the tweets used in this study after accounting for non-overlapping estimation windows and removal of FOMC calendar dates. Sentiment scores are based on probability labels assigned by the ML algorithm, and are therefore shown in percentages. Panel A breaks down the sentiment score distribution along topics, while Panel B presents the sentiment scores distribution per year. The observations correspond to the non-overlapping event windows around individual tweets, where the first tweet of tweet chains (tweets in close succession dealing with one topic) are considered and tweets of other topics and retweets are excluded. The sample spans the period from Q4 2016 to Q4 2018, after removal of FOMC press conference and announcement days. Tweets were obtained using the Twitter API and from the Trump Twitter Archive, and topics and the sentiment scores are assigned based on the ML algorithms described in Section 3.1 and Online Appendix A.

Table 3 Market indicators summary statistics

Panel A: SPY ETF								
Variable	Obs.	Std. Dev.	Min.	P25	Median	Mean	P75	Max.
Prices ($US)	211,311	20.439	208.479	239.590	258.310	256.615	273.190	293.920
Cumulative returns (bps)	211,311	17.033	-204.545	-6.153	0.672	-0.130	6.845	227.952
Log volumes	308,499	1.429	9.148	14.991	15.644	16.022	17.385	18.892
Realized volatility (bps)	211,311	4.603	0.142	2.463	3.917	5.394	6.596	55.510
Panel B: High-frequency VIX series								
Variable	Obs.	Std. Dev.	Min.	P25	Median	Mean	P75	Max.
Index value	211,311	4.409	8.910	10.840	12.310	13.839	15.360	49.210
Cumulative change (bps)	211,311	200.603	-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 Eq. [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 $\text{RV}_{0,30} = \sqrt{\text{CAR}_{0,5}^2 + \text{CAR}_{6,10}^2 + \text{CAR}_{11,15}^2 + \text{CAR}_{16,20}^2 + \text{CAR}_{21,25}^2 + \text{CAR}_{26,30}^2}$. 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 was obtained from the TAQ database, while the minute-level VIX series was obtained from FirstRateData.com.

Table 4 Pre-tweet and matched counterfactual return distributions

Panel A: Kolmogorov-Smirnov *P*-Values					
Sentiment	Economy Tweets	Economy, Fed, and Markets	Employment, Industries, and Production	US-China Trade War	NAFTA/ US-Mexico Trade War
Positive	0.3385	0.2838	0.0067***	0.3981	0.1393
Negative	0.7427	0.6847	0.0933*	0.5010	0.9024

Panel B: Histograms for positive sentiment

Counterfactuals   Tweets

Panel C: Histograms for negative sentiment

Counterfactuals   Tweets

Note: The above table reports the comparison between the return distributions of tweet and non-tweet counterfactual subsamples in the period preceding tweet arrival. Panel A reports the *p*-values of Kolgomorov-Smirnov tests, while Panels B and C depict the return distributions for positive and negative tweet sentiment, respectively. The sample spans the period from Q4 2016 to Q4 2018. The ETF data was obtained from the TAQ database.

Table 5 Post-tweet and matched counterfactual return distributions

Panel A: Kolmogorov-Smirnov P-Values					
Sentiment	Economy Tweets	Economy, Fed, and Markets	Employment, Industries, and Production	US-China Trade War	NAFTA/ US-Mexico Trade War
Positive	0.2027	0.1083	0.0693**	0.1967	0.0305**
Negative	0.2791	0.9367	0.0350**	0.0885*	0.4490

Panel B: Histograms for positive sentiment
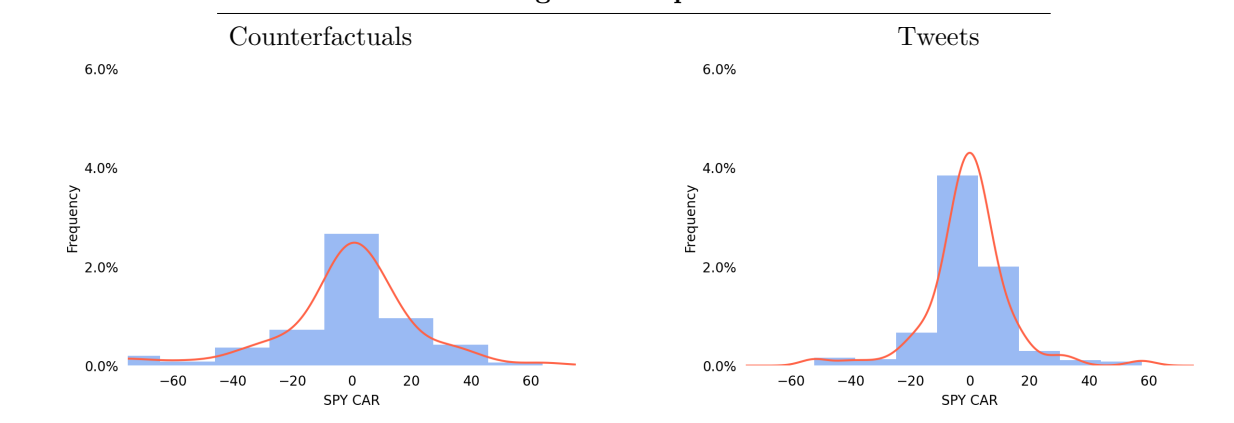
Panel C: Histograms for negative sentiment
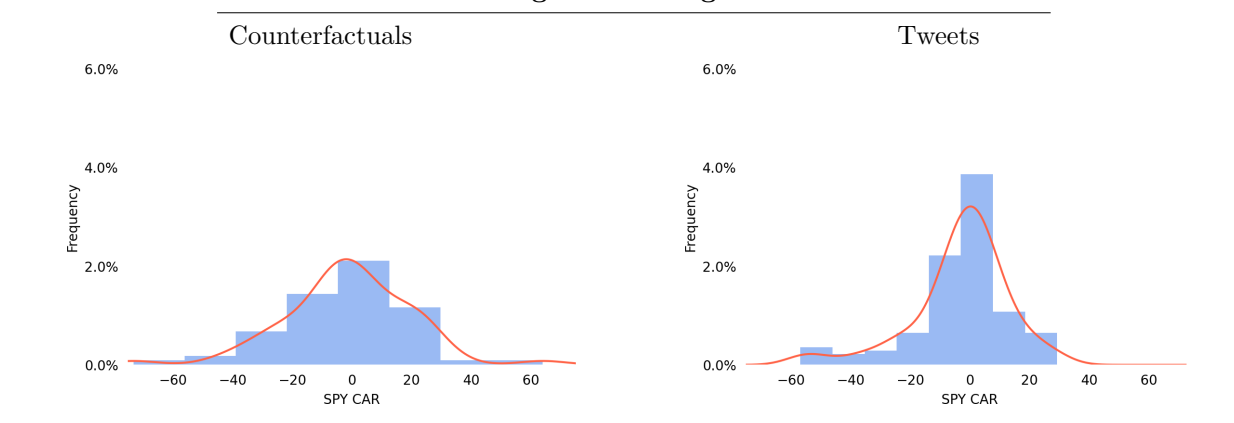
Note: The above table reports the comparison between the return distributions of tweet and non-tweet counterfactual subsamples in the period after tweet arrival. Panel A reports the *p*-values of Kolgomorov-Smirnov tests, while Panels B and C depict the return distributions for positive and negative tweet sentiment, respectively. The sample spans the period from Q4 2016 to Q4 2018. The ETF data was obtained from the TAQ database.

Table 6 Pre- and post-tweet return distributions

Panel A: Kolmogorov-Smirnov *P*-Values

Sentiment	Economy Tweets	Economy, Fed, and Markets	Employment, Industries, and Production	US-China Trade War	NAFTA/ US-Mexico Trade War
Positive	0.4571	0.7802	0.9522	0.8285	0.4447
Negative	0.2791	0.5344	0.0933*	0.1720	0.9024

Panel B: Histograms for positive sentiment

Pre-tweet   Post-tweet

Panel C: Histograms for negative sentiment

Pre-tweet   Post-tweet

Note: The above table reports the comparison between the return distributions before and after tweet arrival. Panel A reports the *p*-values of Kolgomorov-Smirnov tests, while Panels B and C depict the return distributions for positive and negative tweet sentiment, respectively. The sample spans the period from Q4 2016 to Q4 2018. The ETF data was obtained from the TAQ database.
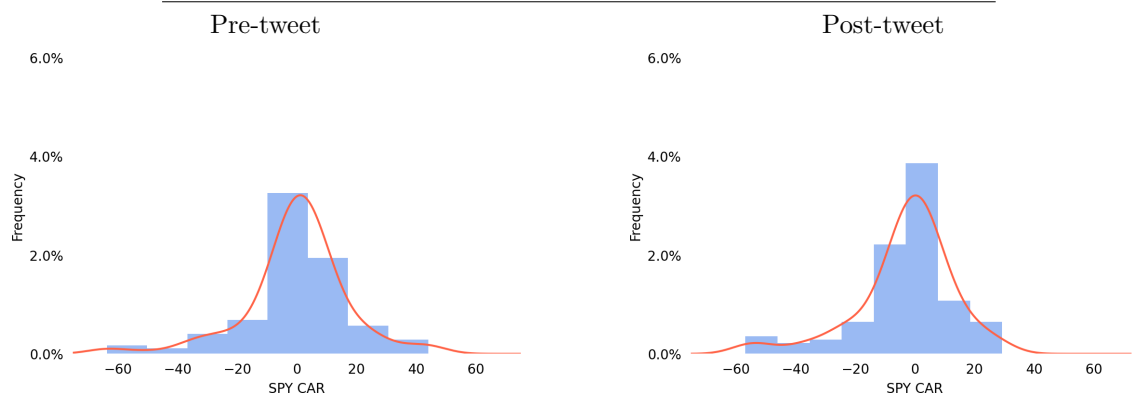
Table 7 Matched-sample SPY ETF regressions

	Economy	Economy, Fed, and Markets	Employment, Industries, and Production	US-China Trade War	NAFTA/ US-Mexico Trade War
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)
$CAR_{t-1} \cdot D_+$	-0.151	0.118	-0.440	-0.046	-0.067
	(0.207)	(0.176)	(0.334)	(0.177)	(0.094)
$CAR_{t-1} \cdot D_-$	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)
$\Delta VOL_{t-1} \cdot D_+$	1.282***	1.149***	1.321***	1.370***	1.163***
	(0.071)	(0.086)	(0.094)	(0.091)	(0.088)
$\Delta VOL_{t-1} \cdot D_-$	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	1.071***	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)
$\Delta RV_{t-1} \cdot D_+$	-0.190	-0.035	-0.151	-0.151	-0.067
	(0.146)	(0.148)	(0.296)	(0.172)	(0.160)
$\Delta RV_{t-1} \cdot D_-$	-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 regression results for cumulative *Returns*, 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, in which 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 tweet tonality, respectively, and zero otherwise. The sample spans the period from Q4 2016 to Q4 2018. Tweets were obtained using the Twitter API and from the Trump Twitter Archive, while the ETF data was retrieved from the TAQ database. Sentiment scores are assigned based on the ML 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 HAC-robust standard errors. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

Table 8 Matched-sample VIX regressions

	Economy	Economy, Fed, and Markets	Employment, Industries, and Production	US-China Trade (War)	NAFTA/ US-Mexico Trade War
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, in which 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 tweet tonality, respectively, and zero otherwise. The sample spans the period from Q4 2016 to Q4 2018. Tweets were obtained using the Twitter API and from the Trump Twitter Archive, while the ETF and VIX data were retrieved from the TAQ database and from FirstRateData.com, respectively. Sentiment scores are assigned based on the ML 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 HAC-robust standard errors. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

Table 9 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
$\text{CAR}_{t-1}(\text{SPY})$	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. We report the total marginal effects (evaluated at the mean) of the displayed variables on the tweet probability in percentage points (e.g., an increase in cumulative returns of the SPY ETF by one 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 were obtained using the Twitter API and from the Trump Twitter Archive, while the ETF and VIX data were retrieved from the TAQ database and from FirstRateData.com, respectively. Sentiment scores are assigned based on the ML 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 HAC-robust standard errors. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

Table 10 Heckman selection model: Second-stage results for the SPY ETF

	Economy	Economy, Fed, and Markets	Employment, Industries, and Production	US-China Trade (War)	NAFTA/ US-Mexico Trade War
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
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
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
N	503	331	227	161	143

Note. The above table displays regression results after inclusion of the IMR from the Heckman model step 1 (Table 9). 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 were obtained using the Twitter API and from the Trump Twitter Archive, while the ETF data was retrieved from the Trade and Quote database. Sentiment scores are assigned based on the ML 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 HAC-robust standard errors. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

Table 11 Heckman selection model: Second-stage results for the VIX index

	Economy	Economy, Fed, and Markets	Employment, Industries, and Production	US-China Trade (War)	NAFTA/ US-Mexico Trade War
	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
N	807	455	269	175	155

Note. The above table displays regression results after inclusion of the IMR from the Heckman model Step 1 (Table 9). 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 were obtained using the Twitter API and from the Trump Twitter Archive, while the VIX data was retrieved from FirstRateData.com, respectively.. Sentiment scores are assigned based on the ML 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 HAC-robust standard errors. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

Table 12 Stepwise regressions

	Economy	Economy, Fed, and Markets	Employment, Industries, and Production	US-China Trade (War)	NAFTA/ US-Mexico Trade War
			Panel A: SPY ETF Returns		
			Dependent variable: $\varepsilon_{\text{SPY},1}$		
Intercept	0.000 (0.995)	-0.000 (1.041)	0.000 (1.620)	-0.000 (2.048)	0.000 (1.633)
$\varepsilon_{\text{SPY},2}$	2.058 (1.637)	-0.024 (1.816)	3.189 (3.696)	6.521* (3.471)	1.680 (2.880)
$R^2_{Adj.}$	0.003	-0.005	-0.003	0.041	-0.008
N	364	211	121	83	77
			Panel B: ΔVIX		
			Dependent variable: $\varepsilon_{\text{VIX},1}$		
Intercept	-0.000 (10.740)	0.000 (12.902)	-0.000 (14.748)	0.000 (17.993)	0.000 (19.182)
$\varepsilon_{\text{VIX},2}$	-24.666 (16.682)	-14.994 (20.599)	-39.265 (35.355)	-62.151** (30.925)	-8.721 (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 Eq. 5, where residuals from Eq. 3 are regressed on those from Eq. 4 in order to assess whether the unexplained information contained in the residuals is correlated. The above sample spans Q4 2016 to Q4 2018. Tweets were obtained using the Twitter API and from the Trump Twitter Archive, while the ETF and VIX data were retrieved from the TAQ database and from FirstRateData.com, respectively. Sentiment scores are assigned based on the ML 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 HAC-robust standard errors. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

Online Appendix

A   Tweet processing with technical details on the ML algorithms

We disentangle Donald Trump's tweets along the *textual sentiment* dimension as well as the *topic* dimensions. Both are facilitated by the use of 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, only the desired number of topics can be selected, however the same is not true of their content. Therefore, LDA can result in somewhat arbitrary topic assignments and demarcations among topics (Russell and Norvig, 2016).

Since we want to specifically analyze the potential market impact of Trump's tweets with economic content, we need 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*, that 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[30]. 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 four 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, and*

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[30]Of these 16 initial topics, 12 do not concern economic content and are therefore not further analyzed for the purpose of this analysis.

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, 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 ML models to classify tweet sentiment instead.

We train an ensemble ML 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 was classified as either neutral, negative, or positive by three individuals in order to limit subjectivity in tonality assignment. This hand-classified sample was used as the training data for an 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 CV 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 ML 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) along with the ensemble model (rightmost column). Algorithms only enter the final ensemble if their CV 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.

[Insert Table A1 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 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 other 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, like 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 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: first, Trump posted more at the extremes than moderate ranges of sentiment, either very positively, or very negatively, and therefore neutral sentiment is rather underrepresented in his tweets. Second, 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. Third, ML 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.[31]

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[31]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..

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C High-frequency event studies

C.1 Methodology

To empirically test whether Trump's Twitter activity had a statistically significant impact on the stock market as 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 Eq. 1 above.

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. Within such a short period, any considerable permanent movement should be driven by the market adjusting to new information rather than any risk premium.[32] 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 C3. The $AC\hat{A}R_{i(T)}$ tested for statistical significance in the event studies are performed in [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 cumulative returns from the tweet minute until the EOD, denoted as [0,EOD] in the tables, in order to capture persistent effects.[33]

[Insert Figure C3 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

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

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

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 whether a tweet elicited a strong and sufficiently persistent market reaction to affect the EOD price and therefore use the maximum-sentiment tweet that occurs within each topic-sentiment specification on any given day. Although we are aware of the caveats regarding 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 $A\hat{CAR}_{i(T)}$ 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 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.[34] In our analysis we exclude tweets that mention single companies, as our focus is on market wide effects.

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[34]One example for this would be the American technology and marketing company T3, which implemented a trading bot based on Trump's tweets after noticing that companies specifically mentioned therein, most often negatively, subsequently experienced 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).

C.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, since we expect the market to respond differently to the tonality of the message, 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 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 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 C1 and C2, we present the results for the period from 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 HAC-robust standard errors. Panels A and B separate positive and negative-sentiment tweets.

In Table C1, 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, and 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 could be due either 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 the tone and consequent separation between positive and negative tweets, we find that the most significant impact is generated by negative tweets, and 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* tweet category for the same event window. One would expect the market to react more strongly to tweets with the most impactful information, which is likely the case for tweets about trade relations between the US and China, where POTUS has a consequential 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 shifted prices to the extent that it impacted EOD closing prices ([0,EOD]).

[Insert Tables C1 and C2 here]

To understand any pre-tweet trends in the market, we perform pre-tweet placebo analyses and report the results in Table C2. Based on evidence from Figure C1 (Panel A), we observe that tweets could often be a 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 (in the pre-event window). The latter would suggest that Trump did not disseminate new, material information to the market but either amplified, or potentially attempted 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 4 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 was released by the tweets,

or it could increase 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 C3 and C4 present the results of post- and pre-tweet event studies of the effect (measured in basis points) of tweets on the 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 HAC-robust standard errors. Panels A and B separate the positive and negative sentiment tweets.

[Insert Tables C3 and C4 here]

The results presented in Panel A of Table C3 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 (see [0,120] and [0, EOD]). We observe that the average tweet effect, captured by the *Economy* category, is the strongest with drops of 32.672 and 102.822 basis points in the index value over a two-hour and the EOD event windows, respectively. Similarly, the *Employment, Industries, and 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 decline of the VIX; the effect remains 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 pooled *Economy* tweets and the *Economy, Fed, and Markets* and *US-China Trade War* topics of 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.

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We explore pre-existing cumulative changes (ACAR in basis points) in VIX in different pre-tweet windows in Panel B of Figure C1 and Table C4. The results of Table C4 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 experienced a decrease on days when tweets occur, but that this trend reversed within the 15 minutes prior to the tweet's arrival. It is possible that the news that were anticipated by the market were revealed, leading to the reversal. We observe this pattern for most topics, albeit not at a statistically significant level, with the exception of *NAFTA/US-Mexico Trade War*.

C.2.1 The effect of changing sentiment

Analyzing the sentiment of 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 C5, respectively.

[Insert Table C5 here]

Panel A of Table C5 reports the results for sentiment reversal. For most tweet topics and on average, changing sentiment (in either direction) did not elicit a significant reaction on the SPY ETF returns, with the exception of tweets about the *Economy, Fed, and Markets*. This points in the direction of the findings of Bianchi et al. (2019), who show

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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 returns tended to increase with large positive surprises, except for the *US-China Trade War* tweets, where the SPY ETF price dropped by 9.336 basis points. For this specific topic, large negative surprises have a similar, yet smaller effect. This second result indicates that the market filtered the different kind of information and reacted only to surprising contents. 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.

C.3 Tables and figures

Panel A: SPY ETF

Panel B: VIX
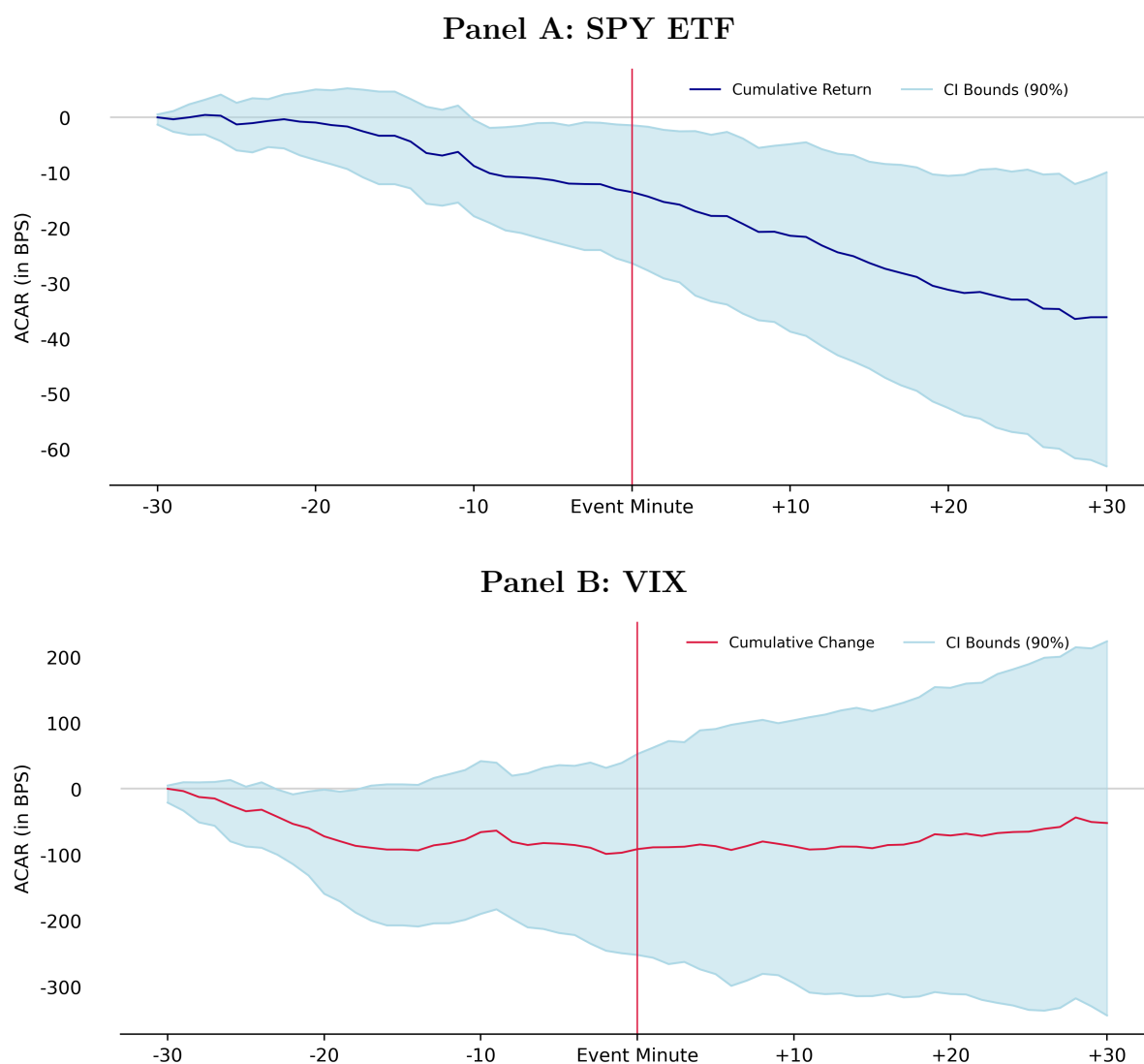
Figure C1 Pre- and post-tweet movements in the SPY ETF and VIX index

The two panels 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.
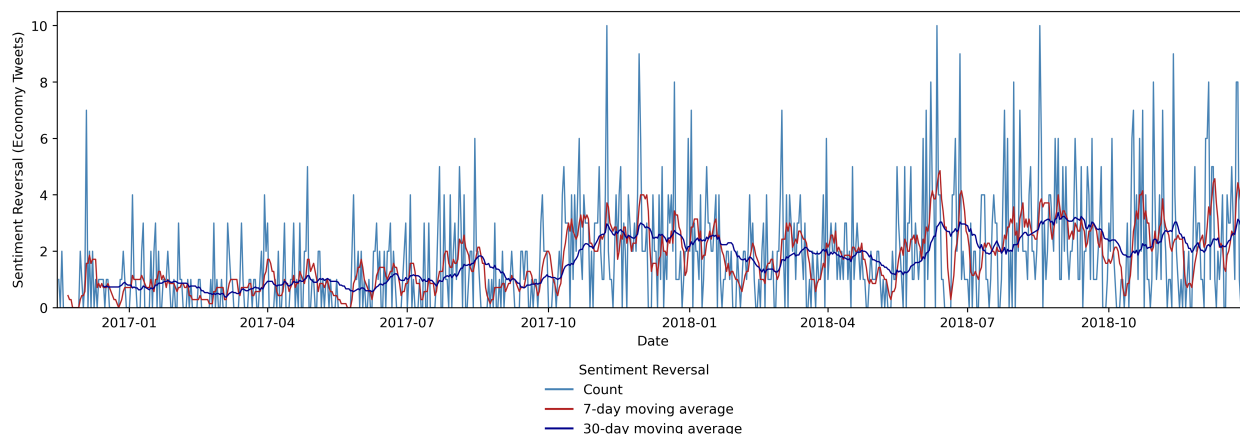
Figure C2 Sentiment reversals

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 were obtained using the Twitter API and from the Trump Twitter Archive.
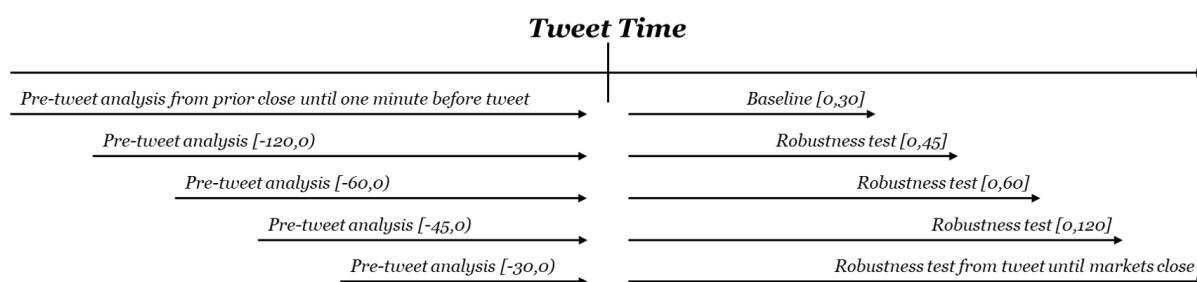
Figure C3 Window lengths for the presented event studies and pre-tweet placebo analyses

The above figure displays the pre- and post-event window lengths we test in our tweet and quasi-placebo event studies. The results for each of the windows depicted above are presented in Section C.2.

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Event Window	Economy Tweets	Economy, Fed, and Markets	Employment, Industries, and Production	US-China Trade War	NAFTA/ US-Mexico 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 cumulative 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 were obtained using the Twitter API and from the Trump Twitter Archive, while the ETF data was obtained from the TAQ database. Sentiment scores are assigned based on the ML 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 HAC-robust standard errors, while the square brackets indicate the number of observations (events) available for the given topic. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

Table C2 Event study: SPY ETF pre-tweet placebo analyses and tweet tonality

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

Note. The above table presents the results of the high-frequency event studies performed on the SPY ETF cumulative 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 were obtained using the Twitter API and from the Trump Twitter Archive, while the ETF data was retrieved from the TAQ database. Sentiment scores are assigned based on the ML 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 HAC-robust standard errors, while the square brackets indicate the number of observations (events) available for the given topic. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

Table C3 VIX post-tweet event studies

Event Window	Economy Tweets	Economy, Fed, and Markets	Employment, Industries, and Production	US-China Trade War	NAFTA/ US-Mexico 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 were obtained using the Twitter API and from the Trump Twitter Archive, while the VIX data was retrieved from FirstRateData.com. Sentiment scores are assigned based on the ML 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 HAC-robust standard errors, while the square brackets indicate the number of observations (events) available for the given topic. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

Table C4 VIX pre-tweet placebo event studies

Event Window	Economy Tweets	Economy, Fed, and Markets	Employment, Industries, and Production	US-China Trade War	NAFTA/ US-Mexico 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 Eq. 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 were obtained using the Twitter API and from the Trump Twitter Archive, while the VIX data was retrieved from FirstRateData.com. Sentiment scores are assigned based on the ML 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 HAC-robust standard errors, while the square brackets indicate the number of observations (events) available for the given topic. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

Table C5 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-Mexico 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 were obtained using the Twitter API and from the Trump Twitter Archive, while the ETF data was retrieved from the TAQ database. Sentiment scores are assigned based on the ML 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 HAC-robust standard errors, while the square brackets indicate the number of observations (events) available for the given topic. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

D   Additional tables and analyses

Table D1 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-tonality tweets, respectively, and zero otherwise.
CAR or cumulative return	CAR is defined as the minute-level abnormal return with expected return of 0, which 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-volumes by aggregating the one-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.
ΔVOL	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. For the [0,30] baseline event window, for example, $RV_{0,30} = \sqrt{CAR_{0,5}^2 + CAR_{6,10}^2 + CAR_{11,15}^2 + CAR_{16,20}^2 + CAR_{21,25}^2 + CAR_{26,30}^2}$.
ΔRV	Analogously to ΔVOL, ΔRV 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.

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Table D2 Matched-sample SPY ETF regressions with quarter FE

	Economy	Economy, Fed, and Markets	Employment, Industries, and Production	US-China Trade (War)	NAFTA/ US-Mexico Trade War
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)
$CAR_{t-1} \cdot D_+$	-0.1429	0.1262	-0.4167	-0.0667	-0.0320
	(0.2187)	(0.1771)	(0.3655)	(0.2013)	(0.1138)
$CAR_{t-1} \cdot D_-$	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)
$\Delta VOL_{t-1} \cdot D_+$	0.0714	-0.0088	0.0643	0.0029	-0.0496
	(0.0434)	(0.0518)	(0.0620)	(0.0621)	(0.0435)
$\Delta VOL_{t-1} \cdot D_-$	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)
$\Delta RV_{t-1} \cdot D_+$	-0.0080	0.3019*	0.3739	0.1464	0.3372**
	(0.1394)	(0.1756)	(0.3184)	(0.1519)	(0.1466)
$\Delta RV_{t-1} \cdot D_-$	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 regression results for cumulative *Returns*, 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-tonality tweets, respectively, and zero otherwise. The sample spans the period from Q4 2016 to Q4 2018. Tweets were obtained using the Twitter API and from the Trump Twitter Archive, while the ETF data was retrieved from the TAQ database. Sentiment scores are assigned based on the ML 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 HAC-robust standard errors. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

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Table D3 Matched-sample VIX regressions with quarter FE

	Economy	Economy, Fed, and Markets	Employment, Industries, and Production	US-China Trade (War)	NAFTA/ US-Mexico Trade War
Intercept	-81.0781***	-112.9189***	-13.5961	-186.3954	-122.9943***
	(14.2412)	(25.8461)	(24.3167)	(146.7061)	(31.2783)
$\Delta \text{VIX} t-1$	-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-tonality tweets, respectively, and zero otherwise. The sample spans the period from Q4 2016 to Q4 2018. Tweets were obtained using the Twitter API and from the Trump Twitter Archive, VIX data was retrieved from FirstRateData.com. Sentiment scores are assigned based on the ML 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 HAC-robust standard errors. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

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Table D4 Matched-sample SPY ETF regressions with 120-minute pre-event window

	Economy	Economy, Fed, and Markets	Employment, Industries, and Production	US-China Trade (War)	NAFTA/ US-Mexico Trade War
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)
$CAR_{t-1} \cdot D_+$	-0.0230	0.1019	-0.2136	0.1716	-0.0124
	(0.1023)	(0.1313)	(0.1653)	(0.1261)	(0.0781)
$CAR_{t-1} \cdot D_-$	-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)
$\Delta VOL_{t-1} * D_+$	-0.3823	-0.1478	-0.6603***	-0.0863	0.8255**
	(0.3084)	(0.3330)	(0.1780)	(0.6150)	(0.4138)
$\Delta VOL_{t-1} * D_-$	-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)
$\Delta RV_{t-1} \cdot D_+$	-0.0581	0.2675*	0.3365	-0.0046	0.0132
	(0.1549)	(0.1499)	(0.2043)	(0.2281)	(0.1404)
$\Delta RV_{t-1} \cdot D_-$	-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 regression results for cumulative *Returns*, 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 tweet tonality, respectively, and zero otherwise. The sample spans the period from Q4 2016 to Q4 2018. Tweets were obtained using the Twitter API and from the Trump Twitter Archive, while the ETF data was retrieved from the TAQ database. Sentiment scores are assigned based on the ML 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 HAC-robust standard errors. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

Table D5 Matched-sample VIX regressions with 120-minute pre-event window

	Economy	Economy, Fed, and Markets	Employment, Industries, and Production	US-China Trade (War)	NAFTA/ US-Mexico Trade War
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)
$\Delta VIX_{t-1} \cdot D_+$	0.1161	0.1518	-0.0208	0.0851	0.1309
	(0.0819)	(0.1112)	(0.1629)	(0.0792)	(0.0983)
$\Delta VIX_{t-1} \cdot D_-$	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 sentiment, respectively, and zero otherwise. The sample spans the period from Q4 2016 to Q4 2018. Tweets were obtained using the Twitter API and from the Trump Twitter Archive, VIX data was retrieved from FirstRateData.com. Sentiment scores are assigned based on the ML 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 HAC-robust standard errors. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

Recent Issues