Signal in the Noise: Trump Tweets and the Currency Market

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Abstract

In this paper, we conduct a textual analysis of Trump tweets. Our method extracts the signal from the noise, by identifying the subset of tweets that contain information on macroeconomic policy or trade content. Informative tweets result in a USD appreciation and a decline in intraday volatility, reflecting Trump's optimistic views on the U.S. economy. These effects are robust to controlling for macroeconomic announcements. We rationalize our findings within a model of Bayesian traders that interpret Trump tweets as a public signal in the FX market. Currency returns are driven by a bias between the public signal and speculators' expectations.

Keywords: Foreign exchange market, textual analysis, Trump, X (Twitter).

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1 Introduction

Since Donald J. Trump began his first U.S. presidential campaign in June 2015, he has extensively used Twitter to communicate directly with the public. With more than 77.5 million followers (as of April 2020), his use of social media demonstrated the significant attention paid to the views shared by the 45^{th} and 47^{th} U.S. President.[1] Trump's presidency, often characterized by unconventional policy announcements and trade rhetoric, has had significant effects on the strength of the U.S. dollar. For example, during the 2024 Presidential election, what became known as *"Trump trades"* reflected market reactions to the threat of tariffs and rising interest rates. Investors anticipated inflationary pressures stemming from Trump's stimulus-driven economic policies, which led to a rallying of the U.S. dollar.[2]

Although the information content of Trump's tweets has been a subject of debate (Washington Post, 2020), a growing body of research has documented their impact on financial markets. For instance, protectionist Trump tweets have been linked to market responses regarding tariffs with China or Mexico (e.g., Benton and Philips, 2018; Ferrari Minesso, Kurcz, and Pagliari, 2022; Matveev and Ruge-Murcia, 2023), while others have influenced perceptions of interest rates (e.g., Bianchi et al., 2023) and stock market behavior, including returns and volatility (Born, Myers, and Clark, 2017; Ge, Kurov, and Wolfe, 2019; Juma'h and Alnsour, 2018; Colonescu et al., 2018; Abdi et al., 2021; Ajjoub, Walker, and Zhao, 2021; Scharnowski, 2022). Understanding the relationship between Trump's tweets and financial markets offers unique insights into the role of political communication in shaping investor expectations and market outcomes, particularly during periods of heightened policy uncertainty and geopolitical tension.

In this paper, we focus on the effect of Trump tweets on the foreign exchange (FX) market, which is the most traded financial market worldwide (BIS, 2022). Trump tweets provide a novel experiment to study the effects of a public signal on spot returns in the currency market. Our contribution is to conduct a textual analysis of Trump tweets to

1. His Twitter account was suspended in January 2021 due to tweets following the U.S. Capitol attack and reinstated in November 2022 by Elon Musk.

2. See Financial Times article "Strong US economy and 'Trump trade' drive dollar rally," available at `https://www.ft.com/content/5f545c98-cfd2-432a-97b4-288d8f4cebb7`.

decipher the signal from the noise. We filter the historical archive of Trump tweets to construct a set of informative Trump tweets related to the macroeconomic outlook and trade. We hypothesize that informative Trump tweets have systematic effects on USD spot returns, reflecting Trump's (optimistic) bias regarding the future macroeconomic fundamentals of the U.S. economy relative to foreign economies.

To explain the mechanism we propose, we start with a model of heterogeneous private information. The market is populated by a set of speculators, each with its private signal on the valuation of the future spot rate. Investors then update their private signal based on the Trump tweet, which is a public signal known to all traders. There are two distinct types of speculators in the model: (rational) Bayesian investors who update their prior based on the information content of the Trump tweet, and (irrational) Trump followers who fully adopt the Trump tweet.

Our analysis generates two predictions. First, we show that Trump tweets can impact spot USD returns that reflect differences between the views of Donald Trump and the speculators on the future valuation of U.S. macroeconomic fundamentals. For example, if Trump is more optimistic (pessimistic) about future U.S. growth than private investors, this leads to a USD appreciation (depreciation). Conversely, if Trump has a more trade protectionist stance than private investors, that reduces expectations of output growth in the rest of the world, leading to a USD appreciation. Second, the Trump tweet leads to a decline in exchange rate volatility if the tweet is more informative than the private signal of investors. In the model framework, we capture the relative informativeness of the public and private signal by its precision.

Turning to the data, we first conduct a textual analysis of Trump tweets to identify the information content related to the macroeconomic outlook, trade, and international developments that are impounded in exchange rates. Our sample period is from 16th June 2015, the starting date of Trump's presidential campaign, to 20th August 2019. We implement two methods to identify macroeconomic and trade tweets. The first approach follows keywords by topics outlined in Baker et al. (2019), which we denote the dictionary method. Second, we use the Biterm Topic Modeling (BTM) approach developed by Yan et al. (2013) to filter out tweets about the macroeconomic outlook, trade policy, and exchange rate topics. This approach is suitable for the analysis of short texts such as tweets.

We analyze the impact of Trump tweets on FX market outcomes and construct measures of FX market activity. Our primary empirical analysis employs a panel specification with FX spot returns and volatility as outcome variables, measured within a one-hour window. Key explanatory variables include an hourly dummy indicating a macroeconomic or trade-related Trump tweet, along with controls for hour-of-day, day-of-week, scheduled Federal Open Market Committee (FOMC) announcements, bid-ask spreads, and financial market fundamentals such as intraday changes in the VIX index.

First, we identify the systematic effects of informative Trump tweets on FX spot returns and evaluate their economic implications for trading strategies. The dollar, on average, appreciates vis-à-vis major bilateral pairs following Trump's tweets. We find significant cumulative returns in the hour after a tweet, with an equal-weighted average return across bilateral currency pairs of approximately 0.005% (0.5 basis points). This appreciation aligns with the nature of Trump's tweets, which often reflect positive views on the U.S. economy relative to other countries and reinforce a protectionist stance on trade policies.[3]

Moreover, these predictable FX movements present an opportunity for an ETF-based trading strategy. Using a U.S. Dollar Index ETF, we estimate a return of approximately 2 basis points within an hour after an informative Trump tweet. Even after accounting for transaction costs, this strategy achieves a Sharpe ratio of 0.69 under realistic trading conditions, highlighting its economic profitability.

Second, we find declines in both intraday FX spot volatility and FX volume around Trump tweet hours. A reduction in volatility suggests that Trump's macroeconomic tweets carry relevant information for FX trading.

A potential concern with our analysis is omitted variable bias, where Trump tweets may coincide with macroeconomic releases or simply echo news from the same day. To

3. Trump recently stated he is a *big fan of USD* and does not want USD to be *hurt* by other currencies. (Yahoo Finance, 2021)

address this, we control for macroeconomic announcements on the day of the tweet, ensuring the observed effects of Trump's informative tweets are not merely reactions to earlier news. Additionally, we test the political diversion hypothesis by analyzing media coverage of the Mueller investigation (Lewandowsky, Jetter, and Ecker, 2020). Our findings suggest that Trump's informative tweets on macroeconomic and trade topics are strategically timed to follow negative political coverage, supporting the view that their timing is aimed at diverting attention from unfavorable news. This provides suggestive evidence that Trump's informative tweets are plausibly exogenous with respect to the FX market, as they are unrelated to earlier macroeconomic announcements.

Finally, we hypothesize that tweets unrelated to macroeconomic or trade issues, labeled as 'uninformative' tweets, should not impact the FX market. Using the BTM method, we identify these tweets as those least likely to address macroeconomic or trade topics. Our analysis confirms that uninformative tweets do not systematically affect FX spot returns or volatility but do result in a slight decline in trading volume. These findings highlight the importance of using textual analysis to identify tweets relevant to the FX market.

The rest of the paper is structured as follows. Section 2 summarizes related literature. Section 3 introduces a model with our theoretical predictions on the effects of Trump tweets on FX returns and volatility. Section 4 outlines the data. Section 5 discusses our empirical findings. Section 6 concludes.

2 Related Literature

The paper contributes to the growing literature on the impact of social media on financial markets, with a focus on Twitter. Research has shown that social media sentiment influences stock market returns and volatility (Bollen, Mao, and Zeng, 2011; Mittal and Goel, 2012; Behrendt and Schmidt, 2018), company-specific performance (e.g., Sprenger et al., 2014; Bartov, Faurel, and Mohanram, 2018), and reactions to monetary policy announcements (Azar and Lo, 2016). In the currency market, Gholampour and Van Wincoop (2017) analyze investor tweets about the EUR/USD exchange rate and develop a sentiment-based trading strategy, while Filippou et al. (2023) find a link between U.S. populist rhetoric and currency excess returns.

Our paper relates to recent research on the effects of Trump tweets across financial markets. Studies have documented their influence on stock returns and volatility (e.g., Born, Myers, and Clark, 2017; Juma'h and Alnsour, 2018; Ge, Kurov, and Wolfe, 2019; Abdi et al., 2021), threats to central bank independence (Bianchi et al., 2023), and trade-related tweets affecting exchange rates, such as the Mexican Peso and Chinese Yuan exchange rates relative to the U.S. Dollar (Benton and Philips, 2018; Ferrari Minesso, Kurcz, and Pagliari, 2022; Matveev and Ruge-Murcia, 2023). Bianchi et al. (2023) find that politicians' tweets, including Trump's, influence asset prices, and Abdi et al. (2021) uncover systematic effects of Trump tweets on financial markets, particularly those related to macroeconomic and trade topics.

Our contribution is to extend this analysis by identifying the macroeconomic and trade content of Trump tweets, including those on Federal Reserve policy and tariff negotiations with Mexico and China. We document the systematic effects of informative Trump tweets on USD spot returns and exchange rate volatility. Specifically, tweets with positive sentiment lead to USD appreciation, reflecting Trump's optimism about the U.S. macroeconomy.

The second major literature our paper relates to is on the microstructure of currency markets. Information asymmetry in currency markets has typically been studied by signing trades in inter-dealer and dealer-customer markets through order flow (e.g., Evans and Lyons, 2002; Ranaldo and Somogyi, 2021). On the theory side, our paper speaks to microstructural models of financial markets that determine prices through a set of informed and "noise" traders, with heterogeneous information on the fundamentals (e.g., Jeanne and Rose, 2002; Bacchetta and Van Wincoop, 2006; Gholampour and Van Wincoop, 2017; Michaelides, Milidonis, and Nishiotis, 2019; Ranaldo and Magistris, 2022; Kruger, 2020; Jeanneret and Sokolovski, 2023).

We contribute to this literature by motivating our empirical setting with a simple model of heterogeneous private information in the FX market and interpreting the Trump tweet as a public signal. The model generates spot returns due to a bias between the public signal and speculators' expectations of future macroeconomic fundamentals.

3 Model

We develop a simple two-period model of FX market trading using public information. Each investor has a prior belief at time t about the exchange rate in the next period $(t+1)$. The framework is inspired by informed trader models (Jeanne and Rose, 2002; Bacchetta and Van Wincoop, 2006; Gholampour and Van Wincoop, 2017), incorporating both private and public signals. The public signal, termed the *Trump tweet*, serves as a common source of information for all speculative traders. Rational Bayesian agents update their prior beliefs using both signals, forming posterior expectations weighted by their relative precision. A subset of traders, labeled as Trump followers, rely exclusively on the public signal, assigning it full weight. This setup examines how public and private signals interact to influence spot returns and volatility.

Exchange Rates. The FX market consists of N agents with heterogeneous priors about the future exchange rate s_t, which is defined in units of foreign currency per U.S. dollar.[4] Following Jeanne and Rose (2002), we employ standard money demand functions for domestic and foreign currencies, linked via purchasing power parity:

$$m_t - p_t = -\alpha i_t + \eta y_t, \tag{1}$$

$$m_t^* - p_t^* = -\alpha i_t^* + \eta y_t^*, \tag{2}$$

$$s_t = p_t^* - p_t. \tag{3}$$

Defining exchange rate fundamentals as $f_t = \frac{m_t^* - m_t}{1+\alpha} + \frac{\eta(y_t - y_t^*)}{1+\alpha}$, the spot rate is expressed as a function of fundamentals and expected future exchange rates:

$$s_t = f_t + \frac{\alpha}{1+\alpha}\mathbb{E}_t[s_{t+1}]. \tag{4}$$

Trump Tweets. The Trump tweet is modeled as an unexpected public signal, unlike

4. An increase in s_t indicates an appreciation of the U.S. dollar.

scheduled announcements such as central bank communications. It provides an expectation of future fundamentals θ^T, with precision σ_T^2:

$$f_{t+1}^T = \theta^T + \epsilon_{t+1}^T, \quad \epsilon^T \sim N(0, \sigma_T^2). \tag{5}$$

We assume public and private signals are uncorrelated, i.e., $\text{cov}(\epsilon^T, \epsilon^j) = 0$, to isolate the impact of the Trump tweet on market behavior.

Bayesian Agents. Bayesian agents combine the public signal θ^T with their private signal θ^j, weighting them by their relative precision:

$$\mathbb{E}[f_{t+1}^j | I_j, I_T] = \omega_j^B \theta^T + (1 - \omega_j^B)\theta^j, \quad \omega_j^B = \frac{\sigma_j^2}{\sigma_T^2 + \sigma_j^2}. \tag{6}$$

When the public signal is highly precise ($\sigma_T^2 \ll \sigma_j^2$), the weight on the public signal ω_j^B approaches 1. Conversely, when the public signal is noisier ($\sigma_T^2 \gg \sigma_j^2$), private signals dominate.

Trump Followers. Trump followers represent a subset of agents who rely exclusively on the public signal, assigning $\omega_j^B = 1$:

$$\mathbb{E}[f_{t+1}^T | I_j, I_T] = \theta^T. \tag{7}$$

Investor Optimization. Agents maximize exponential utility over next-period wealth, $W_{t+1}^j = \rho_t^j b_t^j$, where $\rho_t^j = s_{t+1} - s_t + i_t - i_t^*$ denotes the excess return on the dollar. The optimization problem is:

$$\underset{b_t^j}{\text{maximize}} \quad L = \mathbb{E}[W_{t+1}^j] - \frac{1}{2}\gamma \text{Var}(W_{t+1}^j), \tag{8}$$

subject to:

$$W_{t+1}^j = \rho_t^j b_t^j. \tag{9}$$

The optimal bill demands for Bayesian agents and Trump followers are:

$$b_t^j = \frac{\omega_j^B \theta^T + (1 - \omega_j^B)\theta^j - s_t + i_t - i_t^*}{\gamma({\omega_j^B}^2 \sigma_T^2 + (1 - \omega_j^B)^2 \sigma_j^2)}, \tag{10}$$

$$b_t^j = \frac{\theta^T - s_t + i_t - i_t^*}{\gamma \sigma_T^2}. \tag{11}$$

Market Clearing. Let N_B and N_T denote the number of Bayesian agents and Trump followers, respectively, with $N = N_B + N_T$. The market clears when the net bill supply equals zero:

$$\sum_{j \in N_B} b_t^j + \sum_{j \in N_T} b_t^j = 0. \tag{12}$$

Substituting the optimal bill demands yields the equilibrium spot rate:

$$s_t = i_t - i_t^* + \frac{1}{\Gamma} \left(\Gamma_B \bar{\theta}^j + \Gamma_T \theta^T + \omega_j^B \Gamma_B (\theta^T - \bar{\theta}^j) \right), \tag{13}$$

where:

$$\Gamma_B = \frac{N_B}{(\omega_j^B)^2 \sigma_T^2 + (1 - \omega_j^B)^2 \sigma_j^2}, \quad \Gamma_T = \frac{N_T}{\sigma_T^2}, \quad \Gamma = \Gamma_B + \Gamma_T. \tag{14}$$

Here, $\bar{\theta}^j = \frac{1}{N} \sum_{j=1}^{N} \theta^j$ denotes the average private signal. The equilibrium expression highlights the role of public signal precision and the proportion of Trump followers in determining the spot exchange rate.

Figure 1 illustrates this mechanism. The average of investor priors, denoted by $\bar{\theta}^j$, and the public signal, represented by θ^T (e.g., a Trump tweet), determine the posterior distribution of Bayesian investors. As investors update their beliefs based on the public signal, their posterior distribution shifts toward θ^T. This systematic bias between public and private signals influences equilibrium spot returns.

[FIGURE 1 ABOUT HERE]

Empirical Predictions The model framework generates intuitive and testable implications for the behavior of spot returns and volatility in the FX market, driven by the informational bias between the public signal (Trump tweets) and private expectations. Specifically, we derive predictions on the sensitivity of spot returns to Trump tweets and the resulting variance in spot returns, depending on the precision and content of the public signal. These predictions are tested empirically in subsequent sections. We provide formal derivations for the predictions in Appendix A.

Prediction 1 (Effect of Trump Tweets on FX Spot Returns)**.** *Consider a Trump tweet that conveys a public signal θ^T, with the average of private agent expectations denoted by $\bar{\theta}^j$. The spot* *rate responds to the bias between these signals as follows:*

$$\frac{\partial s_t}{\partial \theta^T} = \frac{1}{\Gamma}\left(\Gamma_T + \omega_j^B \Gamma_B\right), \tag{15}$$

$$\frac{\partial s_t}{\partial \bar{\theta}^j} = \frac{\Gamma_B}{\Gamma}\left(1 - \omega_j^B\right), \tag{16}$$

$$\frac{\partial s_t}{\partial \theta^T} > \frac{\partial s_t}{\partial \bar{\theta}^j} \quad \textit{iff} \quad R < \frac{N_T}{N_B} + 1, \tag{17}$$

where $R = \frac{\sigma_T^2}{\sigma_j^2}$ denotes the relative precision of the public to private signal, N_T is the number of Trump followers and N_B is the number of Bayesian agents.

Prediction 2 (Effect of Public Signal Precision on Spot Return Variance)**.** *Consider the variance of spot returns, defined as $\Delta s_{t+1} = s_{t+1} - s_t$, under public (I_T) and private (I_j) information sets. The variance of spot returns decreases following a Trump tweet if the relative precision of the public signal satisfies the following conditions:*

$$\frac{var(\Delta s_{t+1}|I_j, I_T)}{var(\Delta s_{t+1}|I_j)} = \frac{N_B}{N}\left(\frac{R}{R+1}\right) + \frac{N_T}{N}R, \tag{18}$$

$$\frac{var(\Delta s_{t+1}|I_j, I_T)}{var(\Delta s_{t+1}|I_j)} < 1 \quad \textit{iff} \quad R < \sqrt{\frac{N_B}{N_T} + 1}. \tag{19}$$

When the public signal is sufficiently precise (R is small), the volatility of spot returns declines. Conversely, if the public signal is noisy (R is large), volatility increases, particularly when the number of Trump followers (N_T) is large relative to Bayesian agents (N_B).

Discussion. Prediction 1 explains how spot returns respond to the bias between public and private signals. The Trump tweet acts as a public signal θ^T that influences the spot rate s_t through the bias between θ^T and the average prior belief of Bayesian agents, $\bar{\theta}^j$. The sensitivity of spot returns to Trump tweets increases with the relative precision of the public signal (R) and the relative share of Trump followers $(\frac{N_T}{N})$. When R is small (indicating a precise public signal) or N_T is large, the Trump tweet's impact on spot returns is amplified. Conversely, when R is large or Bayesian agents (N_B) dominate, private signals drive the spot rate.

This relationship is further illustrated by the decomposition of the counterfactual spot return. Comparing the equilibrium spot rate with and without the public signal yields:

$$s_t - s_t^{\text{no public signal}} = \underbrace{\frac{\Gamma_T}{\Gamma}\left(\theta^T - \bar{\theta}^j\right)}_{\text{Bias Trump Followers}} + \underbrace{\frac{\omega_j^B \Gamma_B}{\Gamma}\left(\theta^T - \bar{\theta}^j\right)}_{\text{Bias Bayesian Agents}}, \tag{20}$$

where $s_t^{\text{no public signal}} = i_t - i_t^* + \bar{\theta}^j$. The bias between public and private signals is distributed across Trump followers and Bayesian agents, weighted by their relative market impact. For $N_T \gg N_B$, the Trump followers' bias dominates, magnifying the impact of the public signal on the spot exchange rate.

In the model framework, the bias between the public and private signals arises from differing expectations of future macroeconomic fundamentals. For example, if U.S. growth expectations, following the Trump tweet, systematically exceed speculators' private expectations, i.e., $\mathbb{E}_t[y_{t+1}^T] > \mathbb{E}_t[y_{t+1}^j]$, it implies a positive bias, leading to an appreciation of the U.S. dollar. Similarly, tweets suggesting increased trade barriers or protectionism indicate higher tariffs, relative contraction in foreign output growth, and an appreciation of the U.S. dollar, consistent with empirical findings by Benton and Philips (2018), Matveev and Ruge-Murcia (2023), and Ferrari Minesso, Kurcz, and Pagliari (2022).

Prediction 2 examines how the precision of the public signal affects volatility. When R is small, higher precision in the public signal reduces uncertainty, resulting in lower spot return volatility. Conversely, a noisy public signal (large R) increases volatility, especially when Trump's follower base is significantly larger than the number of Bayesian agents ($N_T \gg N_B$). This highlights that the content and precision of Trump tweets are important for understanding their market impact.

Empirically, these predictions provide a framework for analyzing the market's reaction to Trump tweets. We categorize tweets by sentiment and information content, hypothesizing that tweets with clear macroeconomic content reduce volatility and induce systematic biases in spot returns. In contrast, noisy tweets or those unrelated to macroeconomic fundamentals, such as tweets on political events, are expected to generate higher volatility with little effect on the direction of spot returns. These hypotheses are tested in Section 5.

4 Data

4.1 Donald Trump's Tweets

We obtain an archive of Donald Trump's tweets from `https://www.thetrumparchive.com/`, which collects all tweets from the @realDonaldTrump account. Our sample begins on the 16^{th} of June 2015, the day Donald Trump announced his presidential campaign, and ends on the 20^{th} of August 2019. During this period, a total of 17,865 tweets were posted from his account. These tweets cover various topics.[5]

We use two approaches to identify the information content of Trump's tweets and filter tweets with macroeconomic, trade, or exchange rate content. The first is a dictionary-based method, and the second applies textual analysis using a Biterm Topic Modeling (BTM) approach.[6] For our empirical analysis, we combine tweets identified as relevant using both methods.

4.1.1 Dictionary Approach

Baker et al. (2019) provide a dictionary of policy-related terms relevant to macroeconomic outlook, trade policy, and exchange rates—topics closely connected to FX markets. Other topics, such as healthcare or energy, are less directly tied to currency fluctuations and are excluded. The dictionary's term sets were constructed through careful auditing and validation using a large sample of newspaper articles, ensuring a high level of accuracy. A comprehensive list of terms for each category (macroeconomic outlook, trade policy, and exchange rates) is provided in Table 1.

[TABLE 1 ABOUT HERE]

After filtering tweets containing at least one term from these categories, we manually review them to remove false positives (tweets not expressing the intended topic).

5. The archive also provides a list of topics frequently tweeted about by the 45^{th} and 47^{th} President of the U.S., such as personal superlatives (e.g., "My I.Q. is one of the highest - and you all know it!"), global warming (e.g., "Global warming is a HOAX"), and media disdain (e.g., "CNN Politics just plain dumb").

6. Traditional textual analysis methods, such as LDA or LSA, are less suitable for short texts like tweets due to their reliance on document length for topic identification.

This process yields a sample of 458 tweets.[7] Examples of tweets by topic are provided in Appendix B.1.

4.1.2 Biterm Topic Modeling

BTM, introduced by Yan et al. (2013), addresses the limitations of traditional methods like Latent Dirichlet Allocation (LDA) and Latent Semantic Indexing (LSI) for analyzing short texts.

The BTM approach requires two main inputs: (1) a corpus of text, which includes all tweets after standard text-cleaning procedures (e.g., lowercasing, removing numbers, and eliminating stop words), and (2) the number of topics, which we set at 9. This choice balances interpretability and model fit quality, as discussed by Chang et al. (2009) and Hansen, McMahon, and Prat (2018). Setting 9 topics allows us to identify trade and macroeconomic content intuitively.

The BTM algorithm outputs two key results. First, it provides a list of top keywords for each topic and their associated probabilities. For example, the trade topic includes keywords such as trade, tariff, China, dollar, and deal, while the macroeconomic topic includes keywords such as job, tax, cut, and market. Figure 2 summarizes the keywords for these two topics. Additional examples and full lists of keywords for all topics are provided in Appendix B.

[FIGURE 2 ABOUT HERE]

Second, the BTM method estimates the proportion of topics within each tweet. Each tweet is assigned a vector $\hat{\gamma}_t = [\hat{\gamma}_{t,1}, \ldots, \hat{\gamma}_{t,n}]'$, where $\hat{\gamma}_{t,n}$ represents the proportion of tweet t associated with topic n. We classify a tweet as containing macroeconomic or trade content if at least 30% of its content is related to these topics.[8] After manual review to remove false positives, 422 tweets remain, comprising 180 Trade tweets and 242 Macroeconomics tweets.

7. Retweets are excluded from the sample. The total number of tweets by category (218 trade, 247 macroeconomics outlook, and 3 exchange rates) sums to 468. However, 10 tweets are classified under both macroeconomics outlook and trade, resulting in a total of 458 unique tweets.

8. Reducing the threshold to 20% results in many false positives.

4.1.3 Informative Tweets: Combining the Dictionary and BTM Approach

To construct our sample of informative tweets, we combine tweets identified by the dictionary method and those classified as relevant by the BTM approach. A tweet is categorized as macroeconomic or trade-related if it satisfies either the dictionary criteria or the BTM threshold of 30%.

We identify 297 tweets using the dictionary method alone, 261 tweets using the BTM method alone, and 161 tweets identified by both methods, resulting in a total of 719 unique tweets. Since multiple relevant tweets may be posted in the same hour, the dataset covers 506 unique hours of relevant tweets. This tweet data is merged with FX market data at an hourly frequency for event studies.

The distribution of informative tweets across days of the week and hours of the day (London time) is summarized in Panels A and B of Figure 3, while Panels C and D present the same patterns for all tweets (both informative and uninformative) during the sample period.

[FIGURE 3 ABOUT HERE]

Informative tweets occur throughout the week, with higher frequency on weekdays. Weekend tweets, posted during illiquid FX market periods, are assigned to 10 p.m. on Sunday (London time). Most tweets are posted in the late afternoon and early morning (London time), aligning with morning and evening hours in U.S. Eastern Time (EST).

4.1.4 Sentiment Analysis

We analyze the sentiment of tweets using the dictionary developed by Loughran and McDonald (2011). The sentiment score is defined as:

$$\text{Tweet Sentiment} = \frac{\text{Number of positive words} - \text{Number of negative words}}{\text{Total number of words}}. \tag{21}$$

A higher sentiment score indicates greater optimism about macroeconomic fundamentals. Examples of tweets categorized by sentiment are provided in Appendix B.[9]

9. For example, a positive sentiment tweet reads: *"HAPPY THANKSGIVING, your Country is starting to do really well. Jobs coming back, highest Stock Market EVER, Military getting really strong, we will build the WALL, V.A. taking care of our Vets, great Supreme Court Justice, RECORD CUT IN REGS, lowest unemployment in 17 years....!"*

The sentiment distribution is positively skewed, with 465 positive tweets, 110 negative tweets, and 144 neutral tweets.[10] The average sentiment score is 0.091, with a standard deviation of 0.146. Sentiment scores range from -0.43 to 0.63.

4.2 FX Data

Hourly Volume. We use the CLS FX flows dataset provided by Quandl, covering over 50% of global FX transaction volume across 14 major currency pairs.[11] Hourly transaction volumes are recorded for four participant categories: banks, funds, non-bank financials, and corporations. Our sample covers June 16, 2015, to August 20, 2019.

Hourly Returns. We use high-frequency spot data from Thomson Reuters Tick History and interdealer trades from the Thomson Reuters D3 platform. Exchange rates are quoted in units of foreign currency per USD, and hourly returns are computed as the log difference of the spot exchange rate:

$$\Delta s_{t+1} = s_{t+1} - s_t, \tag{22}$$

where s_t is the log of the last quote (or trade price) at hour t.

Hourly Volatility. Following Mueller, Tahbaz-Salehi, and Vedolin (2017), we calculate realized volatility as the square root of the sum of squared five-minute changes in the spot exchange rate (mid-price) within an hour.

Hourly Bid-Ask Spread. The bid-ask spread is calculated as the difference between ask and bid prices divided by their midpoint, using the last quote of each hour.

10. Neutral tweets have a sentiment score of zero.

11. The dataset includes bilateral exchange rates of the U.S. dollar with Australia, Canada, the Euro Area, Japan, New Zealand, Norway, Sweden, Switzerland, the United Kingdom, Hungary, South Africa, Iceland, Mexico, and Korea. Hong Kong, Singapore dollars, and the Danish krone are excluded due to their currency pegs.

5 Empirical Analysis

In this section, we examine the effects of Trump tweets on various characteristics of the FX market, including returns and intraday volatility, within the framework of the model described in Section 3.

5.1 Panel Regressions: Spot Returns and Volatility

Our baseline regressions pool observations from 14 currency pairs and employ country fixed-effects panel regressions using hourly data. The fixed-effects panel regression specification is given in Equation (23):

$$x_{i,t} = \alpha_i + \beta_1 \mathit{Tweet}_t + \beta_2 X_{t-1} + \mu_d + \sigma_h + \epsilon_{i,t}, \tag{23}$$

where the outcome variable, $x_{i,t}$, represents returns, intraday volatility, or trading volume for currency pair i at time t. The variable Tweet_t is a dummy equal to 1 if a tweet about macroeconomics, trade, or FX is posted by Donald Trump during that hour, and 0 otherwise. The vector X_{t-1} includes a set of control variables, such as the lagged bid-ask spread, a dummy for FOMC announcements, and changes in the intraday CBOE Volatility Index (ΔVIX). The ΔVIX variable is calculated as the cumulative change in the VIX over one-hour (or 30-minute) intervals. The FOMC dummy equals 1 if an FOMC announcement occurs during that hour.

The terms μ_d and σ_h represent time-fixed effects, controlling for the day of the week and hour of the day, respectively. Standard errors are clustered at the currency pair level.

To account for momentum effects and mitigate concerns that Trump tweets may follow macroeconomic news already reflected in exchange rates, we include lags of the outcome variable from $t-1$ to $t-5$ in all specifications.

5.1.1 Trump Tweets and FX Returns

The first prediction of the model is that Trump tweets impact FX spot returns. Specifically, Equation (20) shows that spot returns reflect a bias between the public signal (Trump's tweet) and investors' expectations of future macroeconomic fundamentals. This bias can arise if Trump's tweets are more optimistic about the U.S. economy or more protectionist about trade relations. The coefficient β_1 in Equation (23) measures the impact of Trump tweets on spot returns, capturing any inherent bias introduced by these tweets. The regression results are presented in Table 2.

[TABLE 2 ABOUT HERE]

The positive coefficient for informative Trump tweets in the first column indicates that these tweets lead to an appreciation of the U.S. dollar. On average, the USD appreciates by approximately 0.005 percent (0.5 basis points) during a Trump tweet hour against a basket of currencies.[12]

These results are robust to the inclusion of additional controls, such as the bid-ask spread, FOMC announcements, and ΔVIX, as shown in columns (2) to (4). This supports the model's prediction that FX returns generally reflect Trump's optimistic view of the U.S. economy.

To further explore the relationship between tweet sentiment and FX returns, we run additional regressions linking sentiment scores to spot returns. The results, presented in Table 3, show that tweets with a more optimistic tone have a stronger positive effect on USD spot returns.

[TABLE 3 ABOUT HERE]

The sentiment score, based on the dictionary from Loughran and McDonald (2011), is the independent variable. The coefficient on sentiment is positive and significant in all specifications. In the final column, which includes all controls, the coefficient for optimistic tweets is 0.021 with a *t*-statistic of 2.62. This implies that Trump tweets expressing optimism about the U.S. economy are associated with a significant USD appreciation.

Overall, this analysis confirms the model's prediction that spot returns reflect a bias arising from the public signal in Trump's tweets. Tweets with a positive tone amplify this bias, leading to stronger USD appreciation.

12. We use the notation of units of foreign currency per USD, so a positive coefficient indicates an appreciation of the USD relative to the foreign currency.

The results complement prior research on the effects of Trump tweets on financial markets. For instance, Bianchi et al. (2023) demonstrate that Trump tweets about monetary policy lead to significant changes in interest rate futures, with an average effect of approximately -0.26 basis points within an hour. While their analysis focuses specifically on tweets related to Federal Reserve policy, our study examines a broader set of macroeconomic and trade-related tweets. By utilizing both dictionary and BTM methods, we identify 719 informative tweets, enabling us to estimate the overall impact of Trump tweets on FX markets.

Minute-Level Tweets. Building on the hourly analysis, we investigate the intra-hour impact of Trump tweets by conducting an event study at the minute frequency. Panel A of Figure 4 shows cumulative exchange rate changes around Trump tweets at the minute level for an equally weighted portfolio of 14 currencies. Consistent with the panel regressions, we observe a systematic appreciation of 0.5 basis points against the basket of currencies, peaking within an hour of the tweet.

To address potential endogeneity concerns (e.g., Trump tweets responding to macroeconomic news), we compare tweet impacts on days with and without macroeconomic announcements. Panel B of Figure 4 shows no significant exchange rate response on days with macroeconomic announcements, while Panel C shows a systematic USD appreciation on days without announcements. This suggests that USD appreciation in response to Trump tweets is not driven by contemporaneous macroeconomic news.[13]

[FIGURE 4 ABOUT HERE]

Tweet Sentiment. Expanding on Table 3, Figure 5 examines high-frequency cumulative returns by sentiment. Panel A shows that positive tweets lead to a cumulative USD return of approximately 0.7 basis points, while Panel B shows that negative tweets result in a -2 basis point return. These results confirm that sentiment influences the magnitude and direction of FX market reactions to Trump tweets.

13. Additional tests controlling for macroeconomic announcements in panel regressions are discussed in Section 5.2.

[FIGURE 5 ABOUT HERE]

Trading Strategy. The predictability of exchange rates following informative Trump tweets suggests the potential for a trading strategy using the Invesco DB US Dollar Index (ticker UUP). Panel A of Figure 6 shows the transaction costs, represented by the bid-ask spreads normalized by the mid-quote, while Panel B displays the cumulative returns. Our analysis reveals that a USD ETF index yields a return of approximately 2 basis points within 1 hour following informative Trump tweets. Transaction costs, ranging between 1.5 and 1.75 basis points based on the full spread, naturally absorb some of this return. Accounting for these costs, we compute the annualized Sharpe ratio of the tweet-based trading strategy using hourly return estimates. The baseline Sharpe ratio is 0.69, demonstrating the strategy's profitability under realistic trading conditions.

The economic significance of this strategy can be further enhanced by incorporating tweet sentiment. As shown in Figure 5, spot returns vary depending on whether the tweets convey positive or negative sentiment. To explore this, we condition the trading strategy on the tone of informative tweets. Specifically, we implement a trading rule that goes long when tweets convey positive sentiment and short when tweets convey negative sentiment. This conditional approach reveals significant performance variations: the Sharpe ratio for shorting after negative tweets is 1.63, while the Sharpe ratio for going long after positive tweets is 2.25. Our findings highlight the importance of sentiment analysis in enhancing the profitability of trading strategies, even after accounting for transaction costs.

[FIGURE 6 ABOUT HERE]

Further robustness checks, including event studies with trade-weighted exchange rates and abnormal returns, are discussed in Appendices C and D.

5.1.2 Trump Tweets and FX Volatility and Volume

We proceed to test the model's second prediction, which suggests that FX volatility decreases following informative Trump tweets. Informative tweets are defined as those providing a higher level of precision compared to private information. To address the persistence of volatility, we use innovations in intraday realized volatility as the outcome variable. Table 4 presents the regression results.

In the first column, where the only control variables are day-of-week and hour-of-day dummies, the coefficient for the tweet dummy variable is negative and highly significant, with a t-statistic of -6.19. This indicates that during an hour when Trump posts an informative tweet, FX volatility declines by 0.006 percent (0.6 basis points) on average against a basket of currencies. When we add more control variables in columns (2) to (4), including the bid-ask spread, ΔVIX, and FOMC announcements, the coefficient remains stable in magnitude and highly significant. In the fully specified regression in column (4), the tweet dummy variable continues to show a negative relationship with volatility, with a t-statistic of -7.14.

To ensure the robustness of these results, we perform additional tests using a measure of abnormal volatility surrounding Trump tweets, which is calculated as the difference in volatility during the tweet's time and a period without the tweet, adjusted for changes in the VIX index. These findings are presented in Appendix D.

[TABLE 4 ABOUT HERE]

In addition to the analysis of volatility, we examine the relationship between FX trading volume and informative Trump tweets. In general, trading volume and volatility are positively correlated in FX markets (Bjonnes, Rime, and Solheim, 2005; Ranaldo and Magistris, 2022), and macroeconomic news often amplifies this relationship (Bollerslev, Li, and Xue, 2018). Following Cespa et al. (2022), we calculate abnormal FX trading volume as the log deviation from the moving average of FX volume for the same hour over the past 21 trading days.[14]

The regression results for FX trading volume are presented in Table 5. Column (1) shows a significant 0.63% reduction in abnormal trading volume during hours when informative Trump tweets are posted. In Column (2), adding the bid-ask spread as a

14. In Appendix A, we discuss how our model relates to trading volume. The effects of informative tweets on trading volume depend on both the precision of the public signal and the bias introduced by Trump tweets.

control confirms a negative relationship between volume and illiquidity. Column (3) incorporates ΔVIX, revealing a positive relationship between uncertainty and spot FX trading volume. Finally, Column (4) adds an FOMC dummy variable, showing a 0.56% reduction in abnormal trading volume during Trump tweet hours. This result confirms that the observed reduction in trading volume is not solely driven by monetary policy announcements.

Overall, the results show that both volatility and trading volume decline during hours with informative Trump tweets. This suggests that the information provided by these tweets reduces uncertainty in the market, which, in turn, lowers both trading activity and volatility.[15]

[TABLE 5 ABOUT HERE]

5.2 Robustness Tests

5.2.1 G10 Currencies

To test the robustness of our results, we replicate the panel regression specification from Equation (23) using a subsample of G10 currencies.[16] Table 6 presents the results of this analysis, with columns (1), (2), and (3) showing the effects of informative tweets on hourly returns, volatility, and trading volume, respectively. The regressions include controls for bid-ask spreads, monetary announcements, and fixed effects for both time and currency pairs.

The findings remain consistent with the full-sample results. Informative tweets are associated with an appreciation of the USD, a decline in FX volatility, and a reduction in trading volume within the G10 currency sample. This confirms that the observed effects are not specific to a broader basket of currencies but are also present within the G10 group.

15. Appendix E provides additional evidence by analyzing trading volume for different market participants using CLS data. For funds, banks, and non-financials, there is a significant reduction in trading volume during Trump tweet hours, supporting the findings based on aggregate volume.

16. The G10 currencies include the Australian dollar (AUD), Canadian dollar (CAD), Euro (EUR), Japanese yen (JPY), New Zealand dollar (NZD), Norwegian krone (NOK), Pound sterling (GBP), Swedish krona (SEK), and Swiss franc (CHF).

[TABLE 6 ABOUT HERE]

5.2.2 Macroeconomic Announcements

A potential concern with our estimation is the omitted variable bias caused by Trump tweets that coincide with macroeconomic releases. An alternative explanation is that Trump tweets simply echo macroeconomic news released on the same day. For example, shortly after a macroeconomic release on job openings, Trump tweeted: *"Incredible number just out, 7,036,000 job openings. Astonishing - it's all working! Stock Market up big on tremendous potential of USA. Also, Strong Profits. We are Number One in World, by far!"*. If this is the case, our results may capture agents' responses to macroeconomic announcements rather than to Trump tweets themselves.

[TABLE 7 ABOUT HERE]

To address this concern, we add control variables for macroeconomic releases on output, employment, and trade activity, following Gürkaynak, Sack, and Swanson (2005). In Table 7, Panel A includes a dummy variable equal to 1 if there is at least one macroeconomic announcement on a given day and 0 otherwise. The coefficient for the Trump tweet dummy remains significant, indicating that informative tweets have a distinct impact on returns and volatility even after accounting for macroeconomic releases.

To further account for potential overlap, we add a dummy variable for macroeconomic announcements occurring in the hour preceding the Trump tweet. Results in Panel B show that the effects on spot returns and volatility remain robust, suggesting that the observed patterns are not systematically driven by news released just before the tweets.

Another potential concern is whether structural changes during the sample period, such as the transition from Trump's campaign to his presidency, influence the results. To address this, we include a dummy variable equal to 1 for tweets posted after November 8, 2016, the day Trump won the U.S. presidential election. As shown in Panel C, the results are robust to this adjustment, indicating that the tone or timing of Trump's tweets during his presidency does not materially affect their impact on FX markets.

5.2.3 Trump Tweets and Media Coverage

We further investigate whether Trump tweets serve as a distraction strategy by analyzing their relationship with media coverage of the Mueller investigation. If informative tweets frequently follow negative press coverage, this would support the idea that the timing of these tweets is plausibly exogenous with respect to ongoing macroeconomic trends. Using the dataset provided by Lewandowsky, Jetter, and Ecker (2020), we examine the extent of media coverage related to the Mueller investigation in *The New York Times* and test its association with Trump's tweets.

Table 8 presents the results of logit regressions analyzing the likelihood of Trump posting an informative tweet in response to media coverage of the Mueller investigation. The coefficient for lagged media coverage is positive and statistically significant across all specifications, suggesting that negative press increases the probability of Trump posting an informative tweet in the subsequent hour. To rule out macroeconomic news as a driver, we control for lagged returns, ensuring that the timing of tweets is not influenced by prior movements in exchange rates. These results support the hypothesis that Trump tweets may be strategically timed to divert public attention from unfavorable media coverage.

[TABLE 8 ABOUT HERE]

5.2.4 Uninformative Tweets and the FX Market

Thus far, our analysis has focused on informative Trump tweets related to macroeconomic or trade topics. To assess whether the observed effects are specific to informative tweets, we analyze a set of uninformative tweets, defined as those unrelated to macroeconomic or trade topics.

Uninformative tweets are identified using two criteria. First, they have the lowest probability of being related to macroeconomic or trade topics based on the BTM method. Second, we select a sample size matching the number of informative tweets. These uninformative tweets are then used to replicate the panel regressions, substituting the uninformative tweet hour dummy as the independent variable.

[TABLE 9 ABOUT HERE]

Table 9 presents the results, with columns (1), (2), and (3) showing the effects of uninformative tweets on hourly returns, volatility, and trading volume, respectively. The regressions include controls for bid-ask spreads, monetary announcements, and fixed effects for both time and currency pairs. The findings confirm that uninformative tweets do not significantly impact FX returns or volatility. However, Column (3) reports a small but significant decline in trading volume (0.515%), though weaker than the effect observed for informative tweets. This suggests that the market response is driven primarily by tweets containing macroeconomic or trade-related content.

To further explore the role of Trump's social media influence, we compare retweets and favorites for informative versus uninformative tweets, using these metrics as proxies for market engagement. Appendix B.4 shows that informative tweets receive significantly more retweets and favorites than uninformative ones. This highlights the critical role of Trump's follower base in amplifying the market impact of his tweets.

6 Conclusion

This paper combines dictionary-based and topic-modeling approaches to identify the information content of Donald Trump's tweets. We focus on tweets related to macroeconomic outlook, trade policy, and FX policy, hypothesizing that they carry relevant information for the FX market. Using a theoretical model, we show that these tweets act as a public signal in a market with heterogeneous private information. Differences between Trump's expectations of macroeconomic fundamentals and speculators' expectations can induce a bias in currency returns.

We test our model's predictions using a dataset of Trump tweets and FX price data for 14 bilateral currency pairs quoted against the USD. Consistent with the model, we find that informative Trump tweets are associated with a statistically significant appreciation of the USD and a decline in exchange rate volatility. These effects reflect the generally optimistic tone of Trump's tweets regarding the U.S. economy and support the hypothesis that such tweets convey valuable information to market participants.

To address potential endogeneity, we control for macroeconomic announcements and test whether Trump tweets serve as a distraction from negative media coverage. Our findings suggest that tweets are more likely to focus on macroeconomic or trade topics following periods of negative press coverage, providing further evidence of their exogenous timing. Additionally, a separate analysis of uninformative tweets finds no significant effects on FX returns or volatility, reinforcing the importance of tweet content in driving market reactions.

In summary, we use textual analysis to identify informative tweets with relevant information for the FX market. Our study highlights the substantial impact policymakers have on financial markets through social media platforms.

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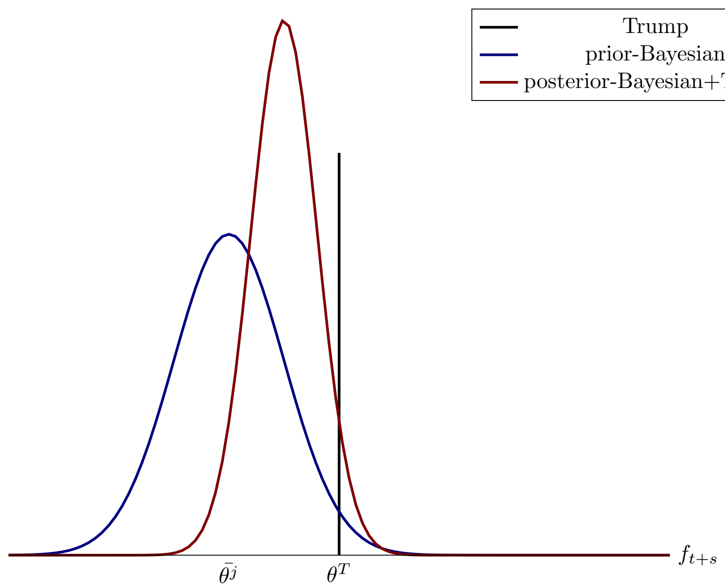
Figures

Figure 1: Bias between Trump and Other Agents on Expectations of Future Fundamentals



This figure illustrates the bias between Trump's expectations of future fundamentals and those of Bayesian agents. The bias causes spot returns to change in proportion to the relative precision of the public signal. Bayesian agents update their signals based on this bias, influencing the spot returns.

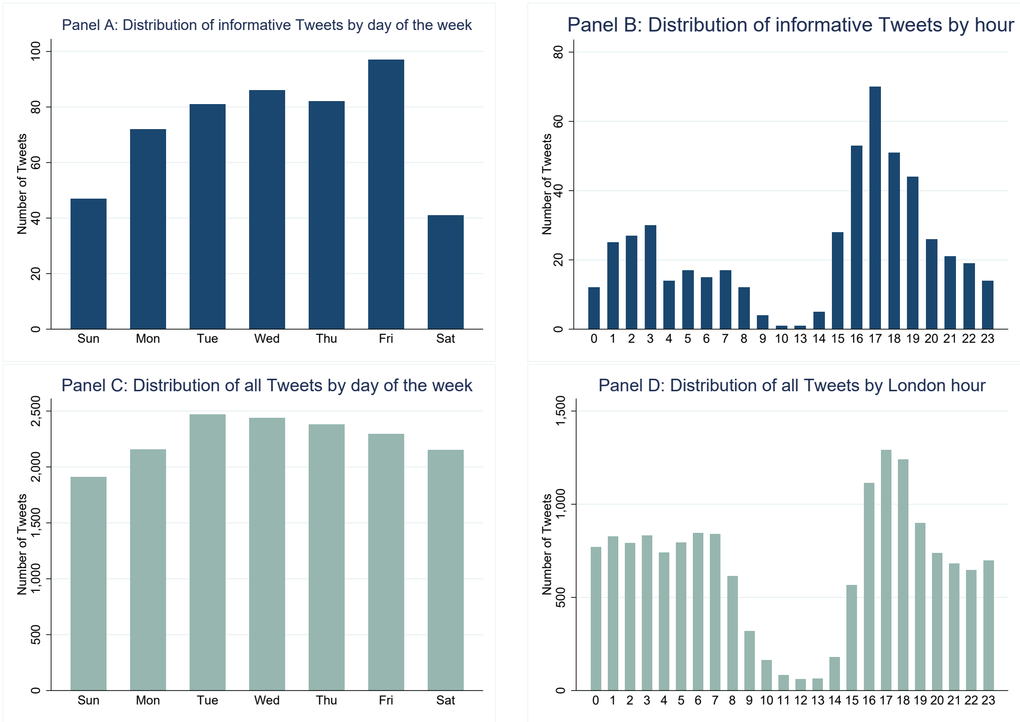
Figure 2: Trade and Macroeconomics Topics Identified by BTM

Trade Topic

Macroeconomics Topic

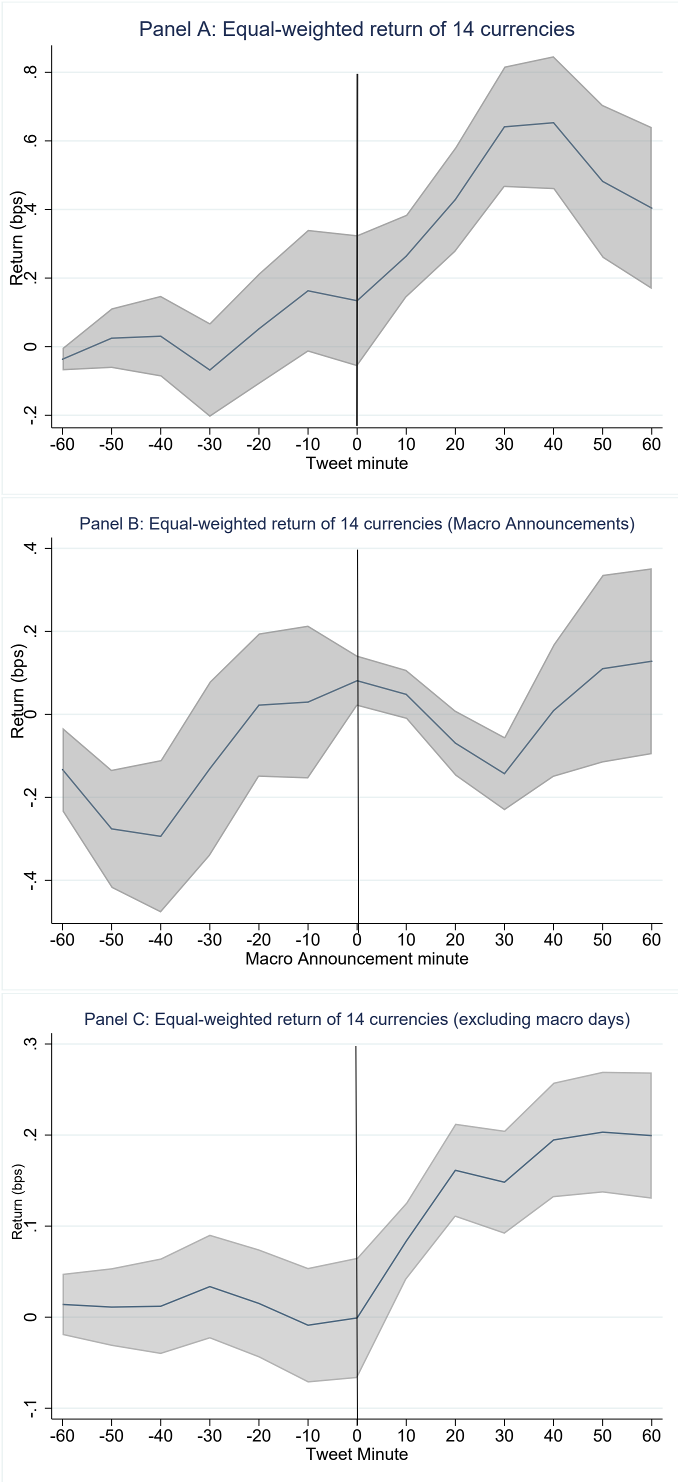
This figure shows the top keywords for two topics identified using the Biterm Topic Modeling (BTM) approach. The trade topic includes keywords such as trade, tariff, China, and deal, while the macroeconomics topic includes keywords such as job, tax, cut, and market.

Figure 3: Time Distribution of Trump Tweets



This figure shows the time distribution of tweets belonging to the Macroeconomics, Trade Policy, and Exchange Rate categories (Panels A and B) and all tweets (Panels C and D). The x-axis represents London time. The data span June 16, 2015, to August 20, 2019.

Figure 4: Event Study of Spot Returns during the Tweet Hour

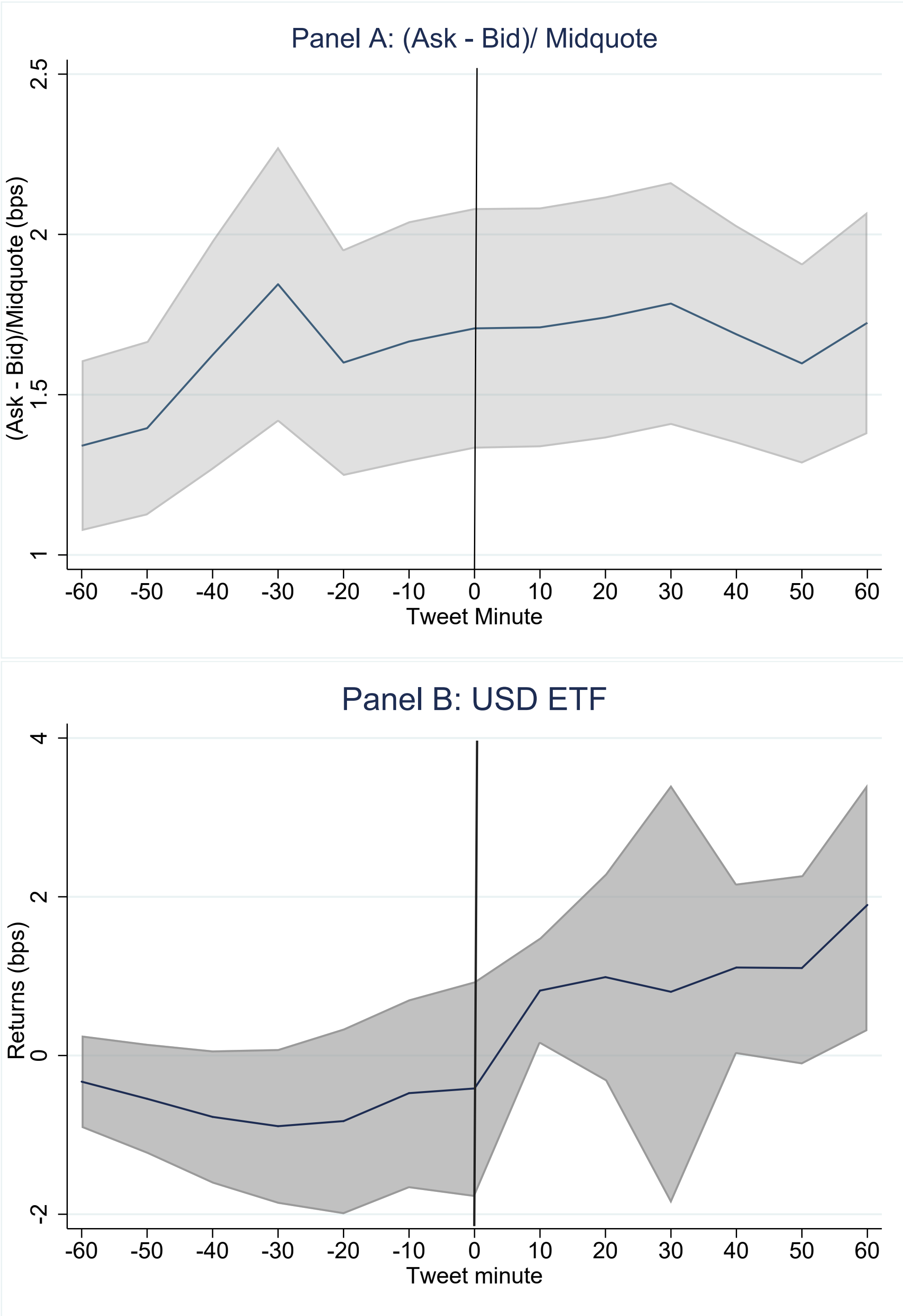


This figure shows the average cumulative spot returns in basis points during the tweet hours for the equal-weighted return of 14 currencies (Panel A), macroeconomic announcement hours (Panel B), and tweet hours excluding macroeconomic announcement days (Panel C). The x-axis represents the minutes during the event, with 0 being the minute in which a tweet is posted (indicated by a vertical line). Negative values on the x-axis represent minutes before informative tweets. The shaded area shows a 95% confidence interval using White heteroscedasticity-robust standard errors.

Figure 5: Event Study of Spot Returns during the Tweet Hour: Positive versus Negative Sentiment Tweets

This figure shows the average cumulative spot returns in basis points during tweet hours for the equal-weighted return of 14 currencies. Panel A presents positive tweets, and Panel B presents negative tweets. The x-axis represents the minutes during the event, with 0 being the minute in which a tweet is posted (indicated by a vertical line). Negative values on the x-axis represent minutes before informative tweets. The shaded area shows a 95% confidence interval using White heteroscedasticity-robust standard errors.

Figure 6: Trading on Trump Tweets Using ETF Dollar Index



This figure shows transaction costs and average cumulative spot returns in basis points during tweet hours for the USD ETF, the Invesco DB US Dollar Index Bullish Fund (ticker UUP). Panel A reports transaction costs as the bid-ask spread normalized by the mid-quote, and Panel B reports the average cumulative returns. The x-axis represents the minutes during the event, with 0 being the minute in which a tweet is posted (indicated by a vertical line). Negative values on the x-axis represent minutes before informative tweets. The shaded area shows a 95% confidence interval using White heteroscedasticity-robust standard errors.

Tables

Table 1: **Category Specific Dictionary**

This table presents the terms used to identify Tweets related to Macroeconomics Outlook, Exchange Rate, and Trade Policy. These term sets are based on Baker et al. (2019)

Dictionary	
Category	Words
Macroeconomics Outlook	gold, silver, gdp, economic growth, depression, recession, economic crisis, macroeconomic indicators, macroeconomic news, rail loadings, railroad loadings, cpi, inflation, consumer prices, ppi, producer prices, housing prices, home prices, homebuilding, homebuilders, housing starts, home sales, building permits, residential sales, mortgages, residential construction, commercial construction, commercial real estate, real estate, labor force, workforce, unemployment, employment, unemployment, insurance, ui claims, jobs report, jobless claims, payroll, underemployment, quits, hires, weekly hours, wages, labor income, labor earnings, corporate bonds, bank loans, interest rates, trade news, trade surplus, trade deficit, national exports, national imports, business investment business inventories, consumer spending, retail sales, consumer purchases, consumer confidence, consumer sentiment, macroeconomic outlook, business sentiment, business confidence, industrial production, ism report, manufacturing index, household credit, household savings, household debt, household borrowing, consumer credit
Exchange Rate	exchange rate, currency crisis, currency devaluation, currency depreciation currency revaluation, currency appreciation, crawling peg, managed float, currency manipulation currency intervention
Trade Policy	trade policy, tariff, import duty, import barrier, import restriction, trade quota, dumping, export tax, export duty, trade treaty, trade agreement, trade act, wto world trade organization, Doha round, Uruguay round, gatt, export restriction, investment restriction, Nafta, North American Free Trade Agreement, Trans-Pacific partnership, TransPacific Partnership, Federal Maritime Commission, International Trade Commission, Jones Act, trade adjustment assistance

Table 2: **Informative Tweets and FX Hourly Returns**

This table presents panel regression results estimating the effect of an hour dummy for informative Tweets on FX hourly returns. Informative tweets are classified using both the BTM and dictionary approaches. In the BTM approach, a tweet is classified as informative if it has at least a 30% probability of belonging to macroeconomic or trade topics. Control variables include the hourly bid-ask spread, hourly ΔVIX, an FOMC dummy, and lagged hourly returns. Hour-of-the-day and day-of-the-week dummies are included in all regressions. Standard errors are clustered by currency. t-statistics are reported in parentheses, with *** indicating significance at the 1% level, ** at the 5% level, and * at the 10% level. The data cover the period from June 16, 2015, to August 20, 2019, at an hourly frequency.

	Dependent variable: FX Returns			
	(1)	(2)	(3)	(4)
Tweet hour$_t$	0.005***	0.005***	0.005***	0.005***
	(3.17)	(3.42)	(3.34)	(3.34)
Return$_{t-1}$	-0.022***	-0.021***	-0.022***	-0.022***
	(-6.21)	(-6.70)	(-6.51)	(-6.53)
Return$_{t-2}$	-0.012***	-0.011***	-0.011***	-0.011***
	(-3.77)	(-3.96)	(-3.78)	(-3.78)
Return$_{t-3}$	-0.006**	-0.006**	-0.006**	-0.006**
	(-2.95)	(-2.71)	(-2.77)	(-2.77)
Return$_{t-4}$	-0.005	-0.006	-0.006	-0.006
	(-1.61)	(-1.56)	(-1.57)	(-1.57)
Return$_{t-5}$	-0.007***	-0.007***	-0.008***	-0.008***
	(-3.85)	(-3.63)	(-3.90)	(-3.89)
Bid Ask Spread$_{t-1}$		0.000	0.000	0.000
		(0.84)	(0.76)	(0.77)
ΔVIX$_{t-1}$			0.029	0.029
			(1.41)	(1.41)
FOMC$_{t-1}$				-0.019*
				(-2.14)
Country FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes
Observations	351,445	332,781	329,553	329,553
R^2	0.12%	0.12%	0.14%	0.14%

Table 3: **Informative Tweets and FX Hourly Returns: Sentiment Analysis**

This table presents panel regression results estimating the impact of informative Tweets' sentiment on FX hourly returns. Informative tweets are classified using both the BTM and dictionary approaches. Under the BTM approach, a tweet is classified as informative if it has at least a 30% probability of belonging to macroeconomic or trade topics. The explanatory variable is a sentiment score assigned to each tweet based on the dictionary developed by Loughran and McDonald (2011), calculated using the relative frequency of positive and negative words in the tweet. A positive sentiment score indicates optimism. Control variables include the hourly bid-ask spread, hourly ΔVIX, and an FOMC dummy. Hour-of-the-day and day-of-the-week dummies are included in all regressions. Standard errors are clustered by currency. t-statistics are reported in parentheses, with *** indicating significance at the 1% level, ** at the 5% level, and * at the 10% level. The data cover the period from June 16, 2015, to August 20, 2019, at an hourly frequency.

	Dependent variable: FX Returns			
	(1)	(2)	(3)	(4)
Sentiment_t	0.018**	0.021**	0.021**	0.021**
	(2.49)	(2.62)	(2.60)	(2.62)
Return_{t-1}	-0.022***	-0.021***	-0.022***	-0.022***
	(-6.22)	(-6.71)	(-6.52)	(-6.53)
Return_{t-2}	-0.012***	-0.011***	-0.011***	-0.011***
	(-3.78)	(-3.97)	(-3.79)	(-3.78)
Return_{t-3}	-0.006**	-0.006**	-0.006**	-0.006**
	(-2.96)	(-2.72)	(-2.78)	(-2.79)
Return_{t-4}	-0.005	-0.006	-0.006	-0.006
	(-1.61)	(-1.56)	(-1.57)	(-1.57)
Return_{t-5}	-0.007***	-0.007***	-0.008***	-0.008***
	(-3.85)	(-3.63)	(-3.90)	(-3.89)
Bid Ask Spread_{t-1}		0.000	0.000	0.000
		(0.83)	(0.74)	(0.76)
ΔVIX_{t-1}			0.029	0.029
			(1.41)	(1.40)
FOMC_{t-1}				-0.019*
				(-2.15)
Observations	351445	332781	329553	329553
R^2	0.13%	0.13%	0.15%	0.15%

Table 4: **Informative Tweets and FX Hourly Realized Volatility**

This table presents panel regression results estimating the effect of an hour dummy for informative Tweets on FX hourly realized volatility. Informative tweets are classified using both the BTM and dictionary approaches. In the BTM approach, a tweet is classified as informative if it has at least a 30% probability of belonging to macroeconomic or trade topics. Control variables include the hourly bid-ask spread, hourly ΔVIX, an FOMC dummy, and lagged hourly volatility. Hour-of-the-day and day-of-the-week dummies are included in all regressions. Standard errors are clustered by currency. t-statistics are reported in parentheses, with *** indicating significance at the 1% level, ** at the 5% level, and * at the 10% level. The data cover the period from June 16, 2015, to August 20, 2019, at an hourly frequency.

	Dependent variable: Realized Volatility			
	(1)	(2)	(3)	(4)
	Informative			
Tweet hour$_t$	-0.006***	-0.006***	-0.007***	-0.007***
	(-6.19)	(-6.96)	(-7.06)	(-7.14)
Volatility$_{t-1}$	-0.135***	-0.142***	-0.143***	-0.146***
	(-8.87)	(-9.69)	(-9.68)	(-9.89)
Volatility$_{t-2}$	0.057***	0.052***	0.053***	0.052***
	(6.96)	(5.94)	(6.12)	(6.04)
Volatility$_{t-3}$	0.083***	0.080***	0.080***	0.080***
	(19.53)	(15.38)	(15.24)	(15.16)
Volatility$_{t-4}$	0.086***	0.085***	0.085***	0.086***
	(33.00)	(28.65)	(28.18)	(28.14)
Volatility$_{t-5}$	0.076***	0.075***	0.075***	0.076***
	(21.78)	(20.40)	(20.35)	(20.44)
Bid Ask Spread$_{t-1}$		0.001**	0.001**	0.001**
		(2.41)	(2.40)	(2.38)
ΔVIX$_{t-1}$			0.010***	0.011***
			(4.38)	(4.40)
FOMC$_{t-1}$				0.110***
				(4.45)
Country FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes
Observations	347,395	328,636	325,562	325,562
R^2	10%	11%	10%	11%

Table 5: **Informative Tweets and Spot FX Trading Volume**

This table presents panel regression results estimating the effect of an hour dummy for informative Tweets on FX hourly trading volume. Informative tweets are classified using both the BTM and dictionary approaches. In the BTM approach, a tweet is classified as informative if it has at least a 30% probability of belonging to macroeconomic or trade topics. Control variables include the hourly bid-ask spread, hourly ΔVIX, an FOMC dummy, and lagged hourly trading volume. Hour-of-the-day and day-of-the-week dummies are included in all regressions. Standard errors are clustered by currency. t-statistics are reported in parentheses, with *** indicating significance at the 1% level, ** at the 5% level, and * at the 10% level. The data cover the period from June 16, 2015, to August 20, 2019, at an hourly frequency.

Dependent variable: Aggregate Trading Volume				
	(1)	(2)	(3)	(4)
	Informative			
Tweet hour$_t$	-0.63***	-0.55***	-0.56***	-0.56***
	(-3.38)	(-3.45)	(-3.47)	(-3.47)
Volume$_{t-1}$	0.35***	0.32***	0.32***	0.32***
	(10.42)	(17.21)	(17.20)	(17.21)
Volume$_{t-2}$	0.10***	0.09***	0.09***	0.09***
	(6.03)	(7.84)	(7.81)	(7.81)
Volume$_{t-3}$	0.06***	0.05***	0.05***	0.05***
	(7.21)	(9.92)	(9.42)	(9.46)
Volume$_{t-4}$	0.03**	0.02**	0.02**	0.02**
	(2.86)	(2.66)	(2.61)	(2.61)
Volume$_{t-5}$	0.00	-0.00	-0.00	-0.00
	(0.00)	(-0.15)	(-0.20)	(-0.20)
Bid Ask Spread$_{t-1}$		-0.04***	-0.04***	-0.04***
		(-5.43)	(-5.40)	(-5.41)
ΔVIX$_{t-1}$			0.34***	0.35***
			(3.85)	(3.88)
FOMC$_{t-1}$				1.46***
				(11.13)
Country FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes
Observations	284,099	279,582	276,927	276,927
R^2	22%	22%	19%	19%

Table 6: **Informative Tweets and FX market (G10 Sample)**

This table presents panel regression results estimating the effect of an hour dummy for informative tweets on FX market characteristics for the G10 sample of currencies. The dependent variables in columns (1), (2), and (3) are hourly returns, intraday volatility, and trading volume, respectively. Control variables include the hourly bid-ask spread, hourly ΔVIX, an FOMC dummy, and lags of the dependent variable from $t-1$ to $t-5$. All regressions include hour-of-the-day and day-of-the-week fixed effects. Standard errors are clustered by currency. t-statistics are reported in parentheses, with *** indicating significance at the 1% level, ** at the 5% level, and * at the 10% level. The sample period spans from June 16, 2015, to August 20, 2019, with data at an hourly frequency.

	Dependent variable: FX market characteristics		
	(1) Return$_t$	(2) Volatility$_t$	(3) Volume$_t$
Tweet hour$_t$	0.005***	-0.01***	-0.41**
	(2.55)	(-11.50)	(-2.40)
Bid Ask Spread$_{t-1}$	-0.000	0.00***	-0.03
	(-0.61)	(7.58)	(-1.49)
ΔVIX$_{t-1}$	0.004	0.00	0.27***
	(0.21)	(0.90)	(2.73)
FOMC$_{t-1}$	-0.008	0.04***	1.36***
	(-1.07)	(8.48)	(9.27)
Dep. Var.$_{t-1}$	-.021***	-0.17***	0.31***
	(-4.50)	(-8.01)	(19.44)
Dep. Var.$_{t-2}$	-0.008*	0.03**	0.08***
	(-1.93)	(3.03)	(8.91)
Dep. Var.$_{t-3}$	-0.008***	0.07***	0.06***
	(-6.08)	(9.24)	(16.56)
Dep. Var.$_{t-4}$	-0.002	0.08***	0.02***
	(-1.00)	(13.93)	(3.48)
Dep. Var.$_{t-5}$	-0.002	0.06***	0.01**
	(-1.61)	(14.11)	(3.22)
Country FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes
Observations	248,914	214,152	214,152
R^2	0.11%	12%	18%

Table 7: **Tweets and FX market controlling for macroeconomic announcements and presidency**

This table presents panel regression results estimating the effect of an hour dummy for informative Tweets on FX market characteristics. The dependent variable in regressions (1), (4), and (7) is hourly returns; in regressions (2), (5), and (8), it is volatility; and in regressions (3), (6), and (9), it is trading volume. Control variables include the hourly bid-ask spread, hourly ΔVIX, and an FOMC dummy. The macroeconomic announcements dummy equals 1 if there is at least one macroeconomic announcement in the preceding hour, and 0 otherwise. The presidency dummy equals 1 during Trump's presidency term, and 0 otherwise. Hour-of-the-day and day-of-the-week dummies are included in all regressions. Standard errors are clustered by currency. t-statistics are reported in parentheses, with *** indicating significance at the 1% level, ** at the 5% level, and * at the 10% level. The data cover the period from June 16, 2015, to August 20, 2019, at an hourly frequency.

	Panel A: Macro announcements day			**Panel B: Macro announcements pre-hour**			**Panel C: Presidency**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Tweet hour$_t$	0.006***	-0.004***	-0.561***	0.006***	-0.007***	-0.515***	0.006***	-0.004***	-0.561***
	(3.31)	(-8.16)	(-3.54)	(3.50)	(-6.42)	(-3.63)	(3.27)	(-4.19)	(-3.50)
Bid Ask Spread$_{t-1}$	0.000	0.001**	-0.082***	0.000	0.001**	-0.085***	0.000	0.000	-0.080***
	(1.04)	(2.48)	(-5.54)	(0.85)	(2.52)	(-5.49)	(0.96)	(1.72)	(-5.20)
ΔVIX$_{t-1}$	0.029	0.012***	0.496***	0.027	0.012***	0.475***	0.029	0.012***	0.470***
	(1.50)	(4.45)	(5.35)	(1.50)	(4.26)	(5.14)	(1.50)	(4.56)	(5.19)
FOMC$_{t-1}$	-0.018*	0.096***	1.606***	-0.019*	0.104***	1.500***	-0.019*	0.096***	1.592***
	(-1.92)	(4.01)	(8.97)	(-1.92)	(4.65)	(10.00)	(-1.92)	(4.03)	(9.98)
Macro$_{day}$	0.003***	0.003***	0.145***						
	(4.82)	(9.09)	(7.09)						
Macro$_{pre}$				-0.001	0.010***	0.117***			
				(-1.02)	(3.08)	(6.05)			
Presidency$_t$							-0.000	-0.014***	0.216*
							(-0.12)	(-7.41)	(2.13)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	329,647	325,618	301,848	329,647	325,618	302,983	329,647	325,618	302,983
R^2	0.09%	7.67%	7.54%	0.08%	7.74%	7.98%	0.09%	7.65%	7.81%

Table 8: **Tweets and Newspaper Articles about Mueller's investigation report**

This table presents logit regression results examining the relationship between the probability of informative Tweets and the publication of newspaper articles about Mueller's investigation in the previous hour. The key independent variable is the lagged Mueller articles dummy, which equals 1 if newspaper articles about Mueller's investigation were published in the previous hour, and 0 otherwise. Control variables include an FOMC dummy, ΔVIX, and the TED spread. Day-of-the-week dummies are included in all regressions. t-statistics are reported in parentheses, with *** indicating significance at the 1% level, ** at the 5% level, and * at the 10% level. The data cover the period from May 17, 2017, to February 6, 2019, at an hourly frequency.

	Dependent variable: Informative Tweet		
	(1)	(2)	(3)
Mueller$_{t-1}$	0.45***	0.48***	0.48***
	(3.34)	(3.39)	(3.40)
Return$_{t-1}$	0.103	0.101	0.101
	(1.20)	(1.13)	(1.12)
Return$_{t-2}$	-0.049	-0.048	-0.048
	(-0.45)	(-0.43)	(-0.43)
Return$_{t-3}$	0.019	-0.085	-0.081
	(0.22)	(-0.09)	(-0.09)
Return$_{t-4}$	-0.035	-0.043	-0.043
	(-0.30)	(-0.35)	(-0.35)
Return$_{t-5}$	0.011	-0.019	-0.018
	(0.11)	(-0.18)	(-0.18)
ΔVIX$_{t-1}$		-0.45	-0.45
		(-1.02)	(-1.03)
FOMC$_{t-1}$			0.00
			(0.30)
Day FE	Yes	Yes	Yes
Observations	8567	8254	8241
R^2	0.15%	0.16%	0.16%

Table 9: **Uninformative Tweets and FX market**

This table presents panel regression results estimating the effect of an hour dummy for informative tweets on FX market characteristics. The dependent variables in columns (1), (2), and (3) are hourly returns, intraday volatility, and trading volume, respectively. Control variables include the hourly bid-ask spread, hourly ΔVIX, an FOMC dummy, and lags of the dependent variable from $t-1$ to $t-5$. All regressions include hour-of-the-day and day-of-the-week fixed effects. Standard errors are clustered by currency. t-statistics are reported in parentheses, with *** indicating significance at the 1% level, ** at the 5% level, and * at the 10% level. The sample period spans from June 16, 2015, to August 20, 2019, with data at an hourly frequency.

Dependent variable: FX market characteristics			
	Return$_t$	Volatility$_t$	Volume$_t$
Tweet hour$_t$	0.01	0.001	-0.515**
	(0.63)	(0.61)	(-2.94)
Bid Ask Spread$_{t-1}$	0.00	0.001**	-0.041***
	(0.97)	(2.38)	(-5.34)
ΔVIX$_{t-1}$	0.03	0.011***	0.336***
	(1.45)	(4.37)	(3.87)
FOMC$_{t-1}$	-0.02***	0.110***	1.459***
	(-2.48)	(4.45)	(11.17)
Dep. Var.$_{t-1}$	-0.02***	-0.146***	0.315***
	(-5.42)	(-9.88)	(17.14)
Dep. Var.$_{t-2}$	-0.01***	0.052***	0.089***
	(-4.24)	(6.04)	(7.82)
Dep. Var.$_{t-3}$	-0.00*	0.080***	0.052***
	(-1.79)	(15.19)	(9.48)
Dep. Var.$_{t-4}$	-0.00	0.086***	0.024**
	(-1.50)	(28.14)	(2.61)
Dep. Var.$_{t-5}$	-0.01***	0.076***	-0.003
	(-2.90)	(20.49)	(-0.20)
Country FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes
Observations	315,092	325,562	276,927
R^2	0.14%	11.21%	18.89%

Internet Appendix to

"Signal in the Noise: Trump Tweets and the Currency Market"

(Not for publication)

We provide a roadmap for each section of our Appendix:

1. Appendix A derives the model solution, including Bayesian weights, optimal bond holdings, and the equilibrium spot rate.

2. Appendix B provides textual analysis of Trump tweets, categorized by topic and sentiment, and outlines methods for identifying informative tweets.

3. Appendix C examines abnormal FX returns and volatility during tweet events.

4. Appendix D studies abnormal volatility and returns matched with non-tweet periods.

5. Appendix E extends the FX volume analysis, showing variations across participant types and informed trading activity.

A Model Solution

Proof of Model Weights

A Bayesian agent will update their prior based on the relative precision of the public and private signals.

$$\mathbb{E}[f^j_{t+1}|I_j, I_T] = \omega^B_j \theta^T + (1 - \omega^B_j)\theta^j \tag{24}$$

Proof of optimal weights:

We use the following property of the conditional expectation of normally distributed random variables:

consider $x_1, x_2 ... x_n$ which are signals of y.

$$x_i = y + \epsilon_i, i = 1, ..., n$$

Each ϵ_i is distributed independently with $\epsilon_i \sim N(0, \sigma^2_i)$

Then the expectation of y conditional on $x_1, x_2, ... x_n$ is given by:

$$E[y|x_1, x_2, ... x_n] = \frac{x_1 \sigma_1^- 2 + ... + x_n \sigma_n^{-2}}{\sigma_1^{-2} + ... + \sigma_n^{-2}}$$

where σ_i^{-2} measures the precision of signal i. Using this property, we can express the expectation of the future spot rate conditional on the public and private signal as:

$$\mathbb{E}[f^j_{t+1}|I_j, I_T] = \frac{\theta^T \sigma_T^{-2} + \theta^j \sigma_j^{-2}}{\sigma_T^{-2} + \sigma_j^{-2}} \tag{25}$$

$$= \frac{\sigma_j^2}{\sigma_T^2 + \sigma_j^2}\theta^T + \frac{\sigma_T^2}{\sigma_T^2 + \sigma_j^2}\theta^j \tag{26}$$

Therefore, we define the optimal weight on the public signal, $\omega^B_j = \frac{\sigma_j^2}{\sigma_T^2 + \sigma_j^2}$, in Equation (24).

Solution of optimal weight and bond holdings

Bayesian Agent

$$\max_{b^j_t, \omega^j_t} \qquad L = \mathbb{E}[W^j_{t+1}] - \frac{1}{2}\gamma Var(W^j_{t+1})$$

subject to:

$$W^j_{t+1} = \rho^j_t b^j_t$$

We can rewrite the maximization problem as follows:

$$\max_{b_t^j} \qquad L = \mathbb{E}[\rho_t^j]b_t^j - \frac{\gamma}{2}{b_t^j}^2({\omega_j^B}^2\sigma_T^2 + (1-\omega_j^B)^2\sigma_j^2)$$

Taking first-order conditions:
FOC w.r.t b_t^j

$$E[\rho_t^j] - \gamma b_t^j[{\omega_j^B}^2\sigma_T^2 + (1-\omega_j^B)^2\sigma_j^2] = 0$$

This gives a solution for bill holdings, using the fact that $E[\rho_t^j] = \omega_j^B\theta^T + (1-\omega_j^B)\theta^j - s_t + i_t - i_t^*$

$$b_t^j = \frac{\omega_j^B\theta^T + (1-\omega_j^B)\theta^j - s_t + i_t - i_t^*}{\gamma({\omega_j^B}^2\sigma_T^2 + (1-\omega_j^B)^2\sigma_j^2)} \tag{27}$$

Trump follower

$$\max_{b_t^j} \qquad L = \mathbb{E}[W_{t+1}^j] - \frac{1}{2}\gamma Var(W_{t+1}^j)$$

subject to:

$$W_{t+1}^j = \rho_t^j b_t^j$$

We can rewrite the maximization problem as follows:

$$\max_{b_t^j} \qquad L = \mathbb{E}[\rho_t^j]b_t^j - \frac{\gamma}{2}{b_t^j}^2\sigma_T^2$$

Taking first-order conditions:
FOC w.r.t b_t^j

$$E[\rho_t^j] - \gamma b_t^j\sigma_T^2 = 0$$

This gives the solution for bill holdings, using the fact that $E[\rho_t^j] = \theta^T - s_t + i_t - i_t^*$

$$b_t^j = \frac{\theta^T - s_t + i_t - i_t^*}{\gamma\sigma_T^2} \tag{28}$$

Proof of Market Clearing Spot Rate

$$\sum_{j\in N_B} \frac{\omega_j^B\theta^T + (1-\omega_j^B)\theta^j - s_t + i_t - i_t^*}{{\omega_j^B}^2\sigma_T^2 + (1-\omega_j^B)^2\sigma_j^2} + \sum_{j\in N_T} \frac{\theta^T - s_t + i_t - i_t^*}{\sigma_T^2} = 0$$

Rearranging terms,

$$\sum_{j\in N_B}\frac{s_t}{{\omega_j^B}^2\sigma_T^2+(1-\omega_j^B)^2\sigma_j^2}+\sum_{j\in N_T}\frac{s_t}{\sigma_T^2}=\sum_{j\in N_B}\frac{\omega_j^B\theta^T+(1-\omega_j^B)\theta^j+i_t-i_t^*}{{\omega_j^B}^2\sigma_T^2+(1-\omega_j^B)^2\sigma_j^2}+\sum_{j\in N_T}\frac{\theta^T+i_t-i_t^*}{\sigma_T^2}$$

$$s_t=i_t-i_t^*+$$
$$\frac{1}{\left(\frac{N_B}{{\omega_j^B}^2\sigma_T^2+(1-\omega_j^B)^2\sigma_j^2}+\frac{N_T}{\sigma_T^2}\right)}\left(\frac{N_B\bar{\theta}^j}{{\omega_j^B}^2\sigma_T^2+(1-\omega_j^B)^2\sigma_j^2}+\frac{N_T\theta^T}{\sigma_T^2}+\frac{\omega_j^B N_B}{{\omega_j^B}^2\sigma_T^2+(1-\omega_j^B)^2\sigma_j^2}(\theta^T-\bar{\theta}^j)\right)$$

The above expression can be simplified to

$$s_t=i_t-i_t^*+\frac{1}{\Gamma}\left(\Gamma_B\bar{\theta}^j+\Gamma_T\theta^T+\omega_j^B\Gamma_B(\theta^T-\bar{\theta}^j)\right) \tag{29}$$

where $\Gamma_B=\frac{N_B}{{\omega_j^B}^2\sigma_T^2+(1-\omega_j^B)^2\sigma_j^2}$, $\Gamma_T=\frac{N_T}{\sigma_T^2}$ and $\Gamma=\Gamma_B+\Gamma_T$.

Proof of Prediction 1

$$\frac{\partial s_t}{\partial\theta^T}=\frac{1}{\Gamma}\left(\Gamma_T+\omega_j^B\Gamma_B\right) \tag{30}$$

$$\frac{\partial s_t}{\partial\bar{\theta}^j}=\frac{\Gamma_B}{\Gamma}\left(1-\omega_j^B\right) \tag{31}$$

We can determine the conditions in which $\frac{\partial s_t}{\partial\theta^T}>\frac{\partial s_t}{\partial\bar{\theta}^j}$:

$$\begin{aligned}\frac{1}{\Gamma}\left(\Gamma_T+\omega_j^B\Gamma_B\right)&>\frac{\Gamma_B}{\Gamma}\left(1-\omega_j^B\right)\\ \Gamma_T+\omega_j^B\Gamma_B&>\Gamma_B\left(1-\omega_j^B\right)\\ \frac{\Gamma_T}{\Gamma_B}&>1-2\omega_j^B \end{aligned} \tag{32}$$

We now use the fact that $\omega_j^B=\frac{\sigma_j^2}{\sigma_T^2+\sigma_j^2}$, and the ratio of Γ_T to Γ_B is simplified to:

$$\begin{aligned}\frac{\Gamma_T}{\Gamma_B}&=\frac{N_T}{N_B}\frac{{\omega_j^B}^2\sigma_T^2+(1-\omega_j^B)^2\sigma_j^2}{\sigma_T^2}\\ &=\frac{N_T}{N_B}\frac{\left(\frac{\sigma_j^2}{\sigma_T^2+\sigma_j^2}\right)^2\sigma_T^2+\left(1-\frac{\sigma_j^2}{\sigma_T^2+\sigma_j^2}\right)^2\sigma_j^2}{\sigma_T^2}\\ &=\frac{N_T}{N_B}\frac{\left(\frac{\sigma_j^2}{\sigma_T^2+\sigma_j^2}\right)^2\sigma_T^2+\left(\frac{\sigma_T^2}{\sigma_T^2+\sigma_j^2}\right)^2\sigma_j^2}{\sigma_T^2}\\ &=\frac{N_T}{N_B}\frac{\sigma_j^2}{\sigma_T^2+\sigma_j^2}\\ &=\frac{N_T}{N_B}\omega_j^B \end{aligned} \tag{33}$$

Finally, we can use this expression to obtain an upper bound for the relative precision of the public signal, which we denote $R = \frac{\sigma_T^2}{\sigma_j^2}$.

$$\begin{aligned}
\frac{N_T}{N_B}\omega_j^B &> 1 - 2\omega_j^B \\
\frac{N_T}{N_B} &> \frac{1}{\omega_j^B} - 2 \\
\frac{\sigma_T^2}{\sigma_j^2} &< \frac{N_T}{N_B} + 1 \qquad (34)\\
R &< \frac{N_T}{N_B} + 1 \qquad (35)
\end{aligned}$$

Proof of Prediction 2

Following Mark (1995) and Della Corte, Sarno, and Tsiakas (2009), we assume a linear relationship between spot returns and exchange rate fundamentals.

$$s_{t+1} - s_t = \beta_0 + \beta_1 f_t - s_t \qquad (36)$$

Under this framework, spot returns are proportional to the variance of fundamentals.

$$var(\Delta s_{t+1}) = \beta^2 var(f_t) \qquad (37)$$

Using the fundamental signal observed by Bayesian speculators and Trump followers, we can write the variance of fundamentals conditioning on the public signal:

$$\begin{aligned}
\mathrm{var}(\Delta s_{t+1}|I_j, I_T) &= \beta^2 \frac{\sum_{j=1}^{N} var(f_t^j)}{N} \qquad (38)\\
&= \beta^2 \left(\frac{N_B}{N} var(f_t^j) + \frac{N_T}{N} var(f_t^T)\right) \qquad (39)
\end{aligned}$$

The variance of fundamentals for Bayesian agents (conditional on public signal) is given by:

$$\begin{aligned}
var(f_t^j) &= {\omega_j^B}^2 \sigma_T^2 + (1 - \omega_j^B)^2 \sigma_j^2 \qquad (40)\\
&= \frac{\sigma_T^2 \sigma_j^2}{\sigma_T^2 + \sigma_j^2}
\end{aligned}$$

where $\omega_j = \frac{\sigma_j^2}{\sigma_T^2 + \sigma_j^2}$, and the variance of fundamentals for Trump followers is $var(f_t^T) = \sigma_T^2$. Substituting this into expression for the variance of spot returns:

$$\mathrm{var}(\Delta s_{t+1}|I_j, I_T) = \beta^2 \left(\frac{N_B}{N} var(f_t^j) + \frac{N_T}{N} var(f_t^T)\right) \qquad (41)$$

$$= \beta^2 \left(\frac{N_B}{N} \frac{\sigma_T^2 \sigma_j^2}{\sigma_T^2 + \sigma_j^2} + \frac{N_T}{N} \sigma_T^2 \right)$$

The variance of spot returns conditional on private information, in the absence of the Trump tweet, is given by $\text{var}(\Delta s_{t+1}|I_j, I_T) = \beta^2 \sigma_j^2$. The ratio of variance of spot returns conditional on the public signal, relative to the variance of spot returns conditional on private information:

$$\frac{\text{var}(\Delta s_{t+1}|I_j, I_T)}{\text{var}(\Delta s_{t+1}|I_j)} = \frac{N_B}{N} \frac{\sigma_T^2}{\sigma_T^2 + \sigma_j^2} + \frac{N_T}{N} \frac{\sigma_T^2}{\sigma_j^2} \tag{42}$$

Expressing the relative precision of the public to private signal is $R = \frac{\sigma_T^2}{\sigma_j^2}$, we can write this as follows:

$$\frac{\text{var}(\Delta s_{t+1}|I_j, I_T)}{\text{var}(\Delta s_{t+1}|I_j)} = \frac{N_B}{N} \left(\frac{R}{R+1} \right) + \frac{N_T}{N} R \tag{43}$$

Finally, we can use this expression to obtain an upper bound for the relative precision of the public signal.

$$\begin{aligned} \frac{N_B}{N} \left(\frac{R}{R+1} \right) + \frac{N_T}{N} R &< 1 \\ \frac{N_B}{N} R + \frac{N_T}{N} R(R+1) &< 1 + R \\ \frac{N_T}{N} R^2 &< 1 \\ R &< \sqrt{\frac{N}{N_T}} \\ R &< \sqrt{\frac{N_B}{N_T} + 1} \end{aligned} \tag{44}$$

FX Volume

The total volume traded is given by $V_{FX} = \frac{1}{2}\sum_{j=1}^{N}|b_t^j|$, which aggregates volume for both Bayesian agents and Trump followers.

We can compute the ratio of volume change for Bayesian agents before and after the tweet.

Conditional on no public signal, a Bayesian agent has the volume:

$$\frac{|b_t^j|}{2} = \frac{1}{2\gamma}\frac{|\theta^j - \bar{\theta}^j|}{\sigma_j^2} \tag{45}$$

Conditional on a public signal, a Bayesian agent has the volume:

$$\frac{|b_t^j|}{2} = \frac{1}{2\gamma}\frac{|\theta^j - \frac{1}{\Gamma}\left(\Gamma_B\bar{\theta}^j + \Gamma_T\theta^T + \omega_j^B\Gamma_B(\theta^T - \bar{\theta}^j)\right)|}{{\omega_j^B}^2\sigma_T^2 + (1-\omega_j^B)^2\sigma_j^2} \tag{46}$$

Conditional on no public signal, a Trump follower has the same volume as the Bayesian agent:

$$\frac{|b_t^j|}{2} = \frac{1}{2\gamma}\frac{|\theta^j - \bar{\theta}^j|}{\sigma_j^2} \tag{47}$$

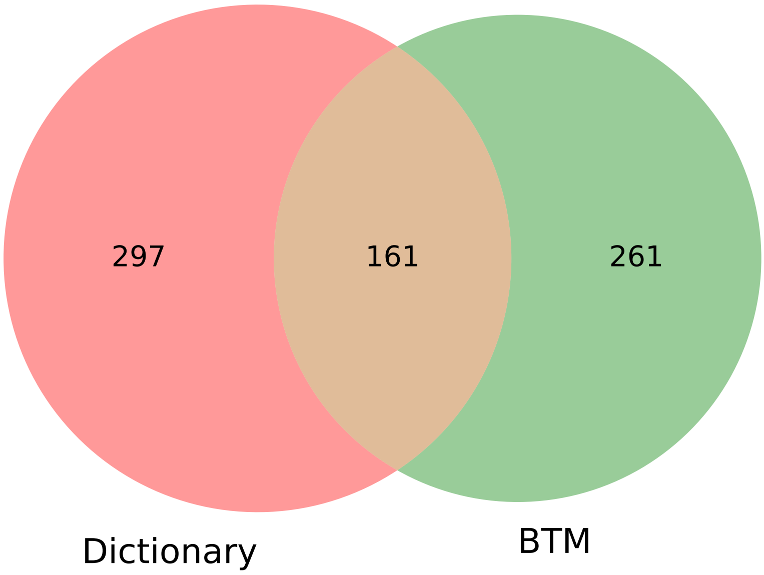
Conditional on a public signal, a Trump follower has the volume:

$$\frac{|b_t^j|}{2} = \frac{1}{2\gamma}\frac{|\theta^T - \frac{1}{\Gamma}\left(\Gamma_B\bar{\theta}^j + \Gamma_T\theta^T + \omega_j^B\Gamma_B(\theta^T - \bar{\theta}^j)\right)|}{\sigma_T^2} \tag{48}$$

The ratio of volume for both the Trump follower and Bayesian agent depends on (i) the relative precision of the public signal R, and (ii) the bias of the public signal with respect to the average of investor priors $\theta^T - \bar{\theta}^j$. Crucially, if Trump tweets are unbiased ($\theta^T = \bar{\theta}^j$), Trump follower volume is reduced to zero in equation (48).

B Textual Analysis: Supplementary Evidence

Figure A1: **Tweets Identified by Dictionary and BTM Approaches**



This figure compares the tweets identified as informative using the Dictionary approach and the Biterm Topic Modeling (BTM) approach. The overlap represents tweets classified as informative by both methods, while non-overlapping areas show tweets identified exclusively by one method.

The figure reports the number of relevant Tweets (trade, macro, and FX tweets) identified by dictionary and bi-term topic modeling approach.

B.1 Sample of Tweets (by Topic)

Some Tweets belonging to 3 categories (Macroeconomics Outlook, Exchange Rate, and Trade Policy) are listed

Macroeconomics Outlook

"Somebody please inform Jay-Z that because of my policies, Black Unemployment has just been reported to be at the LOWEST RATE EVER RECORDED!"

"Beautiful weather all over our great country, a perfect day for all Women to March. Get out there now to celebrate the historic milestones and unprecedented economic success and wealth creation that has taken place over the last 12 months. Lowest female unemployment in 18 years!"

"HAPPY THANKSGIVING, your Country is starting to do really well. Jobs coming back, highest Stock Market EVER, Military getting really strong, we will build the WALL, V.A. taking care of our Vets, great Supreme Court Justice, RECORD CUT IN REGS, lowest unemployment in 17 years....!"

Trade Policy

"I am pleased to inform you that The United States of America has reached a signed agreement with Mexico. The Tariffs scheduled to be implemented by the U.S. on Monday, against Mexico, are hereby indefinitely suspended,"

"When a car is sent to the United States from China, there is a Tariff to be paid of 2 1/2%. When a car is sent to China from the United States, there is a Tariff to be paid of 25%, Does that sound like free or fair trade. No, it sounds like STUPID TRADE - going on for years!"

Exchange Rate

"Based on the historic currency manipulation by China, it is now even more obvious to everyone that Americans are not paying for the Tariffs – they are being paid for compliments of China, and the U.S. is taking in tens of Billions of Dollars! China has always...."

B.2 Sample of Tweets (by Sentiment)

Some Tweets belonging to positive sentiment, negative sentiment or neutral sentiment are listed

Positive sentiment

"Stock market up more than 400 points yesterday. Today looks to be another good one. Companies earnings are great!"

"Fox Poll say best Economy in DECADES!"

"Just out: Consumer confidence hits highest level since 2000."

Negative sentiment

"Toyota Motor said will build a plant in Baja, Mexico, to build Corolla cars for U.S. NO WAY! Build plant in U.S. or pay big border tax. "

"mexico must apprehend all illegals and not let them make the long march up to the united states or we will have no other choice than to close the border andor institute tariffs our country is full"

"the wto is broken when the worlds richest countries claim to be developing countries to avoid wto rules and get special treatment no more today i directed the us trade representative to take action so that countries stop cheating the system at the expense of the usa"

Neutral sentiment

"getting ready to engage g leaders on many issues including economic growth terrorism and security"

"Very important that OPEC increase the flow of Oil. World Markets are fragile price of Oil getting too high. Thank you!"

B.3 BTM: Other topic word clusters

Figure A2: **BTM Topic Keywords**

This figure reports results from the Biterm Topic Modeling (BTM) applied to Trump tweets. Each panel shows the top keywords associated with a specific topic identified by the BTM approach. These keywords reflect the thematic structure of the tweet dataset.

B.4 Informative vs Uninformative tweets

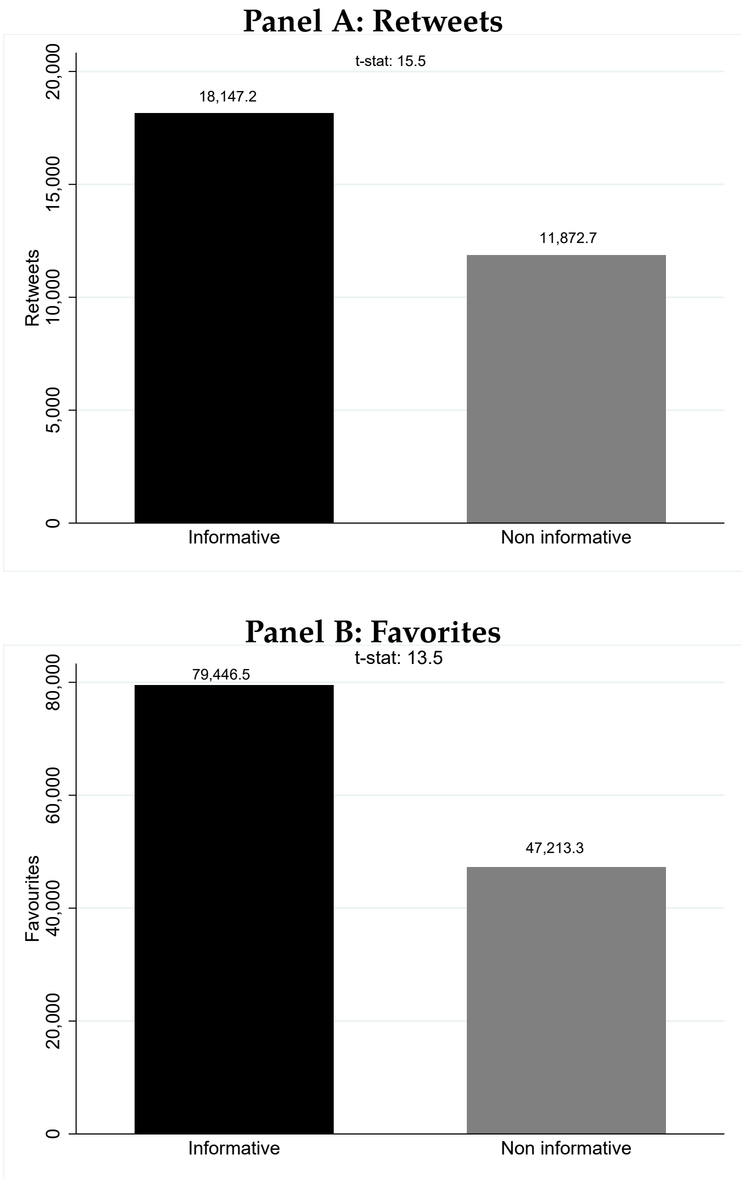


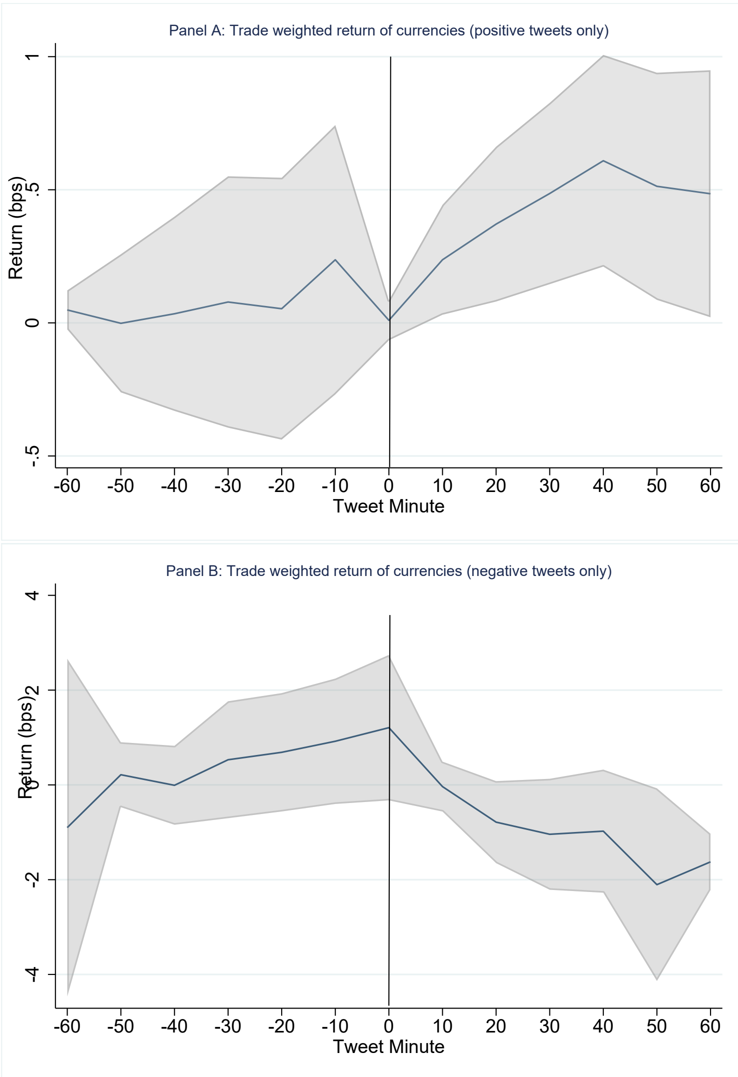
Figure A3: Event study of spot returns during the Tweet hour

This figure shows the aggregate number of retweets (Panel A) and favorites (Panel B) for a sample of informative and uninformative tweets. 719 Informative tweets are selected based on the dictionary and BTM method of observing a probability of belonging to a macroeconomic or trade topic of at least 30%. A sample of uninformative tweets are selected to have the least macroeconomic or trade content based on the probabilities implied from the BTM method, and have the same number as informative tweets. T-statistics are reported on the difference in retweets and favorites of both groups.

C Event Studies

C.1 Trade-Weighted Return

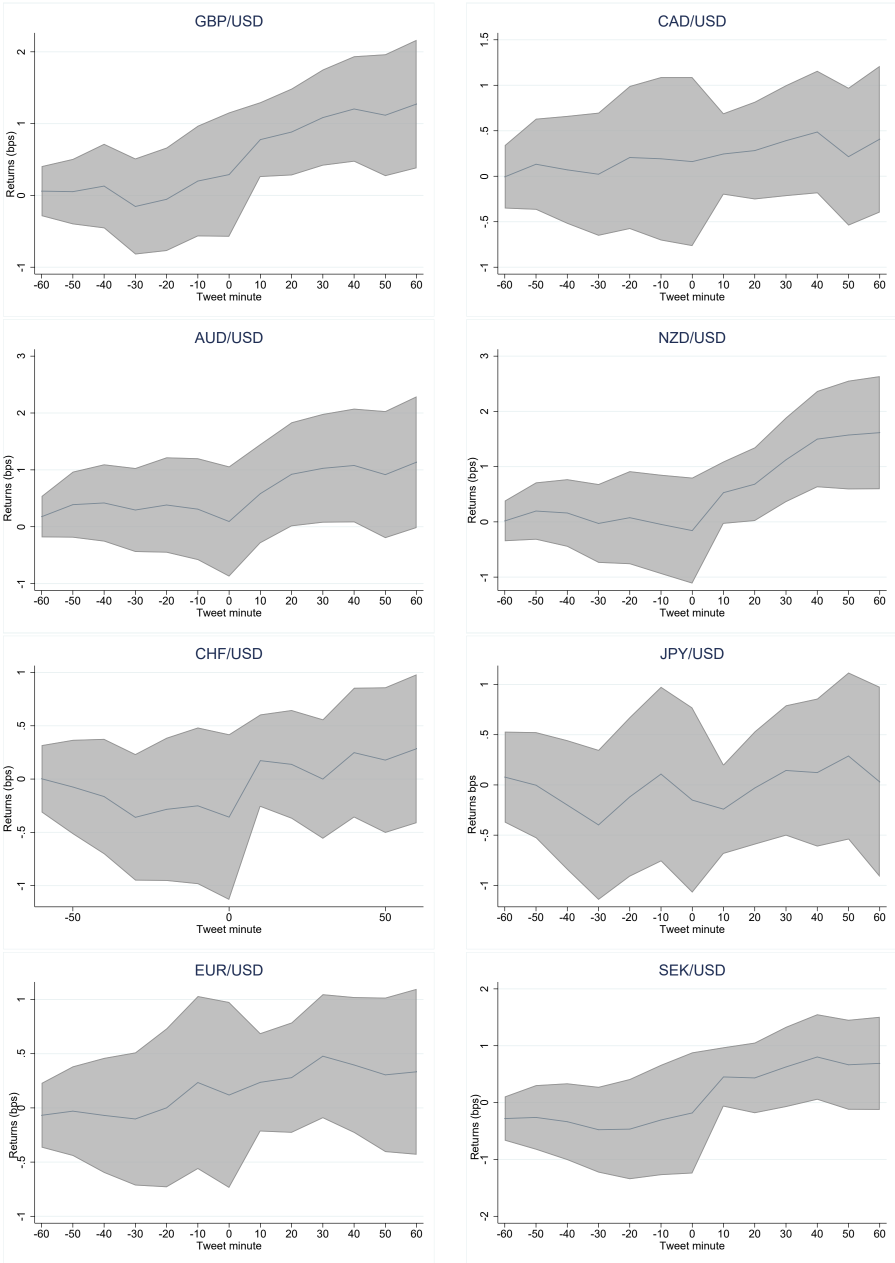
Figure A4: **Event Study of Spot Returns During the Tweet Hour**

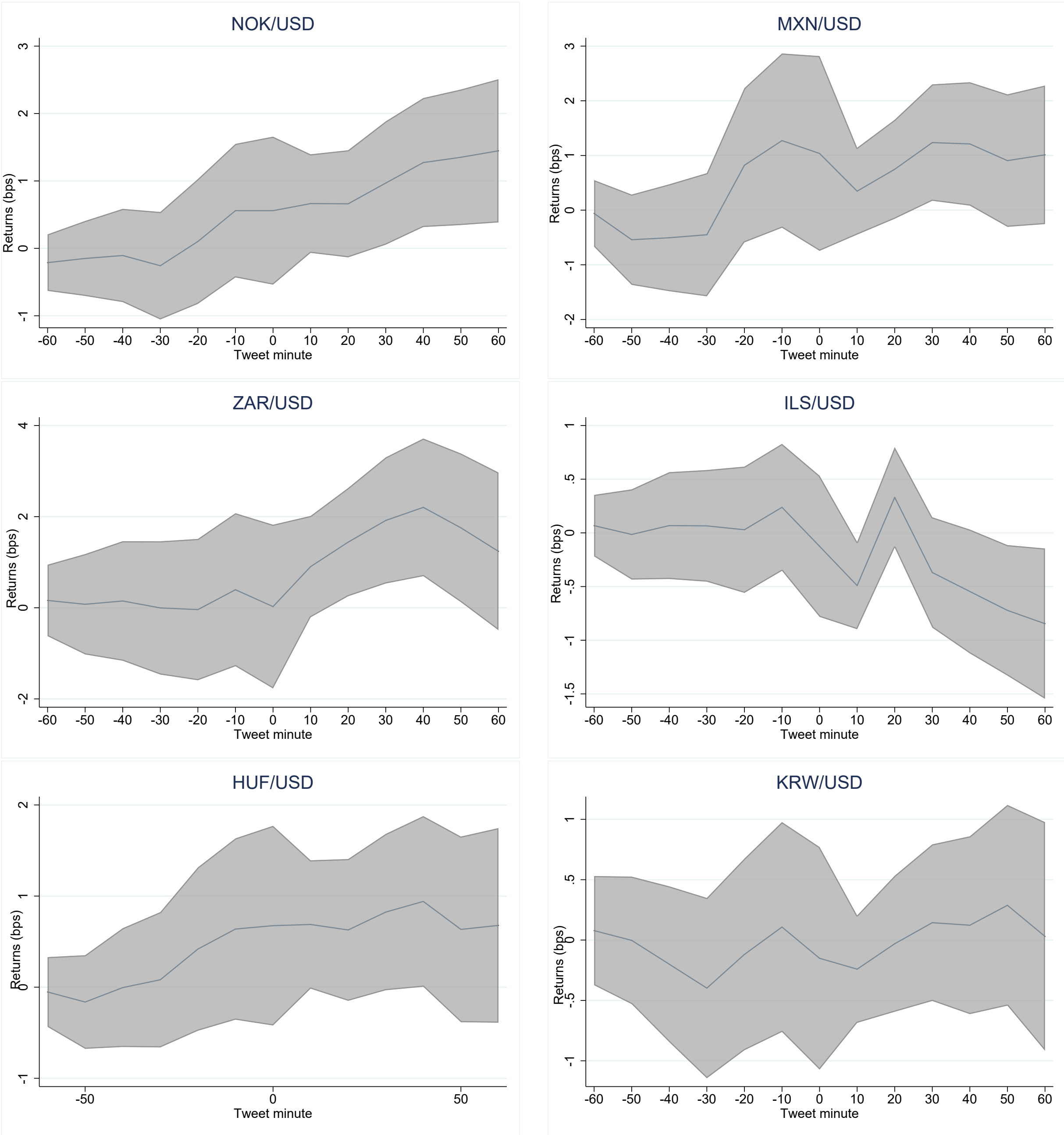


This figure shows the average cumulative spot returns (in basis points) during tweet hours for the trade-weighted return of 14 currencies. Trade weights are based on the BIS effective exchange rate index. Panel A presents results for positive tweets, while Panel B shows results for negative tweets. The x-axis represents the minutes surrounding the event, where 0 indicates the tweet timestamp (denoted by a vertical line), and negative values represent minutes before the tweet. The shaded area corresponds to a 95% confidence interval using White heteroscedasticity-robust standard errors.

C.2 Individual Currencies

Figure A5: **Event Study: Cumulative Returns by Currency**





This figure presents cumulative returns for individual currencies. The x-axis represents minutes relative to the event, where 0 indicates the tweet timestamp. Negative values on the x-axis correspond to minutes before the tweet. The shaded area represents a 95% confidence interval based on White heteroscedasticity-robust standard errors.

D Event studies: abnormal volatility and returns

One criticism of the panel specification outlined in Section 5.1 is that our hourly panel regressions do not consider the precise timestamp of the tweet at a high frequency, such as whether it occurs at the beginning or end of the hour.

To address this concern, we employ an event study approach to examine whether the abnormal return, defined as the difference in return between the time of the tweet and a period without the tweet matched by VIX changes, can be attributed to our control variables. We construct 60-minute (and 30-minute) realized returns by aggregating 1-minute returns cumulatively.

The results are shown in Table A1. Panel A presents the results for the 60-minute window, while Panel B presents the results for the 30-minute window. The intercept, which represents the abnormal return to USD expressed in basis points, is the independent variable of interest in these regressions. This variable displays a positive and statistically significant relationship in all regressions, indicating that the abnormal return during the tweet event time cannot be fully explained by our control variables.

Furthermore, we examine the impact of our control variables on abnormal volatility, which represent the difference in volatility between the time of the tweet and a period without the tweet matched by VIX changes. The results are presented in Table A2. Panel A displays the results for the 60-minute window, while Panel B shows the results for the 30-minute window. In these regressions, the intercept term serves as the independent variable of interest. In both panels, this variable (constant) exhibits a negative and statistically significant relationship in all regressions, indicating that the decrease in volatility during the tweet event time cannot be fully explained by other explanatory variables.

Table A1: **Tweets and FX Hourly Returns**

This table presents panel regression results estimating the effect of an hour dummy for informative Tweets on FX hourly abnormal returns. The dependent variable is the abnormal return, defined as the difference between the return at the minute of a tweet and the return at a matched minute without a tweet, adjusted for VIX. Control variables include the hourly bid-ask spread, hourly ΔVIX, and an FOMC dummy. Hour-of-the-day and day-of-the-week fixed effects are included in all regressions. Panel A uses a 60-minute event window, while Panel B uses a 30-minute window. Standard errors are clustered by currency. t-statistics are reported in parentheses, with *** indicating significance at the 1% level, ** at the 5% level, and * at the 10% level. The sample period covers June 16, 2015, to August 20, 2019.

Panel A: 60-minute window *Dependent variable*: Abnormal Returns			
	(1) Abnormal Return$_t$	(2) Abnormal Return$_t$	(3) Abnormal Return$_t$
Constant	1.781**	1.694**	1.772**
	(2.42)	(2.34)	(2.43)
Bid Ask Spread$_{t-1}$	-0.004*	-0.003	-0.003
	(-1.82)	(-1.72)	(-1.73)
ΔVIX$_{t-1}$		0.000	0.000
		(1.52)	(1.51)
FOMC$_{t-1}$			-0.003***
			(-7.13)
Country FE	Yes	Yes	Yes
Observations	7,882	7,714	7,714
R^2	0.03%	0.03%	0.03%
Panel B: 30-minute window *Dependent variable*: Abnormal Returns			
	(1)	(2)	(3)
Constant	1.511***	1.538***	1.530***
	(6.38)	(6.03)	(6.01)
Bid Ask Spread$_{t-1}$	-0.001	-0.001	-0.001
	(-0.88)	(-1.02)	(-1.02)
ΔVIX$_{t-1}$		-0.000	-0.000
		(-0.47)	(-0.47)
FOMC$_{t-1}$			0.000*
			(2.03)
Country FE	Yes	Yes	Yes
Observations	7,882	7,714	7,714
R^2	0.05%	0.05%	0.05%

Table A2: **Tweets and FX Hourly Realized Volatility Event Study**

This table presents event study regression results estimating the effect of an hour dummy for informative Tweets on FX hourly realized volatility. The dependent variable is the abnormal realized volatility, defined as the difference between volatility at the minute of a tweet and the volatility at a matched minute without a tweet, adjusted for VIX. Control variables include the hourly bid-ask spread, hourly ΔVIX, and an FOMC dummy. Hour-of-the-day and day-of-the-week fixed effects are included in all regressions. Panel A uses a 60-minute event window, while Panel B uses a 30-minute window. Standard errors are clustered by currency. t-statistics are reported in parentheses, with *** indicating significance at the 1% level, ** at the 5% level, and * at the 10% level. The sample period covers June 16, 2015, to August 20, 2019.

Panel A: 60-minute window
Dependent variable: Abnormal Realized Volatility

	(1) Abnormal Volatility$_t$	(2) Abnormal Volatility$_t$	(3) Abnormal Volatility$_t$
Constant	-0.014***	-0.014***	-0.015***
	(-4.98)	(-4.52)	(-4.80)
Bid Ask Spread$_{t-1}$	0.158*	0.170**	0.178**
	(2.03)	(2.21)	(2.24)
ΔVIX$_{t-1}$		-0.212***	-0.211***
		(-3.14)	(-3.13)
FOMC$_{t-1}$			0.473***
			(17.14)
Country FE	Yes	Yes	Yes
Observations	7,714	7,714	7,714
R^2	0.03%	1.59%	4.75%

Panel B: 30-minute window
Dependent variable: Abnormal Realized Volatility

	(1) Abnormal Volatility$_t$	(2) Abnormal Volatility$_t$	(3) Abnormal Volatility$_t$
Constant	-0.010***	-0.009**	-0.009**
	(-3.22)	(-2.73)	(-2.73)
Bid Ask Spread$_{t-1}$	0.149	0.128	0.128
	(0.88)	(0.75)	(0.75)
ΔVIX$_{t-1}$		-0.256**	-0.256**
		(-2.98)	(-2.98)
FOMC$_{t-1}$			0.017
			(1.38)
Country FE	Yes	Yes	Yes
Observations	7,714	7,714	7,714
R^2	0.01%	3.04%	3.05%

E FX volume

The average hourly spot FX trading volume based on London time is depicted in Figure A6. The data is recorded for 5 days a week, with each trading week commencing at 9 p.m. on Sunday and ending at 9 p.m. on Friday (London Time). Thus, it covers market transactions from the opening of the Sydney market on Monday morning to the close of the New York market on Friday evening. During the early morning London time, when only Asian markets are open, trading volume is relatively low. It starts to increase around 7 a.m. as European markets commence their trading day. Trading volume slightly decreases around lunchtime but quickly rebounds and reaches its peak around 1 p.m. when both European and U.S. markets are active. The trading volume gradually declines after 5 p.m. and reaches its lowest level around 10 p.m. when only the Australian market is open.

To maintain consistency with the literature (e.g., Krohn and Sushko, 2022), we exclude data for certain holidays when FX trading volume is relatively thin. These holidays include Christmas (December 24-26), New Year's (December 31-January 2), July 4th, Good Friday, Easter Monday, Memorial Day, Labor Day, Thanksgiving, and the day after.

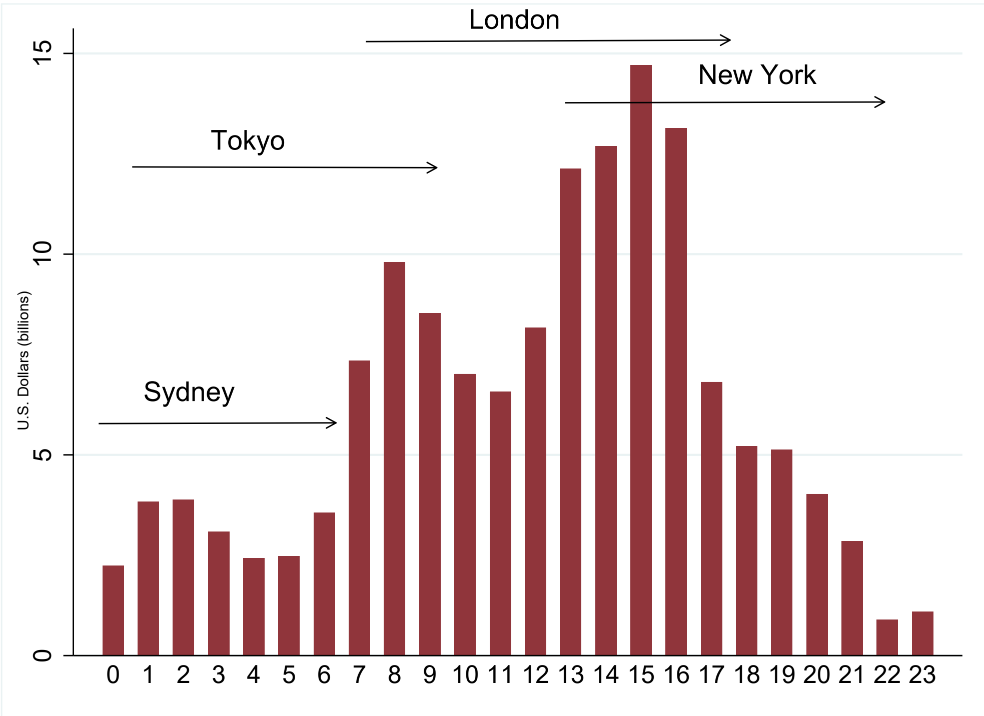


Figure A6: **Spot FX Trading Volume**
This figure presents the average hourly FX spot trading volume (in USD) over a business day in London time. The average is computed across all trading days in the sample, from June 16, 2015, to August 20, 2019. The volume aggregates transactions from 14 currency pairs included in the dataset. The x-axis represents the closing time in London time. Arrows indicate the trading hours of major financial centers: London (7 a.m. to 4 p.m.), New York (12 p.m. to 9 p.m.), Sydney (9 p.m. to 6 a.m.), and Tokyo (11 p.m. to 8 a.m.).

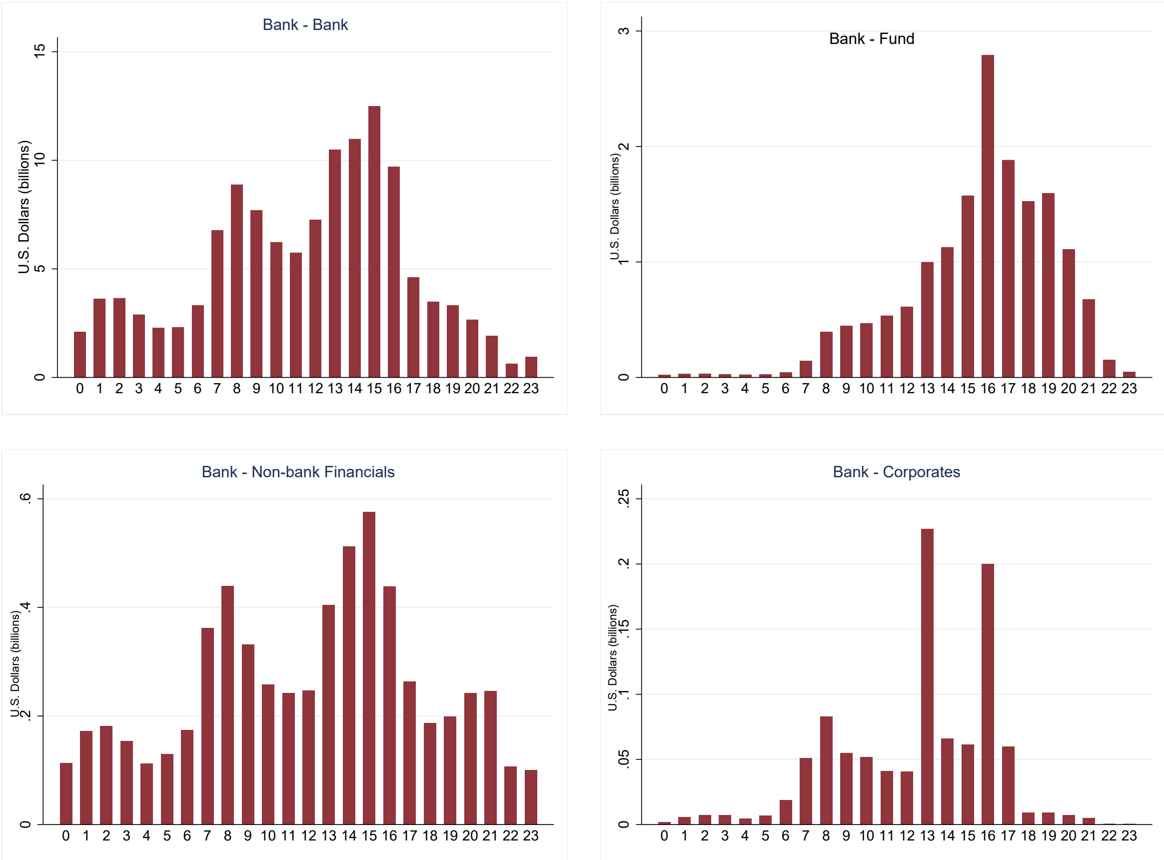
We classify trading volume in the following four groups: transactions between the bank and funds, bank and non-bank financial institutions, bank and corporates, and inter-bank transactions. However, we exclude transactions between two market makers (inter-dealer transactions) or two price takers from our dataset. Figure A7 illustrates the categorization of FX trading volume among different groups of market participants. The majority of trading in the spot FX market included in our dataset (approximately 85%) occurs in inter-bank transactions between a market maker and a price taker bank. On the other hand, trading between banks and corporates represents only around 1% of the total volume.

Next, we investigate whether the effects on FX volume vary across the four groups of market participants: banks, funds, non-financial firms, and corporate firms. Table A3 presents the regression results for FX volume in each group. In Panel A, we examine the impact of tweets on trading activity in inter-bank transactions, where one bank acts as a market maker (dealer) and the other as a price taker. The coefficient of the Tweet dummy variable is consistently negative and highly significant across all specifications.

Similar patterns are observed in the subsequent panels, where we report the results for trading volume between dealer banks and funds, as well as dealer banks and non-bank financial institutions (Panel C). In both panels, when all control variables are included in the regression, the coefficient of the Twitter dummy variable remains negative and significant at the 1% level of significance. Panel D focuses on the trading activity between dealer banks and the corporate sector, such as multinational corporations. The coefficient of the Tweet dummy variable is positive and slightly significant in the first column. However, in the following four columns, this coefficient gradually loses its statistical significance. Therefore, we do not find empirical evidence demonstrating the clear effects of tweets on trading volume between dealer banks and the corporate sector. Overall, the empirical results from Table A3 indicate that Donald Trump's tweets decrease the overall trading volume in the spot FX market, consistent with our results for aggregate volume. When we disaggregate the trading volume by different market participants, this result holds true for three groups of informed market participants. In contrast, we do not find evidence of this effect for the uninformed group of market participants, i.e., the corporate sector.[17]

17. The corporate sector is typically characterized as liquidity traders, using the spot market for hedging purposes rather than speculative activity (Ranaldo and Somogyi, 2021).

Figure A7: **Spot FX Trading Volume by Market Participants**



This figure presents the average hourly FX spot trading volume (in USD) by different market participant groups. The average is computed across all trading days in the sample, from June 16, 2015, to August 20, 2019. The volume aggregates transactions from 14 currency pairs included in the dataset. The x-axis represents the closing time in London time.

Table A3: **Tweets and FX Trading Volume by groups of market participant**

This table presents panel regression results estimating the effect of an hour dummy for informative Tweets on FX trading volume, disaggregated by market participant type. The dependent variable in Panel A is interbank trading volume (market maker vs. price taker banks), in Panel B is bank vs. fund trading volume, in Panel C is bank vs. non-bank financial institution trading volume, and in Panel D is bank vs. corporate trading volume. Control variables include the hourly bid-ask spread, hourly ΔVIX, and an FOMC dummy. Hour-of-the-day and day-of-the-week fixed effects are included in all regressions. Standard errors are clustered by currency. t-statistics are reported in parentheses, with *** indicating significance at the 1% level, ** at the 5% level, and * at the 10% level. The sample period covers June 16, 2015, to August 20, 2019.

	Panel A. Dependent variable: Bank - Bank Trading Volume				*Panel B. Dependent variable*: Bank - Fund Volume			
	(1) Volume$_t$	(2) Volume$_t$	(3) Volume$_t$	(4) Volume$_t$	(1) Volume$_t$	(2) Volume$_t$	(3) Volume$_t$	(4) Volume$_t$
Tweet hour$_t$	-0.677***	-0.607***	-0.613***	-0.610***	-0.516***	-0.496***	-0.529***	-0.522***
	(-2.91)	(-2.84)	(-2.83)	(-2.81)	(-3.04)	(-3.07)	(-3.33)	(-3.26)
BidAskSpread$_{t-1}$		-0.090***	-0.089***	-0.089***		-0.191***	-0.190***	-0.190***
		(-5.86)	(-5.97)	(-5.98)		(-4.01)	(-4.02)	(-4.03)
ΔVIX$_{t-1}$			0.508***	0.511***			1.105***	1.110***
			(4.59)	(4.62)			(4.35)	(4.37)
FOMC$_{t-1}$				1.836***				3.561***
				(10.14)				(5.48)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	268,708	258,428	256,000	256,000	267,376	260,312	257,865	257,865
R^2	3.74%	8.32%	8.33%	8.36%	20.62%	21.25%	21.41%	21.41%

	Panel C. Dependent variable: Bank - Non-Bank Trading Volume				*Panel D. Dependent variable*: Bank - Corporate Volume			
	(1) Volume$_t$	(2) Volume$_t$	(3) Volume$_t$	(4) Volume$_t$	(1) Volume$_t$	(2) Volume$_t$	(3) Volume$_t$	(4) Volume$_t$
Tweet hour$_t$	-0.485***	-0.447***	-0.474***	-0.477***	0.318**	0.279*	0.252	0.237
	(-3.59)	(-3.45)	(-3.73)	(-3.77)	(2.34)	(1.90)	(1.76)	(1.66)
BidAskSpread$_{t-1}$		-0.191***	-0.190***	-0.190***		-0.004	-0.006	-0.006
		(-4.01)	(-4.02)	(-4.03)		(-0.15)	(-0.20)	(-0.20)
ΔVIX$_{t-1}$			1.104***	1.109***			0.183	0.201
			(4.35)	(4.36)			(0.31)	(0.34)
FOMC$_{t-1}$				3.579***				10.665***
				(5.55)				(5.67)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	267,376	260,312	257,865	257,865	95733	91650	90745	90745
R^2	3.98%	9.72%	9.76%	9.81%	1.11%	1.20%	1.17%	1.30%