Signal in the Noise: Trump Tweets and the Currency Market

Ilias Filippou   Arie E. Gozluklu   My T. Nguyen   Ganesh Viswanath-Natraj*

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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 persist after 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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*This paper was previously circulated under the title *The Information Content of Trump Tweets and the Currency Market*. Ilias Filippou: Olin Business School, Washington University in St. Louis, USA. Email: iliasfilippou@wustl.edu; Arie Gozluklu: The University of Warwick, Warwick Business School, UK. Email: Arie.Gozluklu@wbs.ac.uk; My Nguyen: Olin Business School, Washington University in St. Louis, USA. Email: myn@wustl.edu; Ganesh Viswanath-Natraj: The University of Warwick, Warwick Business School, UK. Email: Ganesh.Viswanath-Natraj@wbs.ac.uk. For detailed comments, we would like to thank Jesùs Gorrin, Michael Jetter, Roman Kozhan, Philippe Mueller, Maria Sole Pagliari (discussant), Richard Taffler, Gyuri Venter, Simon Zorka and seminar participants at the American Finance Association (AFA poster session) 2022 conference, the Australasian Finance and Banking Conference 2021, the University of Queen Mary, the Warwick Business School Finance Brownbag and the French Finance (AFFI) Conference.

1 Introduction

Since Donald J. Trump started his U.S. presidential campaign in June 2015, he has extensively used Twitter as a means of communication with the public, with more than 77.5 million followers (as of April 2020) has shown how much attention the public is paying to the views shared by the U.S. 45^{th} President.[1] Although the information content of these tweets is a matter of dispute (Washington Post, 2020), a growing area of research is identifying the effects of his tweets on financial markets, such as the effect of protectionist Trump tweets on tariffs with China or Mexico (e.g., Benton and Philips, 2018; Ferrari Minesso, Kurcz, and Pagliari, 2022; Matveev and Ruge-Murcia, 2023), and tweets influencing the financial market perceptions of interest rates (e.g., Bianchi et al., 2023), and stock market 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).

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 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 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

1. His Twitter account was suspended in January 2021 because of his tweets after the U.S. Capitol attack and reinstated in November 2022 by Elon Musk.

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 topic modeling 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 link Trump tweets to outcomes in the FX market and construct measures of FX market activity. Our main empirical results are based on a panel specification with the outcome variables of FX spot returns and volatility in a one-hour window. Explanatory variables include an hourly dummy for a macroeconomic or trade tweet and controls for hour-of-day, day-of-week, scheduled monetary (FOMC) announcements, bid-ask spreads, and fundamentals in financial markets such as the changes in the intraday VIX index.

We identify the systematic effects of informative Trump tweets on FX spot returns. The dollar tends, on average, to appreciate vis à vis major bilateral pairs following Trump's tweets. We find significant cumulative returns in the hour following the tweet for an equal-weighted average return of all bilateral currency pairs, by approximately 0.005% (0.5 basis points). While the effect is transitory, it is an economically significant appreciation (44% annualized). This appreciation is consistent with the nature of Trump's tweets, which typically reflect his positive views on the U.S. economy (relative to other countries), and trigger a protectionist stance on trade policies.[2] Second, we find declines in our measure of both intraday FX spot volatility and FX volume around Trump tweet hours. A volatility reduction is indicative that Trump tweets on macroeconomic topics carry relevant information for FX trading. In contrast, a placebo analysis using tweets that are on topics unrelated to macroeconomy has no effects on spot returns and volatility.

We address concerns of endogeneity by controlling for macroeconomic releases on the day of the tweet. This rules out an alternative view that the effects of Trump's informative tweets are due to the reaction to news that occurred earlier in the day. Additionally, our analysis tests the political diversion hypothesis using media coverage about Trump's Mueller investigation (Lewandowsky, Jetter, and Ecker, 2020). Our findings demonstrate that Trump's informative tweets on macroeconomic and trade news are timed following negative political coverage. This supports our hypothesis that the timing of informative Trump tweets is driven by news unrelated to macroeconomic conditions, and is therefore not a reaction to macroeconomic announcements that occurred earlier in the day.

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

2 Related Literature

The paper contributes to the growing literature on the impact of Twitter content on financial markets. In the stock market, studies explore the relationship between Twitter sentiment and stock market returns and volatility of stock indices (Bollen, Mao, and Zeng, 2011; Mittal and Goel, 2012; Behrendt and Schmidt, 2018). Other works focus on company-specific tweets (e.g., Sprenger et al., 2014; Bartov, Faurel, and Mohanram, 2018) and Twitter sentiment around FOMC announcements (Azar and Lo, 2016). In the currency market, Gholampour and Van Wincoop (2017) analyze investor tweets regarding the Euro/dollar exchange rate and develop a sentiment-based trading strategy, and Filippou et al. (2023) construct a measure of U.S. populist rhetoric, finding a link between high populist rhetoric and low currency excess returns.

Our paper relates to recent research on the effects of Trump tweets across various financial markets. In the stock market, studies examine their impact on publicly traded firm stock returns and volatility (e.g., Born, Myers, and Clark, 2017; Juma'h and Alnsour, 2018; Colonescu et al., 2018; Ge, Kurov, and Wolfe, 2019; Ajjoub, Walker, and Zhao, 2021; Abdi et al., 2021; Scharnowski, 2022). Other works investigate tweets threatening central bank independence (Bianchi et al., 2023), those with a negative stance on Mexico-U.S. trade affecting the Peso/Dollar exchange rate (Benton and Philips, 2018; Matveev and Ruge-Murcia, 2023), and tweets related to the China-US trade dispute (Ferrari Minesso, Kurcz, and Pagliari, 2022). Bianchi, Cram, and Kung (2023) use high-frequency data of Congress members' tweets and find that individual politicians affect asset prices. Additionally, Abdi et al. (2021) conduct a textual analysis of Trump tweets, uncovering information effects on stock prices, especially related to macroeconomic and trade content. Benton and Philips (2018) and Ferrari Minesso, Kurcz, and Pagliari (2022) find that Trump tweets on Mexico-U.S. trade and China-US trade tensions lead to U.S. dollar appreciation.

Our contribution is to extend the analysis of Trump tweets to identify the macroeconomic and trade content of Trump tweets. This includes tweets on how the Federal Reserve should set interest rates and tariff policies with Mexico and China. We document systematic effects of informative Trump tweets on USD spot returns and exchange rate volatility. In particular, positive sentiment tweets result in a USD appreciation, reflecting Trump's optimism on the US 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 Santucci de Magistris, 2019; Kruger, 2020; Jeanneret and Sokolovski, 2023).

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

3 Model

We develop a simple two-period model of trading in the FX market using public information. In this model, each investor has a prior belief at period t regarding the exchange rate in the next period, denoted as period $t+1$. These traders adopt a similar functional form as informed traders in information models of the exchange (Jeanne and Rose, 2002; Bacchetta and Van Wincoop, 2006; Gholampour and Van Wincoop, 2017). A public signal, referred to as the *Trump tweet*, acts as a common signal that is interpreted by all speculative traders. A rational Bayesian agent combines their prior belief with the public signal. The posterior distribution of the Bayesian agent's signal is determined by taking a weighted average of the public and private information, with the weights depending on the relative precision of each signal.

In addition to Bayesian agents, a fraction of traders are identified as Trump followers, who adjust their prior belief to assign a weight of one to the public signal. By employing this setup, we investigate the influence of the public signal on spot returns and volatility. Our primary mechanism focuses on how a bias between the public and private signal can generate spot returns.

Exchange rates

There is a market consisting of N agents with diverse prior beliefs regarding the future payoff of the exchange rate s_t, denoted as foreign currency per dollar.[3] Each agent has a prior of future fundamentals governing the exchange rate. Following Jeanne and Rose (2002), we use simple money demand functions for the domestic and foreign currencies, and a purchasing power parity relationship connecting prices across the two countries, in the following equations:

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

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

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

Denoting exchange rate fundamentals $f_t = \frac{m_t^* - m_t}{1+\alpha} + \frac{\eta(y_t - y_t^*)}{1+\alpha}$, we derive an expression for s_t as a function of the difference in money supplies and income differences between the domestic and foreign currencies in Equation (4).[4]

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

Prior to the Trump tweet, each investor has a prior on future fundamentals, such as relative money supplies and output in the two countries, which we denote f_{t+1}^j, defined by Equation (5). The investor's expectation of future fundamentals conditional on the private signal is denoted as θ^j. The variance σ_j^2 governs the precision of the private signal.

3. In this notation, an increase in s_t indicates an appreciation of the dollar.
4. Note that we have a two-period model. However, in an infinite horizon, Equation (4) becomes $s_t = f_t + \sum_{s=1}^{\infty} \left(\frac{\alpha}{1+\alpha}\right)^s \mathbb{E}_t[f_{t+s}]$, which states that the spot rate is a function of expected future fundamentals (Engel and West, 2005; Froot and Ramadorai, 2005).

$$f^j_{t+1} = \theta^j + \epsilon^j_{t+1}, \quad \epsilon^j \sim N(0, \sigma^2_j) \tag{5}$$

Trump tweets

We characterize the Trump tweet as a public signal known to all investors, as shown in Equation (6). The arrival of the public signal is unexpected, unlike scheduled monetary announcements by the central bank, which occur at specific times of the day. The public tweet has an expectation of future fundamentals denoted as θ^T, with a precision of the public signal represented by σ^2_T. For our analysis, we assume that the public and private signals are uncorrelated, indicated by $cov(\epsilon^T, \epsilon^j) = 0$.[5]

$$f^T_{t+1} = \theta^T + \epsilon^T_{t+1}, \quad \epsilon^T \sim N(0, \sigma^2_T) \tag{6}$$

Bayesian agents

A rational agent will update their prior based on the public signal. Their expectation, conditional on the public and private information, can be expressed as a weighted average of the public and private signals. Let us denote the weights on the public and private signals for a Bayesian agent as ω^B_j and $1 - \omega^B_j$, respectively, as shown in Equation (27).

$$\mathbb{E}[f^j_{t+1} | I_j, I_T] = \omega^B_j \theta^T + (1 - \omega^B_j)\theta^j \tag{7}$$

A Bayesian agent will update their prior based on the relative precision of the public and private signals. Formally, we define the weight on the public signal as $\omega^B_j = \frac{\sigma^2_j}{\sigma^2_T + \sigma^2_j}$ in Equation (8).[6]

$$\mathbb{E}[f^j_{t+1} | I_j, I_T] = \frac{\sigma^2_j}{\sigma^2_T + \sigma^2_j}\theta^T + \frac{\sigma^2_T}{\sigma^2_T + \sigma^2_j}\theta^j \tag{8}$$

5. This is a simplifying assumption that allows us to isolate the impact of Trump tweets on FX markets, without a mechanical effect due to correlating with private beliefs.

6. Refer to Appendix A for a derivation of the weights on the public and private signals.

If the relative precision of the public signal, denoted as $\frac{\sigma_T^2}{\sigma_j^2}$, tends towards zero, it indicates that the Trump tweet is more precise, and the investor's weight on the public signal approaches one. Conversely, if the public signal is noisier compared to the private signal, the investor assigns a weight of zero to the public signal. Importantly, the information aggregation process of Trump is not known in advance by Bayesian agents.[7]

Trump Followers

Trump followers represent a subset of agents who consider the Trump tweet as their sole signal, assigning a weight of $\omega_j^B = 1$. This is formally defined in Equation (9).

$$\mathbb{E}[f_{t+1}^T | I_j, I_T] = \theta^T \tag{9}$$

Investor optimization

The investor aims to maximize exponential utility over their wealth in the next period, given by $U_t = -e^{-\gamma W_{t+1}}$. They invest their entire wealth in dollar bills, denoted as $W_{t+1} = \rho_t^j b_t^j$. The excess return on the dollar bill is defined in Equation (10), where i_t represents the domestic (U.S.) interest rate and i_t^* represents the foreign interest rate.

$$\rho_t^j = s_{t+1} - s_t + i_t - i_t^* \tag{10}$$

The investor's optimization problem involves maximizing utility while investing all their wealth in dollar bills. This problem can be formulated as a mean-variance problem, maximizing Equation (11) subject to the constraint on next period wealth in Equation (12).

$$\underset{b_t^j}{\text{maximize}} \qquad L = \mathbb{E}[W_{t+1}^j] - \frac{1}{2}\gamma Var(W_{t+1}^j) \tag{11}$$

7. Our model is 2 periods as in a multi-period setting, traders would eventually learn that the Trump signal aggregates private information. This would cause Bayesian agents to assign a weight of 1 to the Trump signal, making all agents become Trump followers. However, as we assume a two-period model, Bayesian agents only form an expectation today (time t) for the payoff in period $t + 1$.

subject to:

$$W_{t+1}^j = \rho_t^j b_t^j \tag{12}$$

The optimal level of bill demand for Bayesian agents can be obtained by solving Equation (13), while the optimal bill demand for Trump followers can be found using Equation (14).

$$b_t^j = \frac{\omega_j^B \theta^T + (1-\omega_j^B)\theta^j - s_t + i_t - i_t^*}{\gamma({\omega_j^B}^2 \sigma_T^2 + (1-\omega_j^B)^2 \sigma_j^2)} \tag{13}$$

$$b_t^j = \frac{\theta^T - s_t + i_t - i_t^*}{\gamma \sigma_T^2} \tag{14}$$

Market clearing

Let's define N_B as the number of Bayesian agents and N_T as the number of Trump followers among the total N agents. In equilibrium, market clearing requires the net bill supply to be zero, as shown in Equation (15). This condition captures the balance between the bill holdings of Bayesian agents and Trump followers.

$$\sum_{j \in N_B} b_t^j + \sum_{j \in N_T} b_t^j = 0 \tag{15}$$

By substituting the optimal bill holdings formulas for Bayesian agents and Trump followers into the market clearing condition, we obtain Equation (16).

$$\sum_{j \in N_B} \frac{\omega_j^B \theta^T + (1-\omega_j^B)\theta^j - s_t + i_t - i_t}{{\omega_j^B}^2 \sigma_T^2 + (1-\omega_j^B)^2 \sigma_j^2} + \sum_{j \in N_T} \frac{\theta^T - s_t + i_t - i_t}{\sigma_T^2} = 0 \tag{16}$$

The equilibrium spot exchange rate is given by Equation (17), where $\bar{\theta^j} = \frac{1}{N}\sum_{j=1}^N \theta^j$ represents the average of investor priors. The last term in the expression accounts for the bias between the Trump tweet and the average of investor priors. The impact of this bias on the market clearing spot rate is influenced by the weight Bayesian agents assign to the Trump tweet and the proportion of Trump followers.

$$s_t = i_t - i_t^* + \frac{1}{\Gamma}\left(\Gamma_B \bar{\theta}^j + \Gamma_T \theta^T + \omega_j^B \Gamma_B (\theta^T - \bar{\theta}^j)\right) \tag{17}$$

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 $\Gamma = \Gamma_B + \Gamma_T$.

The model yields the following testable implications on the effect of Trump tweets on spot returns and volatility.

Prediction 1: An informative Trump tweet affects FX spot returns due to a bias between the Trump tweet and speculators' expectations.

The derivative of the spot rate with respect to a change in the public and private signal is given in Equations (18) and (19) respectively. The sensitivity of the spot rate to Trump tweets is positively increasing in the share of Trump followers and in the relative precision of the public signal. Define the relative precision of the public to private signal $R = \frac{\sigma_T^2}{\sigma_j^2}$. Spot returns are more sensitive to Trump tweets than the private signal if the relative precision of the public signal satisfies the upper bound given by Equation (20). This upper bound depends on the relative shares of Trump followers and Bayesian agents.

$$\frac{\partial s_t}{\partial \theta^T} = \frac{1}{\Gamma}\left(\Gamma_T + \omega_j^B \Gamma_B\right) \tag{18}$$

$$\frac{\partial s_t}{\partial \bar{\theta}^j} = \frac{\Gamma_B}{\Gamma}\left(1 - \omega_j^B\right) \tag{19}$$

$$\frac{\partial s_t}{\partial \theta^T} > \frac{\partial s_t}{\partial \bar{\theta}^j} \quad \text{iff} \quad R < \frac{N^T}{N^B} + 1 \tag{20}$$

Proof: see Appendix

[FIGURE 1 ABOUT HERE]

The bias in fundamentals is illustrated in Figure 1, where the average of investor priors is denoted by $\bar{\theta}^j$ and the public signal (Trump tweet) is represented by θ^T. The public signal causes the posterior distribution of Bayesian investors to shift toward the public signal.

The relative sensitivities of the spot price to the public and private signals are compared in Equation (20). The upper bound is increasing in the ratio of Trump followers to

Bayesian agents. When the public signal is more precise than the private signal, the sensitivity of spot returns to Trump tweets is always strictly greater than the private signal for any ratio of Trump followers to Bayesian agents.

We can determine a counterfactual spot return, by comparing the spot price in an equilibrium with public signal adoption in equation (17), with the spot rate in an equilibrium without the public signal, which we denote $s_t^{\text{no public signal}}$.[8] The counterfactual spot return can be decomposed into a bias between public and private signals, with a weight $\frac{\Gamma_T}{\Gamma}$ given to Trump followers, and a weight of $\frac{\omega_j^B \Gamma_B}{\Gamma}$ given to Bayesian agents.

$$s_t - s_t^{\text{no public signal}} = \underbrace{\frac{\Gamma_T}{\Gamma}\left(\theta^T - \bar{\theta^j}\right)}_{\text{Bias Trump Followers}} + \underbrace{\frac{\omega_j^B \Gamma_B}{\Gamma}\left(\theta^T - \bar{\theta^j}\right)}_{\text{Bias Bayesian Agents}} \tag{21}$$

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

We empirically test the model prediction by examining spot returns following Trump tweets, specifically focusing on tweets related to macroeconomic and trade content. Furthermore, the direction of the bias between the public and private signals depends on the sentiment of the tweets. In our framework in Section 5.1, we formally test the effect of the tone of Trump tweets through sentiment analysis. Controlling for the tone, we hypothesize that tweets expressing greater optimism about the macroeconomy will be associated with a systematic appreciation of the USD.

8. Without the public signal, there are only Bayesian agents, and the spot rate in equilibrium is $s_t = i_t - i_t^* + \bar{\theta}_j$

Prediction 2: Variance of spot returns is lower if the public signal is sufficiently precise.

Define spot returns $\Delta s_{t+1} = s_{t+1} - s_t$. *Define the relative precision of the public to private signal* $R = \frac{\sigma_T^2}{\sigma_j^2}$. *The variance of spot returns declines following the Trump tweet if the ratio of the volatility of the public to private signal is less than the upper bound given by (22). This upper bound depends on the relative shares of Trump followers and Bayesian agents.*

$$\frac{\text{var}(\Delta s_{t+1}|I_j, I_T)}{\text{var}(\Delta s_{t+1}|I_j)} = \frac{N_B}{N}\left(\frac{R}{R+1}\right) + \frac{N_T}{N}R \tag{22}$$

$$\frac{\text{var}(\Delta s_{t+1}|I_j, I_T)}{\text{var}(\Delta s_{t+1}|I_j)} < 1 \quad \text{iff} \quad R < \sqrt{\frac{N_B}{N_T} + 1} \tag{23}$$

Proof: see Appendix[9]

The impact of the Trump tweet on the variance of spot returns depends on the relative precision of the public signal. When the public signal is more precise, the upper bound in Equation (23) is always satisfied for any ratio of Bayesian agents to Trump followers, and we predict a decline in volatility of spot returns. In contrast, a noisy public signal can increase volatility of spot returns provided the share of Trump followers is sufficiently high.

Within our empirical framework, we can examine whether there exists a differential effect of Trump tweets based on their information content. We hypothesize that tweets with higher information content, particularly those related to macroeconomic and trade topics, has a negative effect on volatility. On the other hand, tweets discussing uninformative topics, such as political events like the Mueller investigation, would have little to no impact on the volatility of spot returns. We formally test these hypotheses in section 5.1.

9. In our derivation, we follow Mark (1995) and Della Corte, Sarno, and Tsiakas (2009) which relates spot returns to economic fundamentals. This allows us to map the variance of the fundamental signal of investors to the variance of spot returns.

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 account @realDonaldTrump. We are interested in the period starting from 16^{th} of June 2015, as it is the day Donald Trump announced his presidential campaign. Our sample ends in 20^{th} of August 2019. During this period, there were 17,865 tweets posted from his account in total. As expected, there are various topics covered in these tweets.[10]

We have two approaches to identify the information content of Trump tweets and to filter tweets that have macroeconomic, trade, or exchange rate content. The first approach uses a dictionary approach, and the second uses a textual analysis based on a biterm topic modeling approach.[11] We combine the relevant Tweets identified by these two methods for our empirical analysis.

4.1.1 Dictionary approach

Baker et al. (2019) provides a dictionary of policy-related terms about the macroeconomics outlook, trade policy, and exchange rate topics that are most relevant for the FX market. Other topics such as healthcare and energy are clearly much less connected with currencies. Therefore, our focus is on Tweets containing terms falling into macroeconomic outlook, trade policy, and exchange rate categories. Term sets in this dictionary are constructed by careful audit and validation with a large sample of newspaper articles, so it should generate a good level of accuracy. A comprehensive list of these terms associated with three categories (macroeconomics outlook, trade policy, and exchange rates) can be found in Table 1.

[TABLE 1 ABOUT HERE]

10. The website from which we obtain the data also provides a list of some topics frequently tweeted by the 45th 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").

11. Conventional textual analysis algorithms like LDA or LSA are difficult to use in this setting as their algorithms are not well suited to defining topics with short messages.

After filtering tweets containing at least one term in any of these three specific categories, we do a manual reading of those tweets to remove all tweets not expressing the topic intended (false positives). We are left with a sample of 458 tweets.[12] In particular, there are 218 tweets about trade, 247 tweets about macroeconomics outlook, and 3 tweets about exchange rates. A sample of tweets by topic can be found in Appendix B.1.

4.1.2 Biterm topic modeling (BTM) approach

The BTM (Biterm Topic Model) is a topic modeling approach introduced by Yan et al. (2013) to overcome limitations associated with traditional topic modeling methods like LDA (Latent Dirichlet Allocation) and LSI (Latent Semantic Indexing) in discovering the content of short texts. To the best of our knowledge, we are the first to utilize this textual analysis method in the finance literature.

The BTM approach requires two inputs. The first input is the corpus, which is the collection of words. We apply the BTM approach to our complete set of tweets after applying standard text-cleaning procedures, such as lowercasing, removal of numbers, and elimination of English stop words. The second input is the number of topics, which we set as 9. The choice of the optimal number of topics involves tradeoffs between interpretation and model fit quality (Chang et al., 2009; Hansen, McMahon, and Prat, 2018). In our case, selecting 9 topics allows for an intuitive interpretation of trade and macroeconomic content.

The BTM algorithm generates two sets of outputs. The first set includes the list of top keywords for each topic and the corresponding probabilities of observing each word in the topic. For each topic n, there exists a set of vectors $\hat{\beta}_n = [\hat{\beta}_{n,1}, \ldots, \hat{\beta}_{n,J}]'$, where $\hat{\beta}_{n,j}$ represents the probability that word j belongs to topic n. We summarize the keywords for two topics identified as having relevant information content in Figure 2). The keywords for the trade topic pertain to trade-related topics, including terms like trade, tariff, China, dollar, and deal. Similarly, the keywords for the macroeconomic topic include terms like job, tax, cut, market. Example sentences for macroeconomic and trade topics, along with the complete list of top keywords for other topics, can be found in Appendix B.

12. Retweets are excluded from the sample.

[FIGURE 2 ABOUT HERE]

Now that we have identified the keywords in each topic, we use a second set of outputs that measures the proportion of topics for each tweet. Formally, we define a set of vectors for each tweet $\hat{\gamma}_t = [\hat{\gamma}_{t,1}, \hat{\gamma}_{t,2}, \hat{\gamma}_{t,3}, ..., \hat{\gamma}_{t,n}]'$, in which $\hat{\gamma}_{t,n}$ measures the proportion of tweet t that is made up of topic n. Our condition for a tweet with macroeconomic or trade content is a probability associated with Trade or Macroeconomics topics being at least 30%.[13] We also check all these Tweets manually to remove false positives, leaving us with a filtered set of 180 Trade and 242 Macroeconomics tweets.

4.1.3 Combined Tweets by Dictionary and BTM approach

We aggregate all the tweets identified by the dictionary and BTM approach as containing relevant information for the FX markets. We count a total of 297 tweets (dictionary only), 261 tweets (Biterm only) and 161 tweets that were identified with both methods, which is a total of 719 tweets. There are instances when multiple relevant tweets are posted within the same hour. Therefore, in total, we have 506 hours with relevant tweets. We merge the tweet data with indicative quotes data at an hourly frequency while we utilize the exact timing of the tweets for event studies.

The distribution of these tweets across the days of the week and hours of the day, based on London time, is summarized in Panel A and Panel B of Figure 3. In Panel C and Panel D of the same figure, we present these patterns for all tweets posted during the sample period.

[FIGURE 3 ABOUT HERE]

It can be observed that informative tweets occur on all days of the week, with higher frequency during weekdays. As weekend tweets occur during a period of relative illiquidity in the FX market, we treat them as if they were posted during the first hour of the next trading week (10 pm on Sunday, London Time). Regarding the hour of the day, the majority of tweets are posted in the late afternoon and early morning, London Time, which corresponds to the morning and evening hours based on US EST time.

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

4.1.4 Sentiment Analysis

We also consider the sentiment or tone of the tweets using sentiment analysis. To measure sentiment, we assign a sentiment score to each tweet based on the dictionary developed by Loughran and McDonald (2011). Specifically, we count the number of positive and negative words that match the dictionary and compute the sentiment of the tweet for the topics with macroeconomic or trade content. The measure takes the following form:

$$\text{Tweet Sentiment} = \frac{\text{Number of positive words-Number of negative words}}{\text{Total number of words}} \tag{24}$$

Therefore an increase in the tweet sentiment indicates higher optimism about macroeconomic fundamentals. We report sample tweets categorized by sentiment in Appendix B.[14]

4.2 Intraday FX volume, returns, volatility and bid-ask spread

Hourly Volume: We utilize the CLS FX flows dataset provided by Quandl. CLS Group handles more than 50% of global FX transaction volume, including spot, swap, and forward transactions, for up to 14 bilateral currency pairs.[15] These pairs are also used in papers studying CLS market data (e.g., Fischer and Ranaldo, 2011; Cespa et al., 2022; Hasbrouck and Levich, 2019; Ranaldo and Somogyi, 2021). The dataset records hourly transaction volumes for four groups of market participants: banks, funds, non-bank financial institutions, and corporations. Market makers, typically banks, interact with price takers in the market, which are divided into three categories: funds, non-bank financials, and corporates. Our sample spans from June 16, 2015, to August 20, 2019.

Hourly Returns: We obtain tick-by-tick high-frequency data for spot indicative quotes from Thomson Reuters Tick History and interdealer trades from the Thomson Reuters

14. For example, a positive sentiment tweet is *"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....!"*

15. The included currency pairs represent bilateral exchange rates of the U.S. with Australia, Canada, the Euro Area, Japan, New Zealand, Norway, Sweden, Switzerland, the United Kingdom, Hungary, South Africa, Iceland, Mexico, and Korea. The Hong Kong and Singapore dollars, as well as the Danish krone, are excluded as they are pegged to the USD or Euro.

D3 platform. These datasets provide indicative quotes and interdealer trades sampled at millisecond frequency.

In our analysis, all currency exchange rates are quoted against the USD, so an increase in the spot exchange rate (S) indicates an appreciation of the USD. We compute the exchange rate return as the logarithmic difference in the spot exchange rate over an hour:

$$\Delta s_{t+1} = s_{t+1} - s_t, \tag{25}$$

where s_t represents the logarithm of the midpoint (trade price) of the last quote (trade) at hour t.

Hourly Volatility: Following the approach of Mueller, Tahbaz-Salehi, and Vedolin (2017), we construct intraday realized volatility. Specifically, we calculate spot exchange rate changes sampled at five-minute intervals based on the mid-price of the quote. The hourly realized variance is computed as the sum of squared changes, and the hourly volatility is the square root of the realized hourly variance.

Hourly Bid-Ask Spread: We first obtain the last quote of each hour and then calculate the bid-ask spread indicator as the difference between the ask and bid prices divided by the midpoint.

5 Empirical analysis

In this section, we discover the effects of Trump tweets on several characteristics of the FX market, including returns and intraday volatility in light of the model described in Section 3.

5.1 Panel regressions: spot returns and volatility

In our baseline regressions, we pool all observations from 14 currency pairs and run country fixed-effects panel regressions with hourly data. Our fixed-effects panel regression specification is in Equation (26).

$$x_{i,t} = \alpha_i + \beta_1 Tweet_t + \beta_2 X_{t-1} + \mu_d + \sigma_h + \epsilon_{i,t} \tag{26}$$

The outcome variable $x_{i,t}$ is returns and intraday volatility for currency pair i at time t. $Tweet_t$ is the dummy variable equal to 1 if there is a tweet about macroeconomics outlook, trade, or FX posted by Donald Trump at that hour and 0 otherwise, X_t is a set of control variables (i.e., lagged bid-ask spread, FOMC dummy, ΔVIX). VIX is the intraday CBOE Volatility Index (from Thompson Reuters Tick History). We cumulative one-minute changes in the VIX index over one-hour (30-min) intervals. FOMC dummy is equal to 1 if during that hour FOMC announcements are announced, and 0 otherwise. μ_d and σ_h are time-fixed effects that control for the day of week and hour-of-day, respectively. Standard errors are clustered at the level of the currency pair.

5.1.1 Trump tweets and FX returns

The first prediction of the model is the impact of Trump tweets on FX spot returns. In particular, equation (21) shows that spot returns reflect a bias in the expectation of future macroeconomic fundamentals between the public signal and the expectations of investors. For example, this bias can be due to Trump tweets being more optimistic about the U.S. economy, or more protectionist about trade relations. The coefficient β_1 in Equation (26) serves as a measure of the impact of Trump tweets on spot returns, capturing any inherent bias introduced by these tweets. Regression results are reported in Table 2.

[TABLE 2 ABOUT HERE]

The positive coefficient of informative Trump tweet hour in the first column suggests those tweets lead to an appreciation of the U.S. dollar. Our estimates suggest that the USD appreciates by an average of 0.005 percent (0.5 basis points) during a Trump tweet hour against a basket of currencies.[16] While our effects are intra-day, we note that this is an economically significant return, which is equal to 0.12% daily, and 44% annualized.[17]

The results are robust to adding additional controls, such as bid-ask spread, FOMC meetings, and the ΔVIX in columns (2) to (4). These results support the model prediction that FX returns reflect, on average, Trump's optimistic view of the U.S. economy.

16. We are using a notation of units of foreign currency per USD. Therefore a positive coefficient indicates an appreciation of the USD with respect to the foreign currency.
17. For comparison, the daily standard deviation of the USD Trade-Weighted index return in the period 2014-2024 is approximately 0.30% daily (FRED).

We also hypothesize that tweets with no macroeconomic content are uninformative, and should have no systematic effects on spot returns. In column (5) we conduct a placebo test using a set of uninformative tweets, which typically relate to politics or the media, and find no systematic effect on spot returns. This result is in line with our model framework that only tweets that relate to expectations on macroeconomic fundamentals matter for the exchange rate.

We have presented results for all Trump tweet hours, however, our model suggests that the direction of bias depends on the tone of the tweets. We therefore expect a positive relation between Trump tweet's tone and the USD spot return. Regressions showing the link between the sentiment score of tweets and currency returns are reported in Table 3. We run regressions with the independent variable of interest being the sentiment score, which records the net positive language words in a tweet based on the dictionary in Loughran and McDonald (2011). The coefficient of sentiment score is positive and strongly significant in all regressions. In the last column, with the full set of control variables, the coefficient of an optimistic tweet is 0.032 with a t-statistic of 7.15. This result implies that relevant Trump tweets with positive sentiment, that is, optimistic views about the U.S. economy, are associated with USD appreciation. This is consistent with our model prediction that spot returns reflect a bias between Trump expectations and private information.

[TABLE 3 ABOUT HERE]

Minute-level Tweets. The results obtained from the previous analysis are primarily based on hourly spot returns. However, we now delve into investigating the impact of Trump tweets on spot returns within the hour, specifically implementing an event study at the minute frequency, employing a methodology similar to that used in investigating minute-level ETF returns in the stock market (Abdi et al., 2021) and analyzing intraday volatility and liquidity (Scharnowski, 2022). Panel A of Figure 4 displays cumulative exchange rate changes around Trump tweets at the minute frequency 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 which peaks within an hour of the tweet.

Finally, to control for potential source of endogeneity Trump tweets respond to macroeconomic news, we conduct an event study analysis for Trump tweets that occur on days with and without macroeconomic announcements in panels B and C. Panel B shows results of Trump tweets on days of macroeconomic announcements. We find that there is no significant response to macroeconomic announcements. Specifically, we observe a depreciation that is followed by an appreciation of the USD after the macroeconomic announcement. In Panel C of Figure 4, we show cumulative returns around Trump's tweets after excluding days with macroeconomic announcements. We still observe a systematic appreciation of the USD against a basket of currencies is robust after excluding days with macroeconomic announcements.[18] In Appendix C, we conduct an event study at the minute frequency for each currency pair and report the results. Moreover, in Appendix D, we show the results are robust to a measure of abnormal returns around Trump tweets, which involves calculating the difference in returns between the tweet's time and a period without the tweet, matched by VIX changes.

[FIGURE 4 ABOUT HERE]

5.1.2 Trump Tweets and FX Volatility and Volume

We proceed to test the model's second prediction, which asserts that FX volatility decreases for informative Trump tweets. In this context, we define informative Trump tweets as those with higher precision compared to private information. To address volatility persistence, we employ innovations to intraday realized volatility as the relevant outcome variable. The regression results are presented in Table 4.

In the first column, where the day of the week and hour of the day dummies are the only control variables, the coefficient of the tweet dummy variable is negative and highly significant with a t-statistic of -6.19. Our estimates suggest a decline in volatility of 0.007 percent (0.7 basis points) during a Trump tweet hour against a basket of currencies. As we introduce additional control variables in the subsequent columns (2) to (4), the

18. We run further tests on endogeneity and control for macroeconomic announcements in the panel specification in Section 5.2.

magnitude of the coefficient for the tweet dummy remains unchanged and retains its high level of significance. When we include the full set of control variables in the regression in column (4), the coefficient of our variable of interest remains negative with a t-statistic of -6.97. Similar to our analysis for spot returns, in the final column we conduct a placebo test using a set of uninformative tweets and find no significant effects of Trump tweets on volatility. This suggests that consistent with our model's prediction, it is specifically informative tweets that lead to a decline in volatility. In Appendix D, we demonstrate the robustness of our results by employing a measure of abnormal volatility surrounding Trump tweets. This measure captures the difference in volatility between the time of the tweet and a period without the tweet while accounting for changes in VIX index.

[TABLE 4 ABOUT HERE]

In addition to the volatility results, we analyze the relationship between FX trading volume and relevant Trump tweets. Volume and volatility are typically positively correlated in FX markets (Bjonnes, Rime, and Solheim, 2005; Ranaldo and Magistris, 2022), with a positive volume-volatility trade-off conditional on macroeconomic news (Bollerslev, Li, and Xue, 2018). Following Cespa et al. (2022), we construct a measure of abnormal FX trading volume by calculating the log deviation from the moving average of FX volume at the same hour over the last 21 trading days.

Table 5 summarizes regression results for FX spot trading volume. The first column shows a significant 0.56% decrease in abnormal volume during hours with informative tweets. Adding bid-ask spread in the second column confirms the negative relationship between illiquidity and volume. The third column introduces ΔVIX, revealing a positive link between uncertainty and spot FX volume. In column (4), FOMC dummy maintains a negative relationship with tweet hours, indicating decreased abnormal volume, and a positive relationship with FOMC announcements, suggesting increased volume. Controlling for monetary announcements addresses concerns of news-driven findings. Finally, we show that uninformative tweets also result in a decline in trading volume in column (5), however we observe a 0.40% decline in volume. This is consistent with our return and volatility effects being weaker for uninformative tweets.

Overall, the results suggest lower spot FX trading volume during hours of Trump tweets, consistent with the observed decline in volatility. Therefore, we observe a positive association between volume and volatility conditional on Trump tweets.[19]

[TABLE 5 ABOUT HERE]

5.2 Robustness tests

5.2.1 G10 Currencies

We replicate specification (26) with a sub-sample of G10 currencies.[20] Table 6 presents the results of panel regressions examining the impact of informative Tweets on FX market characteristics within the G10 currency sample. The dependent variables in columns (1), (2), and (3) represent hourly returns, volatility, and volume, respectively. As before, the regressions include controls for bid-ask spreads, monetary announcements, and currency and time fixed effects. Our results remain robust to using a sample of G10 currencies. In particular, the variable of Tweet hour is linked with a US dollar appreciation, and a decline in volatility and trading volume.

[TABLE 6 ABOUT HERE]

5.2.2 Macroeconomic announcements

A potential concern with our estimation is an omitted variable bias due to Trump tweets coinciding with macroeconomic releases. An alternative view posits that Trump tweets echo macroeconomic news released that day. For example, shortly after a macroeconomic release on job openings, Trump tweets *"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*

19. Appendix E shows results using a cross-section of market participants in the CLS data (funds, banks, non-financials and corporates), and finds that for the first three groups a statistically significant negative effect of volume during hours of Trump tweets, further supporting our evidence using aggregate FX volume.

20. 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).

Profits. We are Number One in World, by far!". If Trump tweets are responding to macroeconomic news, then the effects we find may be attributed to agents updating their signals based on macroeconomic releases instead of the Trump tweet.

[TABLE 7 ABOUT HERE]

In the panel specification, we control for the omitted variable bias by including dummies for macroeconomic releases on output, employment, and trading activity in Table 7. We add an additional control that is a dummy variable which is equal to 1 if there is at least one macroeconomic announcement on that day and 0 otherwise. The list of macroeconomic releases is based on Gürkaynak, Sack, and Swanson (2005). These include capacity utilization, Consumer confidence, inflation, employment costs, GDP, initial claims, leading indicators, new home sales, non-farm payrolls, PPI, retail sales, and the unemployment rate. Results of baseline regressions with this new dummy variable are shown in panel A of Table 7. The coefficient on the tweet hour dummy is robust to include a variable that captures macroeconomic releases, with an appreciation in spot returns and a decline in volatility.

A further test is to consider macroeconomic announcements that occur directly before the tweet. For example, this can alleviate concerns that the decline in volatility is systematically following an increase in trading activity during the macroeconomic announcement. We add a dummy variable that takes the value of 1 when the macroeconomic announcement occurs in the preceding hour of the tweet. Regressions in panel B show that our effects on spot returns and volatility are robust to controlling for macroeconomic announcements in the preceding hour.

Another concern is if our results are driven by a structural break in the sample: Donald Trump announced his candidacy and thus our sample contains both the campaign period and his presidency. One could argue that the tone of his tweets has changed over time as a result of his presidency (Clarke and Grieve, 2019). We include a presidency dummy in panel C of Table 7, which is a variable equal to 1 if the date is after 8^{th} of November 2016, the day Trump won the election as the U.S. President. Results from regressions suggest that the Presidency dummy does not alter the effects of informative

Trump tweets on FX returns and volatility.

5.2.3 Trump tweets and media coverage

We investigate whether Trump tweets are used as a distraction strategy by testing the link between tweets and media coverage of Mueller's investigation in the New York Times. If Trump tweets on informative topics are following negative press coverage, it supports our hypothesis that the timing of these tweets is plausibly exogenous with respect to current macroeconomic trends. We use the dataset for media coverage of Mueller's investigation provided in Lewandowsky, Jetter, and Ecker (2020). Logit regressions are implemented to examine whether media coverage of Mueller's investigation increases the probability of Trump tweeting in the next hour. Results are shown in Table 8.

[TABLE 8 ABOUT HERE]

In this table, we show the relationship between informative tweets and media coverage of Mueller's investigation. The coefficient of the lagged media coverage dummy is positive and statistically significant in all specifications, which suggests that media coverage of this potentially harmful topic for Trump's image increases the probability of him posting an informative tweet in the next hour. Overall, results from this analysis provide suggestive evidence that tweets are used as a distraction strategy. In particular, when there is media negative press coverage, Trump is likely to post informative tweets to change the narrative.

6 Conclusion

In this paper, we combine two approaches of textual analysis, the dictionary approach, and the biterm topic modeling approach, to identify the information content of tweets posted by Donald Trump. We hypothesize that Trump tweets about the macroeconomic outlook, trade policy, and FX policy are relevant for trading in the FX market. Through a model, we show that informative Trump tweets act as a common public signal in a market of heterogeneous private information. In a framework where the spot exchange rate conveys information on future macroeconomic fundamentals, differences between Trump's expectations of future macroeconomic fundamentals and speculators can induce a bias in currency returns.

We test our model predictions using a rich dataset of Trump tweets and price data for up to 14 bilateral pairs with respect to the USD. Supporting the model, we find empirical evidence that these tweets have an impact on FX trading activity. We find a statistically significant appreciation of the USD during Trump tweets with macroeconomic and trade content and a decline in exchange rate volatility. The appreciation of the USD reflects the generally optimistic views of Trump on the U.S. economy. We also tested a model prediction on how Trump tweets impact volatility in the FX market. A decline in volatility is consistent with the Trump tweet having information content. A placebo analysis using uninformative tweets on alternative non-macroeconomic topics reveals no significant effects on FX markets, supporting our hypothesis that only tweets containing relevant information for FX trading can have an impact on the currency market.

We address endogeneity concerns, by controlling for macroeconomic releases, ruling out the possibility that the effects of Trump tweets are solely due to the reaction to earlier news. Additionally, we examine whether Trump's tweets were intended to divert attention from negative media coverage or if they provided commentary on current macroeconomic trends. We find that Trump's tweets are more likely to address informative subjects such as macroeconomic and trade news following periods of negative press coverage on political topics like the Mueller investigation.

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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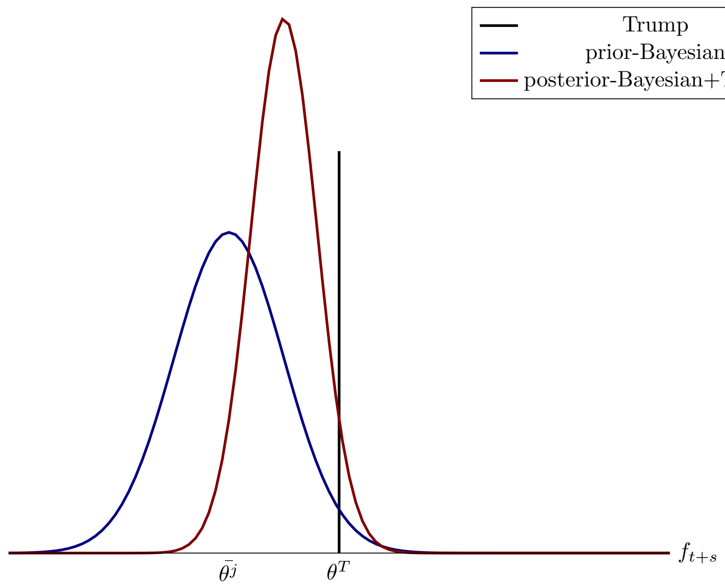
Figures

Figure 1: Bias between Trump and other agents on expectations of future fundamentals



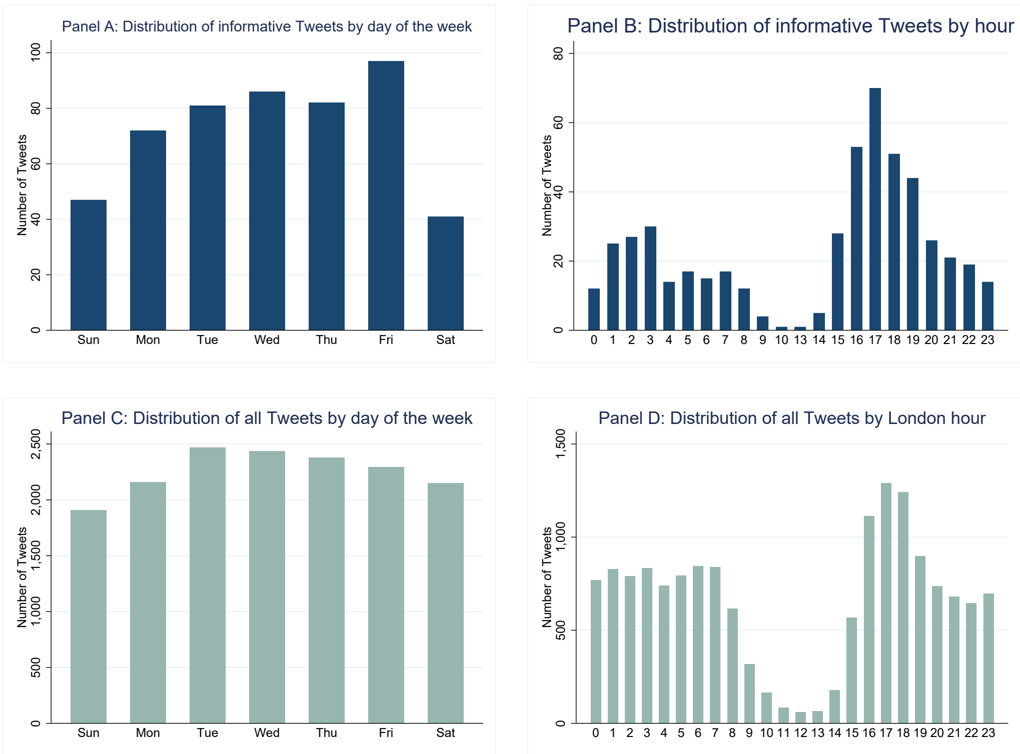
Trump expectations of future fundamentals differ from agent expectations. Bayesian agents update their signal, causing spot returns to change which is proportional to the bias, and the relative precision of the public signal.

Figure 2: Trade and Macroeconomics Topics from BTM

Trade Topic

Macroeconomics Topic

Figure 3: Time distribution of Trump Tweets



The figure shows the time distribution of Tweets belonging to Macroeconomics, Trade Policy, and Exchange Rate categories in Panel A and Panel B. The time distribution of all Tweets is shown in Panel C and Panel D. The number shown on the x-axis is the closing time based on London time. The data are between 16th June 2015 and 20th August 2019.

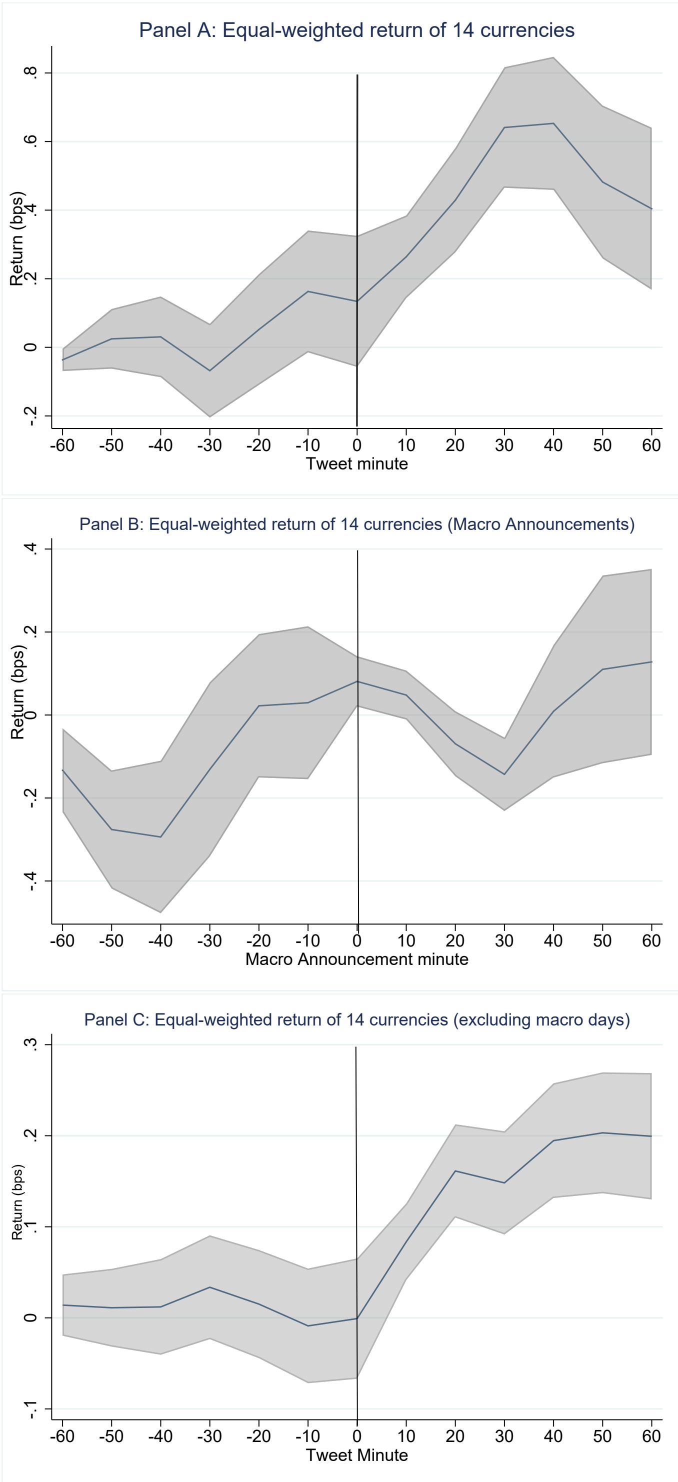


Figure 4: Event study of spot returns during the Tweet hour

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

Table 1: **Category Specific Dictionary**

This table reports 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: **Tweets and FX Hourly Returns**

This table reports panel regressions results for the estimation of informative and uninformative Tweets hour dummy on FX hourly returns. Regressions (1) to (4) use informative tweets on macroeconomic, trade, or exchange rate topics. Regression (5) uses uninformative tweets on alternative topics. The control variables are hourly bid-ask spread, hourly ΔVIX, and 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 squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are hourly between 16^{th} of June 2015 and 20^{th} of August 2019.

	Dependent variable: Returns				
	(1)	(2)	(3)	(4)	(5)
	Informative				Uninformative
Tweet hour$_t$	0.005***	0.005***	0.005***	0.005***	0.001
	(3.17)	(3.41)	(3.34)	(3.34)	(0.54)
Bid Ask Spread$_{t-1}$		0.000	0.000	0.000	0.000
		(0.91)	(0.83)	(0.84)	(0.83)
ΔVIX_{t-1}			0.027	0.027	0.025
			(1.40)	(1.40)	(0.88)
FOMC$_{t-1}$				-0.019*	-0.025**
				(-2.10)	(-2.68)
Country FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes
Observations	351,630	332,897	329,647	329,647	329,629
R^2	0.07%	0.06%	0.08%	0.08%	0.09%

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

This table reports panel regressions results for the estimation of informative Tweets' sentiment on FX hourly returns. The control variables are hourly bid-ask spread, hourly ΔVIX, and FOMC dummy. Hour-of-the-day and day-of-the-week dummies are included in all regressions. In Panel A, the independent variable of interest is Positive Tweet. In Panel B, the independent variable of interest is the Negative Tweet. Standard errors are clustered by currency. t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are hourly between 16^{th} of June 2015 and 20^{th} of August 2019.

	Dependent variable: Returns			
	(1)	(2)	(3)	(4)
Sentiment_t	0.038^{***}	0.031^{***}	0.032^{***}	0.032^{***}
	(7.12)	(7.27)	(7.14)	(7.15)
$\text{Bid Ask Spread}_{t-1}$		0.000	0.000	0.000
		(0.87)	(0.78)	(0.79)
ΔVIX_{t-1}			0.023	0.023
			(1.31)	(1.30)
FOMC_{t-1}				-0.019^{*}
				(-2.10)
Country FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes
Observations	351,630	332,897	329,647	329,647
R^2	0.07%	0.06%	0.08%	0.08%

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

This table reports panel regressions results for the estimation of informative and uninformative Tweets hour dummy on FX hourly realized volatility. Regressions (1) to (4) use informative tweets on macroeconomic, trade or exchange rate topics. Regression (5) uses uninformative tweets on alternative topics. The control variables are hourly bid-ask spread, hourly ΔVIX, and 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 squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are hourly between 16^{th} of June 2015 and 20^{th} of August 2019.

	Dependent variable: Realized Volatility				
	(1)	(2)	(3)	(4)	(5)
		Informative			Uninformative
Tweet hour$_t$	-0.007***	-0.007***	-0.007***	-0.007***	-0.000
	(-6.19)	(-6.81)	(-6.93)	(-6.97)	(0.00)
Bid Ask Spread$_{t-1}$		0.001**	0.001**	0.001**	0.001**
		(2.51)	(2.51)	(2.49)	(2.51)
ΔVIX_{t-1}			0.012***	0.012***	0.012***
			(4.37)	(4.39)	(4.39)
FOMC$_{t-1}$				0.097***	0.097***
				(4.03)	(4.03)
Country FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes
Observations	347,465	328,692	325,618	325,618	325,618
R^2	6.83%	7.31%	7.36%	7.64%	7.65%

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

This table reports panel regressions results for the estimation of informative and uninformative Tweets hour dummy on FX hourly trading volume. Regressions (1) to (4) use informative tweets on macroeconomic, trade or exchange rate topics. Regression (5) uses uninformative tweets on alternative topics. The control variables are hourly bid-ask spread, hourly ΔVIX, and 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 squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are hourly between 16^{th} of June 2015 and 20^{th} of August 2019.

Dependent variable: Aggregate Trading Volume					
	(1)	(2)	(3)	(4)	(5)
		Informative			Uninformative
Tweet hour$_t$	-0.564***	-0.501***	-0.513***	-0.514***	-0.405***
	(-3.51)	(-3.56)	(-3.61)	(-3.62)	(-3.56)
Bid Ask Spread$_{t-1}$		-0.085***	-0.085***	-0.085***	0.001**
		(-5.37)	(-5.48)	(-5.48)	(2.49)
ΔVIX_{t-1}			0.473***	0.476***	0.012***
			(5.13)	(5.15)	(4.36)
FOMC$_{t-1}$				1.578***	0.097***
				(9.83)	(4.04)
Country FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes
Observations	317,025	305,887	302,983	302,983	302,753
R^2	3.49%	7.94%	7.94%	7.97%	7.81%

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

This table reports panel regressions results for the estimation of informative Tweets hour dummy on FX market characteristics. Dependent variables in regressions (1), (2), and (3) are hourly returns, volatility and volume respectively. The control variables are hourly bid ask spread, hourly ΔVIX, and 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 squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are hourly between 16^{th} of June 2015 and 20^{th} of August 2019.

	Dependent variable: FX market characteristics		
	(1) Return$_t$	(2) Volatility$_t$	(3) Volume$_t$
Tweet hour$_t$	0.004***	-0.008***	-0.370**
	(3.15)	(-6.67)	(-2.33)
Bid Ask Spread$_{t-1}$	0.004***	0.001***	-0.071***
	(3.15)	(3.80)	(-3.33)
ΔVIX_{t-1}	0.004***	0.001***	0.359***
	(3.15)	(3.80)	(4.45)
FOMC$_{t-1}$	0.004**	0.010***	1.437***
	(3.15)	(4.61)	(10.80)
Country FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes
Observations	248,914	245,356	232,466
R^2	0.11%	8.68%	6.73%

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

This table reports panel regressions results for the estimation of informative Tweets hour dummy on FX market characteristics. The dependent variable in regressions (1), (4), and (7) are hourly returns, and the dependent variable in regressions (2), (4) and (6) is volatility, and the dependent variable in regressions (3), (6) and (9) is volume. The control variables are hourly bid-ask spread, hourly ΔVIX, and FOMC dummy. Macroeconomic announcements is a dummy variable that is equal to 1 if there is at least one macroeconomic announcement the hour before and 0 otherwise. Presidency is a dummy variable which is equal to 1 if it is 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 squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are hourly between 16^{th} of June 2015 and 20^{th} of August 2019.

	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$_t$	0.005***	-0.004***	-0.561***	0.005***	-0.007***	-0.515***	0.005***	-0.004***	-0.561***
	(3.39)	(-8.16)	(-3.54)	(3.32)	(-6.42)	(-3.63)	(3.31)	(-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***
	(0.79)	(2.48)	(-5.54)	(0.85)	(2.52)	(-5.49)	(0.79)	(1.72)	(-5.20)
ΔVIX$_{t-1}$	0.023	0.012***	0.496***	0.027	0.012***	0.475***	0.023	0.012***	0.470***
	(1.30)	(4.45)	(5.35)	(1.40)	(4.26)	(5.14)	(1.30)	(4.56)	(5.19)
FOMC$_{t-1}$	-0.019*	0.096***	1.606***	-0.019*	0.104***	1.500***	-0.019*	0.096***	1.592***
	(-2.09)	(4.01)	(8.97)	(-2.09)	(4.65)	(10.00)	(-2.10)	(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***			
				(1.64)	(3.08)	(6.05)			
Presidency$_t$							-0.000	-0.014***	0.216*
							(-0.29)	(-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 reports logit regressions results showing the link between the probability of informative Tweets and the publication of newspaper articles about Mueller's investigation in the previous hour. The independent variable of interest is the lagged Mueller articles dummy, which takes the value of 1 if there is a publication of newspaper articles about Mueller's investigation in the previous hour and 0 otherwise. The control variables are FOMC dummy, ΔVIX, and TED Spread. Day-of-the-week dummies are included in all regressions. t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are hourly between 17^{th} of May 2017 and 6^{th} of February 2019.

Dependent variable: Informative Tweet			
	(1)	(2)	(3)
Mueller_{t-1}	0.413***	0.428***	0.425***
	(2.99)	(3.04)	(3.03)
ΔVIX_{t-1}		0.432	0.430
		(1.01)	(1.00)
FOMC_{t-1}			0.364
			(0.91)
Day FE	Yes	Yes	Yes
Obs	10,368	10,368	10,224
R^2	0.12%	0.11%	0.11%

Internet Appendix to

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

(Not for publication)

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.

$$\mathbb{E}[f^j_{t+1}|I_j, I_T] = \omega^B_j \theta^T + (1 - \omega^B_j)\theta^j \tag{27}$$

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 $\epsilon_i \sim N(0, \sigma_i^2)$

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:

$$\mathbb{E}[f^j_{t+1}|I_j, I_T] = \frac{\theta^T\sigma_T^{-2} + \theta^j\sigma_j^{-2}}{\sigma_T^{-2} + \sigma_j^{-2}} \tag{28}$$

$$= \frac{\sigma_j^2}{\sigma_T^2 + \sigma_j^2}\theta^T + \frac{\sigma_T^2}{\sigma_T^2 + \sigma_j^2}\theta^j \tag{29}$$

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 (27).

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 $E[\rho_t^j] = \omega_j^B\theta^T + (1-\omega_j^B)\theta^j - s_t + i_t - i_t^*$

$$b_t^j = \frac{\omega_j^B\theta^T + (1-\omega_j^B)\theta^j - s_t + i_t - i_t^*}{\gamma({\omega_j^B}^2\sigma_T^2 + (1-\omega_j^B)^2\sigma_j^2)} \tag{30}$$

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 $E[\rho_t^j] = \theta^T - s_t + i_t - i_t^*$

$$b_t^j = \frac{\theta^T - s_t + i_t - i_t^*}{\gamma\sigma_T^2} \tag{31}$$

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,

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

$$s_t=i_t-i_t^*+\frac{1}{\left(\frac{N_B}{\omega_j^{B2}\sigma_T^2+(1-\omega_j^B)^2\sigma_j^2}+\frac{N_T}{\sigma_T^2}\right)}\left(\frac{N_B\bar{\theta}^j}{\omega_j^{B2}\sigma_T^2+(1-\omega_j^B)^2\sigma_j^2}+\frac{N_T\theta^T}{\sigma_T^2}+\frac{\omega_j^BN_B}{\omega_j^{B2}\sigma_T^2+(1-\omega_j^B)^2\sigma_j^2}(\theta^T-\bar{\theta}^j\right.$$

The above expression can be simplified to

$$s_t=i_t-i_t^*+\frac{1}{\Gamma}\left(\Gamma_B\bar{\theta}^j+\Gamma_T\theta^T+\omega_j^B\Gamma_B(\theta^T-\bar{\theta}^j)\right) \tag{32}$$

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

$$\frac{\partial s_t}{\partial\theta^T}=\frac{1}{\Gamma}\left(\Gamma_T+\omega_j^B\Gamma_B\right) \tag{33}$$

$$\frac{\partial s_t}{\partial\bar{\theta}^j}=\frac{\Gamma_B}{\Gamma}\left(1-\omega_j^B\right) \tag{34}$$

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

$$\begin{aligned}\frac{1}{\Gamma}\left(\Gamma_T+\omega_j^B\Gamma_B\right)&>\frac{\Gamma_B}{\Gamma}\left(1-\omega_j^B\right)\\ \Gamma_T+\omega_j^B\Gamma_B&>\Gamma_B\left(1-\omega_j^B\right)\\ \frac{\Gamma_T}{\Gamma_B}&>1-2\omega_j^B\end{aligned} \tag{35}$$

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:

$$\begin{aligned}\frac{\Gamma_T}{\Gamma_B}&=\frac{N_T}{N_B}\frac{{\omega_j^B}^2\sigma_T^2+(1-\omega_j^B)^2\sigma_j^2}{\sigma_T^2}\\ &=\frac{N_T}{N_B}\frac{\left(\frac{\sigma_j^2}{\sigma_T^2+\sigma_j^2}\right)^2\sigma_T^2+\left(1-\frac{\sigma_j^2}{\sigma_T^2+\sigma_j^2}\right)^2\sigma_j^2}{\sigma_T^2}\\ &=\frac{N_T}{N_B}\frac{\left(\frac{\sigma_j^2}{\sigma_T^2+\sigma_j^2}\right)^2\sigma_T^2+\left(\frac{\sigma_T^2}{\sigma_T^2+\sigma_j^2}\right)^2\sigma_j^2}{\sigma_T^2}\\ &=\frac{N_T}{N_B}\frac{\sigma_j^2}{\sigma_T^2+\sigma_j^2}\\ &=\frac{N_T}{N_B}\omega_j^B\end{aligned} \tag{36}$$

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

$$
\begin{aligned}
\frac{N_T}{N_B}\omega_j^B &> 1 - 2\omega_j^B \\
\frac{N_T}{N_B} &> \frac{1}{\omega_j^B} - 2 \\
\frac{\sigma_T^2}{\sigma_j^2} &< \frac{N_T}{N_B} + 1 \qquad (37)\\
R &< \frac{N_T}{N_B} + 1 \qquad (38)
\end{aligned}
$$

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.

$$
s_{t+1} - s_t = \beta_0 + \beta_1 f_t - s_t \qquad (39)
$$

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

$$
var(\Delta s_{t+1}) = \beta^2 var(f_t) \qquad (40)
$$

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

$$
\begin{aligned}
\text{var}(\Delta s_{t+1}|I_j, I_T) &= \beta^2 \frac{\sum_{j=1}^{N} var(f_t^j)}{N} \qquad (41)\\
&= \beta^2 \left(\frac{N_B}{N} var(f_t^j) + \frac{N_T}{N} var(f_t^T) \right) \qquad (42)
\end{aligned}
$$

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

$$
\begin{aligned}
var(f_t^j) &= {\omega_j^B}^2 \sigma_T^2 + (1 - \omega_j^B)^2 \sigma_j^2 \qquad (43)\\
&= \frac{\sigma_T^2 \sigma_j^2}{\sigma_T^2 + \sigma_j^2}
\end{aligned}
$$

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:

$$
\begin{aligned}
\text{var}(\Delta s_{t+1}|I_j, I_T) &= \beta^2 \left(\frac{N_B}{N} var(f_t^j) + \frac{N_T}{N} var(f_t^T) \right) \qquad (44)\\
&= \beta^2 \left(\frac{N_B}{N} \frac{\sigma_T^2 \sigma_j^2}{\sigma_T^2 + \sigma_j^2} + \frac{N_T}{N} \sigma_T^2 \right)
\end{aligned}
$$

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:

$$\frac{\text{var}(\Delta s_{t+1}|I_j, I_T)}{\text{var}(\Delta s_{t+1}|I_j)} = \frac{N_B}{N}\frac{\sigma_T^2}{\sigma_T^2 + \sigma_j^2} + \frac{N_T}{N}\frac{\sigma_T^2}{\sigma_j^2} \tag{45}$$

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:

$$\frac{\text{var}(\Delta s_{t+1}|I_j, I_T)}{\text{var}(\Delta s_{t+1}|I_j)} = \frac{N_B}{N}\left(\frac{R}{R+1}\right) + \frac{N_T}{N}R \tag{46}$$

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

$$\begin{aligned} \frac{N_B}{N}\left(\frac{R}{R+1}\right) + \frac{N_T}{N}R &< 1 \\ \frac{N_B}{N}R + \frac{N_T}{N}R(R+1) &< 1 + R \\ \frac{N_T}{N}R^2 &< 1 \\ R &< \sqrt{\frac{N}{N_T}} \\ R &< \sqrt{\frac{N_B}{N_T} + 1} \end{aligned} \tag{47}$$

B Textual Analysis: Supplementary Evidence

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

B.1 Sample of Tweets (by Topic)

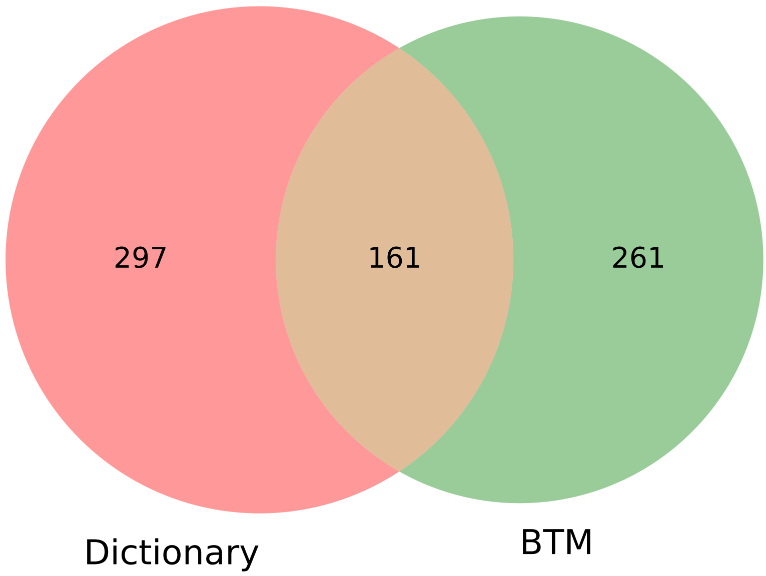
Some Tweets belonging to 3 categories (Macroeconomics Outlook, Exchange Rate, and Trade Policy) are listed

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

Figure A1: Tweets identified by Dictionary approach and BTM approach



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!"

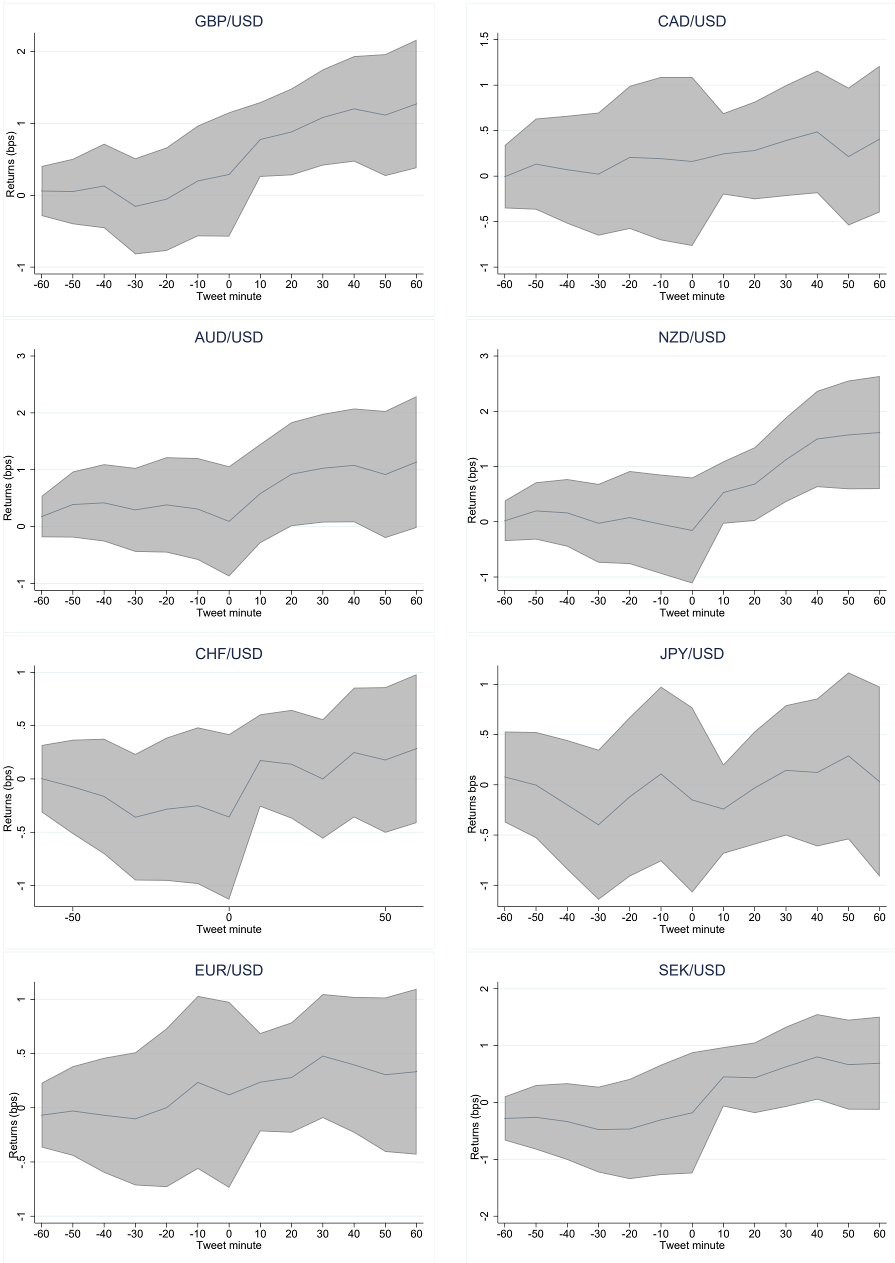
B.3 BTM: Other topic word clusters

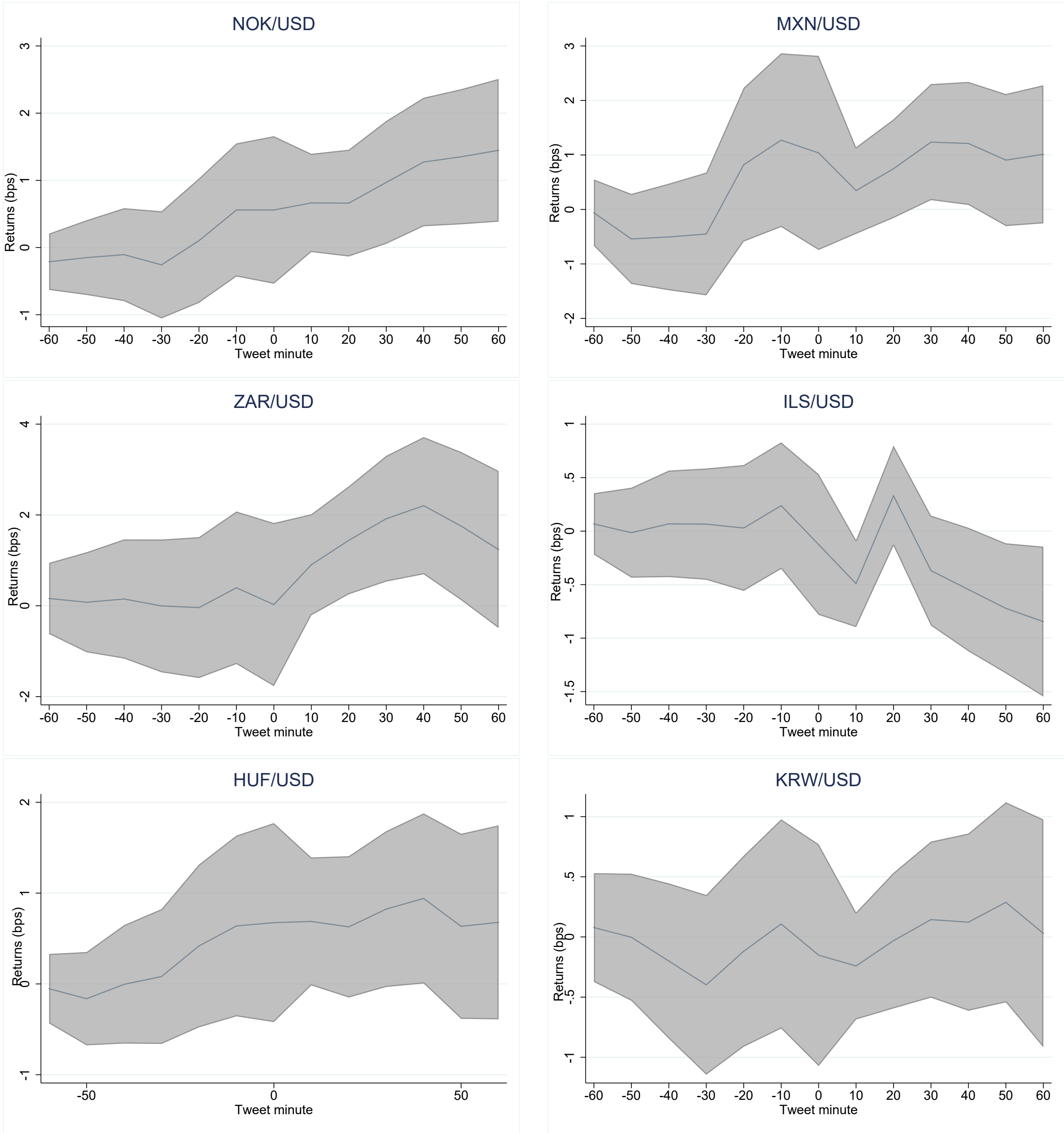
Figure A2: BTM Topic Keywords

The graph reports results from BTM implemented on Tweets. For each topic, the top keywords are reported.

C Event studies: individual currencies

Figure A3: Event study: Cumulative returns by currency





The figure reports the cumulative returns for individual currencies. The y-axis shows the minutes during the event, with 0 being the minute in which a tweet is posted. The negative values on the y-axis are the number of minutes before tweets. The shaded area shows a 95% confidence interval using 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**

Dependent variable is abnormal return, which is constructed as the difference between return at the minute with a tweet and without tweet matched by VIX. The constant is the independent variable of interest (expressed in basis points). The control variables are hourly bid-ask spread, hourly ΔVIX, and FOMC dummy. Hour-of-the-day and day-of-the-week dummies are included in all regressions. Panel A is a 60-minute window and Panel B is a 30-minute window. Standard errors are clustered by currency. t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are hourly between 16^{th} of June 2015 and 20^{th} of August 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 reports event study regressions. The dependent variable is abnormal realized volatility, which is constructed as the difference between volatility at the minute with a tweet and without a tweet matched by VIX. The control variables are hourly bid-ask spread, hourly ΔVIX, and FOMC dummy. Hour-of-the-day and day-of-the-week dummies are included in all regressions. Panel A is a 60-minute window and Panel B is a 30-minute window. Standard errors are clustered by currency. t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are hourly between 16^{th} of June 2015 and 20^{th} of August 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 A4. 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.

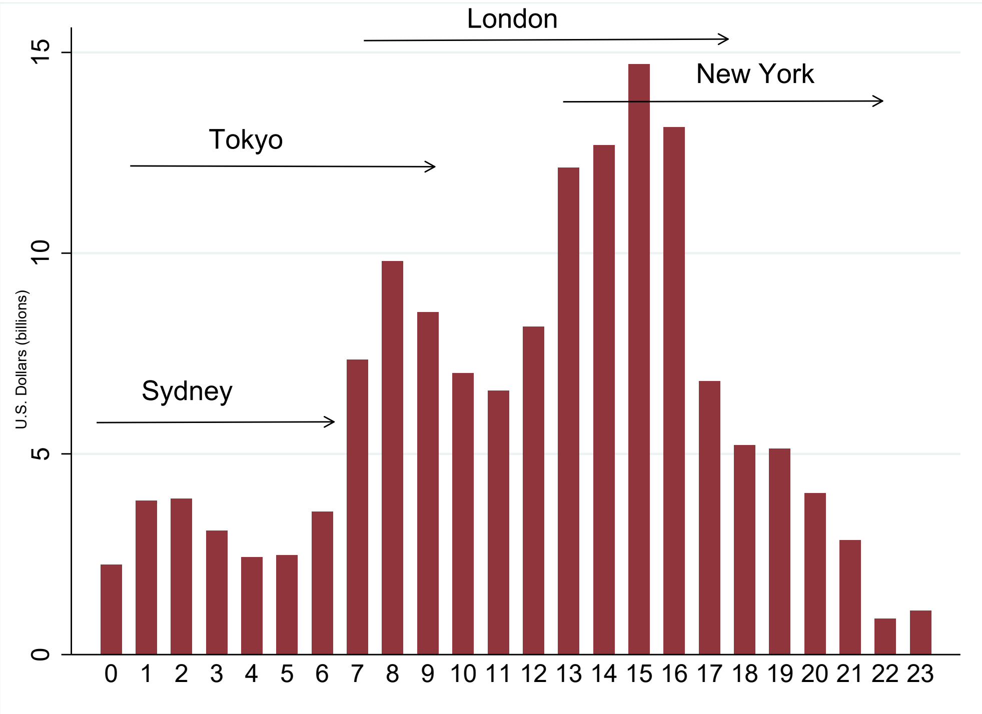


Figure A4: Spot FX Trading Volume

The figure reports the average hourly FX spot volume (in USDs) throughout a business trading day (London Time). The average is constructed across all trading days in our sample, from 16th June 2015 to 20th August 2019. Volume is the sum of 14 pairs of currency included in our sample. The number shown on the x-axis is the closing time based on London time. Arrows show market trading hours in London (from 7am to 4pm), New York (from 12pm to 9pm), Sydney (from 9pm to 6am) and Tokyo (from 11pm to 8am).

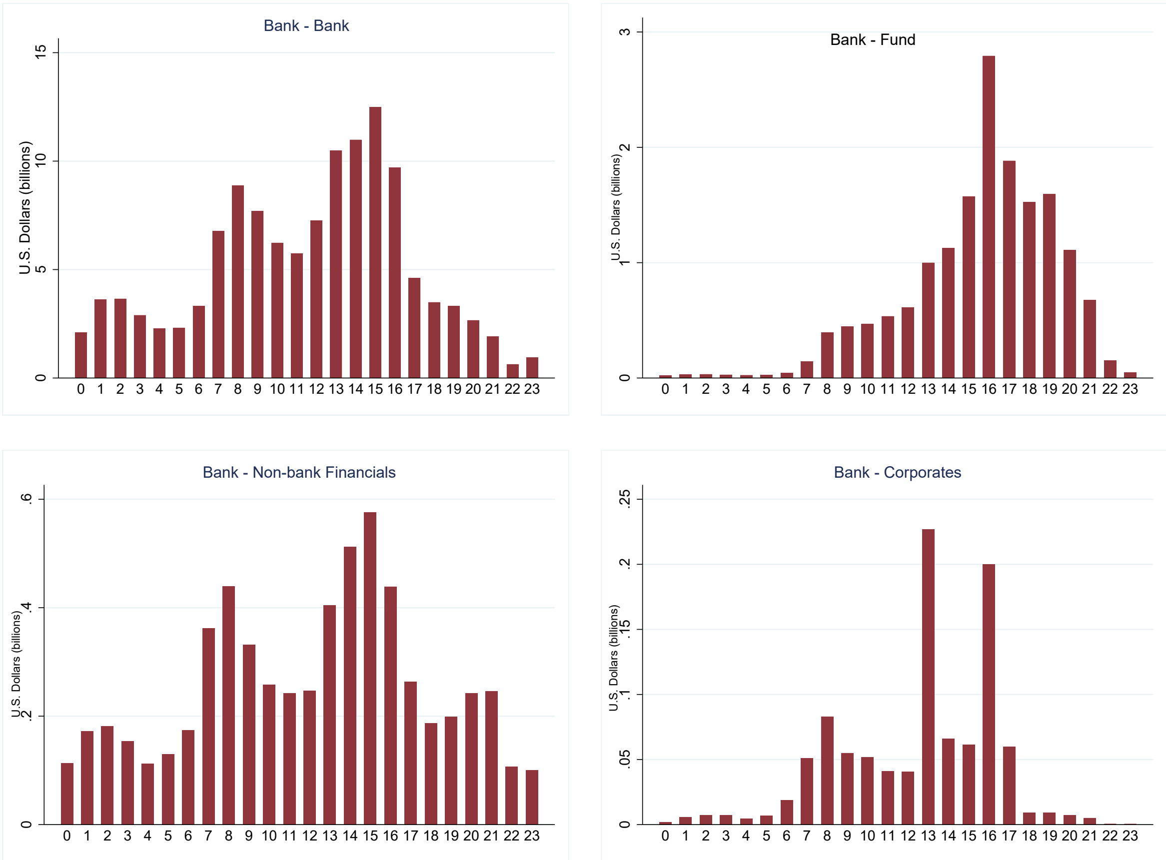
We classify trading volume in the following four groups: transactions between the bank and funds, bank and non-bank financial institutions, bank and corporates, and inter-bank transactions. However, we exclude transactions between two market makers (inter-dealer transactions) or two price takers from our dataset. Figure A5 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.[21]

21. 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 A5: Spot FX Trading Volume by participants



The figure reports the average hourly FX spot volume (in USDs) throughout a business trading day (London Time) by different groups of market participants. The average is constructed across all trading days in our sample, from 16th June 2015 to 20th August 2019. Volume is the sum of 14 pairs of currency included in our sample. The number shown on the x-axis is the closing time based on London time.

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

This table reports panel regressions results for the estimation of Tweets hour dummy on FX Trading Volume. The control variables are hourly bid-ask spread, hourly ΔVIX, and FOMC dummy. Hour-of-the-day and day-of-the-week dummies are included in all regressions. In Panel A, the dependent variable is the trading volume between the market maker bank and the price taker bank. In Panel B, the dependent variable is the trading volume between the market maker bank and the price taker fund. In Panel C, the dependent variable is the trading volume between market maker bank and price taker non-bank financials. In Panel D, the dependent variable is the trading volume between market-maker banks and price-taker corporates. Standard errors are clustered by currency. t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are hourly between 16^{th} of June 2015 and 20^{th} of August 2019.

	Panel A. Dependent variable: Bank - Bank Trading Volume				*Panel B. Dependent variable*: Bank - Fund Volume			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Volume_t	Volume_t	Volume_t	Volume_t	Volume_t	Volume_t	Volume_t	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)
$\text{BidAskSpread}_{t-1}$		-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)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Volume_t	Volume_t	Volume_t	Volume_t	Volume_t	Volume_t	Volume_t	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)
$\text{BidAskSpread}_{t-1}$		-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%