The Information Content of Trump Tweets and the Currency Market

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Abstract

Using textual analysis, we identify the set of Trump tweets that contain information on macroeconomic policy, trade, or exchange rate content. We find that informative Trump tweets reduce speculative trading in foreign exchange markets, with a corresponding decline in trading volume, volatility, bid-ask spreads, and induce a positive bias in returns reflecting Trump's (optimistic) views on the U.S. economy. Two-thirds of his informative tweets are optimistic. This bias serves as a diversion strategy from negative media coverage. We rationalize these results within a model of Trump tweets revealing economic content as a public signal that reduces disagreement among speculators.

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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 to the public. Although he is not the first U.S. president to be active on social media, his personal Twitter account attracts enormous attention at an unprecedented level due to various aspects, such as the frequency, content, and language of his tweets.[1] The figure of 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. Although the information content of these tweets is a matter of dispute, a growing area of research is identifying the effects of his tweets on financial markets.[2] For example, research by Bank of America suggests that days with more than 35 Trump tweets see negative returns of the Dow Index. The JPMorgan 'Volfefe' index, on the other hand, tracks how Trump tweets move the bond markets. In contrast, this paper focuses on the information content of Trump tweets related to the macroeconomic outlook and trade on the foreign exchange (FX) market, which is the most traded financial market worldwide (BIS, 2019).[3]

Trump tweets provide a novel experiment to study the effects of an unexpected public signal on trading, volatility and returns in the currency market. Exchange rates in principle aggregate macroeconomic information on future fundamentals of a country, yet the link between economic fundamentals and foreign exchange markets is difficult to connect in a high-frequency environment. To shed light on the effects of Trump tweets on exchange rates, we use textual analysis to filter the set of Trump tweets that contain information on future macroeconomic fundamentals relevant for FX market participants. This includes tweets on trade, such as tariffs with China or Mexico, tweets on U.S. employment figures, or tweets influencing the financial market perceptions of interest rates (e.g., Bianchi, Kung, and Kind, 2019). In a market with heterogeneous private information in spot rate expectations, a common public signal can reduce investor disagreement in the FX market (e.g., Ranaldo and Santucci de Magistris, 2019; Kruger, 2020). We hypothesize Trump tweets cause a reduction in investor disagreement, and in turn, a decline in FX volume, volatility and bid-ask spreads. Spot returns during Trump tweet hours reflect an (optimistic) bias regarding the future macroeconomic fundamentals of the U.S. and foreign economies.

[1] His Twitter account has been permanently suspended in January 2021 because of his tweets after the U.S. Capitol attack.

[2] https://www.washingtonpost.com/technology/2020/05/26/trump-twitter-label-fact-check/

[3] https://www.bis.org/statistics/rpfx19_fx.pdf

We next investigate whether Trump chooses to reveal information content about macro economy and trade randomly or his public signals have an ulterior motive to distract the media from negative press. In particular, we test the media diversion hypothesis using media coverage about Trump's Mueller investigation (Lewandowsky, Jetter, and Ecker, 2020) and its link to the optimistic bias about the future state of the U.S. economy.

To explain the mechanism, we start with a model of heterogeneous private information and Trump tweets as a public signal in the FX market. The market is populated by a set of speculators, each with their own private signal on the valuation of the future spot rate. Investors then update their private signal based on the Trump tweet, which we assume is known to all traders. There are two distinct types of speculators in the model: (rational) Bayesian investors who update their prior based on the information content of the Trump tweet, and (irrational) Trump followers who fully adopt the Trump tweet. Our analysis generates three predictions. First, as investors trade on a common signal, there is a decline in the dispersion of investor beliefs on valuations of the future spot rate. We show that a rise in the share of Trump followers leads to a decline in investor disagreement, and in turn a decline in the volume of trading in the currency market. Second, the Trump tweet leads to a decline in exchange rate volatility if the tweet is more informative than the private signal. If speculators rely on the public information via informative Trump tweets over their private signals, the corresponding reduction in asymmetric information leads to a reduction in bid-ask spreads. Finally, we show that Trump tweets induce a bias in spot returns reflecting differences between the (optimistic) views of Trump and the speculators on the future valuation of macroeconomic fundamentals.

Turning to the data, we first conduct a textual analysis on 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 Macro and Trade tweets. The first approach follows keywords by topics outlined in Baker, Bloom, Davis, and Kost (2019). Second, we use the topic modelling approach developed by Yan, Guo, Lan, and Cheng (2013) to filter out tweets about macroeconomics outlook, trade policy, and exchange rate topics. This approach is suitable for an analysis of short texts and hence ideal for the analysis of tweets. To our knowledge, we are the first paper to use this approach in the finance literature.

We proceed to link Trump tweets to outcomes in the FX market, and construct our measures of FX market activity. For FX volume, we use CLS, a real time gross settlement system which is the largest available dataset on trading volume across a wide range of market participants, e.g., banks, funds and corporations, for up to 16 bilateral pairs at an hourly frequency (e.g., Hasbrouck and Levich, 2019). We combine our hourly volume data with currency spot rates from Thomson Reuters Tick History. In addition, we have data on bid-ask quotes for a series of banks, and construct intraday measures of volatility based on high frequency changes in the spot rate.

Our main empirical results test a panel specification with the outcome variables of FX volume, volatility, bid-ask spreads and spot returns. Explanatory variables include an hourly dummy for a macro or trade tweet, and controls for hour-of-day, day-of-week, scheduled monetary announcements, fundamentals in financial markets such as the VIX index. We find statistical evidence that Tweet hours are associated with a decrease in FX trading volume. This result holds for all groups in our sample, with the biggest decline observed for banks, non-bank financial institutions and funds. Second, we find declines in our measure of intraday FX spot volatility and bid-ask spreads around Trump tweet hours, indicative of a reduction in investor disagreement during tweet hours. Third, we identify systematic effects of Trump tweets on FX spot returns. The dollar tends on average to appreciate with respect to major bilateral pairs during Trump tweet hours. We find significant cumulative returns in the hour following the tweet for an equal weighted average return of all 16 bilateral pairs, as well as a USD ETF index. This appreciation is consistent with the nature of Trump tweets, that reflect typically his positive views on the U.S. economy (relative to other countries), and trigger a protectionist stance on trade policies. We show that Trump tweets are more likely to be informative following the hours with news about Mueller investigation. Importantly, only positive tweets (optimistic bias about the U.S. economy) are a reaction to the negative press coverage in the previous hour.

In robustness exercises, we show that the results hold when controlling for a set of macroeconomic releases that occur on the day of the tweet. This rules out an alternative view that the effects of Trump tweets are due to the reaction of news that occurred earlier in the day. We also provide a placebo test to show that Trump tweets in the set of non-macro/trade topics do not have significant effects on FX markets. Finally, we test the proposed mechanism through which Trump tweets cause a decline in trading volume and volatility. In a FX market populated by speculators with heterogeneous information, Trump tweets result in a reduction in investor disagreement. We test this mechanism by constructing a proxy for FX disagreement from options data. We hypothesize that during Trump tweet hours, the common signal reduces the dispersion in the future valuation of exchange rate fundamentals, and therefore reduces the measure of disagreement based on the options pricing.[4] In line with our hypothesis, we find a statistically significant reduction in our measured proxy for investor disagreement during Trump tweet hours.

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 volume, volatility and returns. Section 4 outlines the data. Section 5 discusses our empirical findings. Section 6 concludes.

2 Related Literature

The paper contributes to a growing literature on studying the effects of Twitter content on financial markets. Focusing on the stock market, studies examine the relationship between Twitter sentiment and the stock market returns and volatility of stock indices (Bollen, Mao, and Zeng, 2011; Mittal and Goel, 2012; Behrendt and Schmidt, 2018), the effects of company-specific tweets (e.g., Sprenger, Tumasjan, Sandner, and Welpe 2014, Bartov, Faurel, and Mohanram 2018), and the impact of twitter sentiment around FOMC announcements on stock returns (Azar and Lo, 2016). Focusing on the currency market, Gholampour and Van Wincoop (2017) examine investor tweets regarding the Euro/dollar exchange rate and classify them into positive, negative, and neutral opinions. They create a trading strategy based on this sentiment and find that the Sharpe ratio of this strategy outperforms that of carry trade.[5]

Turning to Trump tweets, there are a number of recent papers on studying the effects of Trump tweets on the stock market, interest rate futures and the currency market. The effects of Trump tweets on publicly traded firm stock returns and volatility (e.g., Ge, Kurov, and Wolfe, 2018; Born, Myers, and Clark, 2017; Ajjoub, Walker, and Zhao, 2019; Juma'h and Alnsour, 2018; Colonescu et al., 2018; Abdi, Kormanyos, Pelizzon, Getmansky Sherman, and Simon, 2021; Scharnowski, 2021), tweets on threatening central bank independence signalling a lower future path of the Federal Funds rate (Bianchi et al., 2019), and tweets with a negative stance on Mexico-U.S. trade on the Peso/Dollar exchange rate (Benton and Philips, 2018), tweets on the China-US trade dispute (Ferrari, Kurcz, and Pagliari, 2021), and the role of tweets on macroeconomic policies to divert attention from media articles on

[4]The measure of options disagreement we use is the absolute value of the moneyness ratio based on Salomé (2020). The metric is intuitively measuring the difference between the strike and current spot price after controlling for volatility and time to expiry.

[5]In related work, Filippou, Gozluklu, Nguyen, and Taylor (2020) construct a measure of U.S. populist rhetoric –using a broad set of newspapers– and find that currencies which perform well (badly) when U.S. populist rhetoric is high offer low (high) currency excess returns. In addition, Filippou, Taylor, and Wang (2020) show that FX news sentiment is a strong negative predictor of the cross-section of currency returns.

the Mueller report (Lewandowsky et al., 2020). Abdi et al. (2021) conduct a textual analysis of Trump tweets and investigate whether Trump tweets contain information relevant for stock prices. The authors find evidence that Trump tweets are responding to information earlier in the day, and information effects for a subset of Trump tweets on the NAFTA trade agreement and the US China trade war, which is consistent with our hypothesis that Trump tweets with macroeconomic and trade content are more informative. Benton and Philips (2018) and Ferrari et al. (2021) find that Trump tweets on Mexico-U.S. trade relations and China-US Trade tensions cause an appreciation of the U.S. dollar. Our results extend their analysis by conducting a textual analysis to identify the macroeconomic and trade content of Trump tweets. This will include tweets on how the Federal Reserve should set interest rates, trade tensions with Korea, the Middle East and Mexico. Second, we examine the effects of informative trading on a number of metrics measuring returns and liquidity for a larger wide basket of currencies. Third, through a model, we illustrate how Trump tweets can affect spot returns due to differences in expectations of future exchange rate fundamentals between Trump and investors.

The second major literature our paper relates to is on the microstructure of currency markets. Information asymmetry in currency markets have 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). More recently, a number of papers have examined the information content of FX trading volume using CLS data (e.g., Fischer and Ranaldo, 2011; Hasbrouck and Levich, 2019; Cespa, Gargano, Riddiough, and Sarno, 2021). On the theory side, our paper speaks to microstructural models of the FX spot market that connect trading and volatility through a set of informed and "noise" traders, with heterogeneous information on the fundamentals of the exchange rate (e.g., Jeanne and Rose, 2002; Bacchetta and Van Wincoop, 2006; Gholampour and Van Wincoop, 2017). We adapt the model framework to include a discussion of the introduction of a public signal, the Trump tweet, on spot volume and volatility. Traders are differentiated in how they update their signal based on the Trump tweet, with two sets of agents, rational Bayesian agents, and irrational Trump followers, that have differing weights on private and public information.

Finally, we make a connection between FX market microstructure and the literature on investor disagreement in financial markets. The theory of investor disagreement assumes that investors have heterogeneous priors on the payoff of the asset (Hong and Stein, 2007). Differences in investor information sets translate to disagreement on the future payoff, and can induce trading and increase volatility, a finding consistent with studies in both stock and currency markets (e.g., Ranaldo and Santucci de Magistris, 2019; Kruger, 2020). On this front, our paper is closely related to Ranaldo and Santucci de Magistris (2019), which also has a model of FX trading and heterogeneous information, and use an unexpected monetary policy event of the Swiss National Bank in 2015 to show how increased investor disagreement translated to increases in volume and volatility. We find complementary evidence in our paper through an alternative event: using the information content of Trump tweets. We hypothesize that Trump tweets cause a reduction in investor disagreement, which in turn leads to less trading, lower volatility, and reduced asymmetric information through lower bid ask spreads.

3 Model

We derive a simple model of trading in the FX market with public information. Each investor has a prior of the exchange rate in one period from now. These traders follow a similar functional form to 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, the Trump tweet, is a common signal interpreted by all speculative traders. A rational Bayesian agent combines their prior with the public signal. The posterior distribution of the Bayesian agent's signal is a weighted average of the public and private information, with the weights a function of the relative precision of each signal. In addition to Bayesian agents, a fraction of traders are characterized as Trump followers, and update their prior to put a weight of one on the public signal. Using this setting, we examine the impact of the public signal on the volume of trading, volatility and spot returns. Our key mechanism is that the public signal induces a decline in investor disagreement, a channel that can lead to a decline in trading volume and volatility, consistent with models of investor disagreement in FX and stock markets (Ranaldo and Santucci de Magistris, 2019; Kruger, 2020).

Exchange rates

Consider a market of N agents with heterogeneous priors on the future payoff of the exchange rate s_t dollars per unit of foreign currency.[6] The expectations of the future exchange rate s^j_{t+1} for agent j is defined in equation 1. The expectation conditional on the private signal is θ^j. The precision of the private signal is governed by the variance σ^2_j.

[6]Under this notation, an increase in s_t implies a depreciation of the dollar.

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

Trump tweets

We characterize the Trump tweet in equation 2 as a public signal known to all investors. The arrival of the public signal is unexpected. For example, tweets can occur at any time of the day, unlike scheduled monetary announcements of the central bank. The public tweet has expectation θ^T, with precision of the public signal governed by σ^2_T. For our analysis, we assume the public and private signal are uncorrelated, $cov(\epsilon^T, \epsilon^j) = 0$.

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

An important assumption we make is that the Trump tweet aggregates private information, and is equal to the average of the investor priors, $\theta^T = \frac{1}{N}\sum_{j=1}^N \theta^j$. Critically, the information aggregation of Trump is not known in advance by Bayesian agents.[7]

Bayesian agents

A rational agent will update their prior based on the public signal. Their expectation, conditional on the public and private information, is a weighted average of the public and private signal. Let us denote the weights on the public and private signal for a Bayesian agent as ω^B_j and $1 - \omega^B_j$ respectively, in equation 3.

$$\mathbb{E}[s^j_{t+1} | I_j, I_T] = \omega^B_j \theta^T + (1 - \omega^B_j)\theta^j \tag{3}$$

A Bayesian agent will update their prior based on the relative precision of the public and private signal. Formally, we define the weight on the public signal, $\omega^B_j = \frac{\sigma^2_j}{\sigma^2_T + \sigma^2_j}$, in equation 4.

[7] If we model multiple periods traders will learn that the Trump signal is aggregating private information, causing Bayesian agents to put a weight of 1 on the Trump signal. Therefore all agents would be Trump followers in a multi-period setting. We avoid this problem by assuming a 2 period model, that is, the Bayesian agents only form an expectation today (time t) of the payoff in period $t + 1$.

$$\mathbb{E}[s_{t+1}^j | I_j, I_T] = \frac{\sigma_j^2}{\sigma_T^2 + \sigma_j^2}\theta^T + \frac{\sigma_T^2}{\sigma_T^2 + \sigma_j^2}\theta^j \tag{4}$$

If the relative precision of the public signal is $\frac{\sigma_T^2}{\sigma_j^2} \to 0$, the Trump tweet is more precise, and the investor's weight on the public signal approaches one. Conversely, if the public signal is noisy relative to the private signal, the investor puts a weight of zero on the public signal.

Trump Followers

As well as Bayesian agents, a subset of agents are characterized as Trump followers. These traders adopt the Trump tweet as their complete signal. This is defined formally in equation 5.

$$\mathbb{E}[s_{t+1}^j | I_j, I_T] = \theta^T \tag{5}$$

In the context of our model, an increase in the number of Trump followers reduces investor disagreement in the FX market about the future spot rate. We can see this visually in Figure 1, which plots the distribution of investor priors, and the posterior distribution of each agent type. Under the assumption that the Trump tweet is centered at the distribution, if a fraction of agents are Trump followers, the distribution of posteriors is now more compact around θ_T. The reduction in investor disagreement reduces the dispersion in investor expectations of the future spot rate, with implications for the amount of trading and volatility of the spot rate, consistent with related literature on the link between investor disagreement and volume and volatility in FX and stock markets (Ranaldo and Santucci de Magistris, 2019; Kruger, 2020).[8]

Investor optimization

The investor maximizes exponential utility over their next period wealth, $U_t = -e^{-\gamma W_{t+1}}$, and invests entire wealth in foreign currency bonds $W_{t+1} = \rho_t^j b_t^j$. The excess return made

[8] Ranaldo and Somogyi (2021) has similar predictions to our model, and show that an increase in the dispersion of trader expectations of the future payoff lead to an increase in trading and volatility in the currency market. We depart from their framework in showing the channels through which a public signal can generate a decline in information disagreement.

on the foreign currency bond for a Bayesian agent is defined in equation 6. Similarly, the excess return on the domestic bond for a Trump follower is given by equation 7.

$$\rho_t^{j,B} = \omega_j^B s_{t_1}^T + (1-\omega_j^B) s_{t+1}^j - s_t + i_t^* - i_t \tag{6}$$

$$\rho_t^{j,T} = s_{t+1}^T - s_t + i_t^* - i_t \tag{7}$$

The optimization problem of the investor is to maximize utility subject to all wealth invested in domestic bonds. This is given by a mean-variance problem, maximizing equation 8 subject to the constraint on next period wealth in equation 9.

$$\max_{b_t^j} \qquad L = \mathbb{E}[W_{t+1}^j] - \frac{1}{2}\gamma Var(W_{t+1}^j) \tag{8}$$

subject to:

$$W_t^j = \rho_t^j b_t^j \tag{9}$$

Solving for the optimal level of bond demand by Bayesian agents in equation 10, and optimal bond demand by Trump followers in equation 11.

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

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

Market clearing

Given a total of N agents, let us define N_B as the number of Bayesian agents and N_T denote the number of Trump followers. In equilibrium, market clearing requires the net bond supply to be equal to zero, giving rise to equation 12.[9]

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

Substituting the formulae for optimal bond holdings by Bayesian agents and Trump followers into the market clearing condition yields equation 13.

$$\sum_{j\in N_B} \frac{\omega_j^B \theta^T + (1-\omega_j^B)\theta^j - s_t + i_t^* - i_t}{\omega_j^{B^2}\sigma_T^2 + (1-\omega_j^B)^2\sigma_j^2} + \sum_{j\in N_T} \frac{\theta^T - s_t + i_t^* - i_t}{\sigma_T^2} = 0 \tag{13}$$

Under the simplifying assumption that the Trump tweet is equal to the average of investor priors, $\theta^T = \frac{1}{N}\sum_{j=1}^{N} \theta_j$, the equilibrium spot exchange rate is given by equation 14.

$$s_t = \theta^T + i_t^* - i_t \tag{14}$$

Asset pricing view of the exchange rate

We now determine the equilibrium exchange rate based on equilibrium in money markets, following Jeanne and Rose (2002). First we use simple money demand functions for home and foreign in equations 15 and 16.

$$m_t - p_t = -\alpha i_t + \eta y_t \tag{15}$$

$$m_t^* - p_t^* = -\alpha i_t^* + \eta y_t^* \tag{16}$$

[9] This is similar to the market clearing condition in Bacchetta and Van Wincoop (2006) and Gholampour and Van Wincoop (2017), in which the net bond demands of informed and liquidity (noise) traders are equal to zero. The deviation in our model is the distinction between informed traders and Trump followers.

Imposing purchasing power parity in equation 17, 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 18.

$$s_t = p_t - p_t^* \tag{17}$$

$$s_t = m_t - m_t^* + \alpha(i_t - i_t^*) - \eta(y_t - y_t^*) \tag{18}$$

Let us denote future fundamentals f_t in equation 19.

$$f_t = \frac{m_t - m_t^*}{1+\alpha} - \frac{\eta(y_t - y_t^*)}{1+\alpha} \tag{19}$$

We now obtain an expression for s_t in terms of fundamentals m_t and y_t, and the expected future spot rate, which is a weighted average of the Trump tweet and the public signal.

$$s_t = f_t + \frac{\alpha}{1+\alpha}\mathbb{E}_t[s_{t+1}] \tag{20}$$

Iterating forward, we obtain equation 21, which states that the spot rate is a function of expected future fundamentals (Engel and West, 2005; Froot and Ramadorai, 2005).

$$s_t = f_t + \sum_{s=1}^{\infty}\left(\frac{\alpha}{1+\alpha}\right)^s \mathbb{E}_t[f_{t+s}] \tag{21}$$

We now present three predictions on the introduction of the Trump tweet on the volume of trading, the conditional volatility of the spot exchange rate, and the bias of spot returns.

Prediction 1: Trading volume decreases as the share of Trump followers increases.

Define aggregate bilateral FX volume as $V_{FX} = \frac{1}{2}\sum_{j=1}^{N}|b_t^j|$. *The effect on FX volume is given by equation 22. All else equal, a higher fraction of Trump followers will lower trading volume.*

$$\frac{V_{FX}|I_j, I_T}{V_{FX}|I_j} = \frac{\sum_{j \in N_B} |\frac{\theta^j - \theta^T}{\sigma_j^2}|}{\sum_{j \in N_B} |\frac{\theta^j - \theta^T}{\sigma_j^2}| + \sum_{j \in N_T} |\frac{\theta^j - \theta^T}{\sigma_j^2}|} < 1 \tag{22}$$

Proof: see appendix.

The ratio of trading volume is then proportional to the fraction of Bayesian agents. The intuition is that an increase in the fraction of Trump followers leads to a reduction in investor disagreement about the future spot rate. The reduction in disagreement, in turn, causes a decline in net trading as a larger fraction of investors have exchange rate expectations that yield zero excess returns, and zero trading in the currency market.

Mathematically, we can see show the reduction in investor disagreement by examining the bond holdings of Trump followers and Bayesian agents. Assuming the Trump tweet is equal to the average of investor priors, Trump followers earn a zero expected excess return. Therefore, their optimal bond holdings in equilibrium are zero, and they do not trade in the market. In contrast, the bond holdings of Bayesian agents in the equilibrium with public information is equal to their bond holdings without the public signal.

Prediction 2: Conditional variance of the future spot rate is lower if the Trump tweet is informative.

The volatility of the spot exchange rate conditional on private and public information is reduced if the share of Bayesian agents is less than the upper bound given by equation 24. This depends on the relative precision of the Trump signal $R = \frac{\sigma_T^2}{\sigma_j^2}$ and the relative share of Bayesian agents $\frac{N_B}{N}$.

$$\frac{var(s_{t+1|I_j, I_T})}{var(s_{t+1|I_j})} = R\left(1 - \frac{N_B}{N}\frac{R}{1+R}\right) \tag{23}$$

$$\frac{var(s_{t+1|I_j, I_T})}{var(s_{t+1|I_j})} < 1 \quad \text{if} \quad \frac{N_B}{N} > \frac{R^2 - 1}{R^2} \tag{24}$$

Proof: see Appendix

The effect of the Trump tweet on the conditional variance of the spot rate depends on the information content of the signal. If the Trump signal is more precise than the private signal, the variance of the future spot rate for Bayesian agents and Trump followers are always lower in the equilibrium with public information. Mathematically, the threshold $\frac{N_B}{N} > 0 > \frac{R^2-1}{R^2}$ is satisfied for any fraction of Bayesian agents when the public signal is relatively more precise, $R < 1$.

If the Trump tweet does not have information content, and the public signal is imprecise, the effect of spot rate volatility conditional on the public and private signal is ambiguous. While there is still a decline in conditional variance for Bayesian agents, Trump followers now experience an increase in spot rate volatility conditional on the public signal. Mathematically, there is a decline in conditional volatility of the spot rate if and only if the share of Bayesian agents is sufficiently high, given by the threshold in equation 24.

If Trump tweets are informative, more Bayesian agents will rely on public information over their private signals, which in turn should lead to a reduction in information asymmetry in the currency market. We conjecture that the decline in information asymmetry leads to dealers quoting smaller bid-ask spreads, as they are more willing to take the other side of trades based on public information. Therefore, an informative public signal via Trump tweets should reduce not only the dispersion of investor beliefs on the future spot rate, but also bid-ask spreads in the FX market.[10]

Prediction 3: An informative Trump tweet affects FX spot returns due to a bias between the Trump tweet and speculators' expectations.

Define the exchange rate fundamental $f_t = \frac{m_t - m_t^*}{1+\alpha} - \frac{\eta(y_t - y_t^*)}{1+\alpha}$. *The spot rate with the introduction of the Trump tweet is defined in equation 25. The dollar can appreciate due to a bias between Trump expectations of future fundamentals and expectations of the average speculator.*

$$s_{t|I_T,I_j} - s_{t|I_j} = \underbrace{\frac{w_j^B N_B + N_T}{N}}_{\text{public signal adoption}} \sum_{s=1}^{\infty} \left(\frac{\alpha}{1+\alpha}\right)^s \underbrace{\left(\mathbb{E}_t[f_{t+s}^T] - \frac{1}{N}\sum_{j \in N} E[f_{t+s}^j]\right)}_{\text{bias}} \tag{25}$$

Proof: see Appendix

[10] While we do not model bid-ask spreads explicitly, based on the theory in Glosten and Milgrom (1985), the bid-ask spread is a positive function of the share of informed traders in the market. Therefore, a decline in the share of informed traders, due to adoption of the public signal by Trump followers, reduces the effective share of informed (private) traders, and in turn leads dealers to quote smaller bid-ask spreads. Alternatively, one could also rationalize the reduction in bid-ask spreads in an inventory model with competitive dealers where the bid-ask spread is a function of the dealers' risk aversion, asset volatility, aggregate trade size and the number of dealers (De Jong and Rindi, 2009).

The change in the spot rate conditional on public information is a weighted average of the bias in Trump's expectations of future fundamentals. This is equal to the difference between the average of investor priors and the Trump signal for Trump followers. The bias is weighted by the share of agents that adopt the public signal, and is given by the $\frac{w_j^B N_B + N_T}{N}$. This is increasing in the weight given by Bayesian agents to the public signal. We illustrate the bias in fundamentals in Figure 1. The average of investor priors is given by $\bar{f_{t+s}}$, and Trump's prior of the future fundamental is given by f^T_{t+s}. The posterior distribution of Trump followers and Bayesian agents shifts toward Trump expectations, and this causes a change in the spot exchange rate based on equation 21.[11]

The bias between Trump's exchange rate fundamentals and the fundamentals of speculators causes a change in the spot exchange rate. We can further decompose the direction of the bias into differences between expectations of future fundamentals, output growth and the money supply. For example, if growth expectations at home (U.S.) are systematically higher for the Trump tweet, $\mathbb{E}_t[y^T_{t+s}] > E_t[y^j_{t+s}] \forall s = 0, 1, 2,.$ This implies the bias will be negative, causing an appreciation of the U.S. dollar. Similarly, tweets that imply an increase in trade barriers and protectionism imply higher tariffs, a relative contraction in foreign output growth, and an appreciation of the dollar spot exchange rate. We test this empirically by examining spot returns during Trump tweets, with respect to tweets with macroeconomic and trade content.

[11] Note that we are assuming a bias in investor priors on the future macroeconomic fundamentals. This relaxes the assumption on the prior of the Trump signal being equal to the average of investor priors, $\theta^T = \frac{1}{N}\sum_{j=1}^{N} \theta_j$.

4 Data

4.1 Donald Trump's Tweets

We obtain an archive of Donald Trump's tweets from http://www.trumptwitterarchive.com, which collects all tweets from account @realDonaldTrump. We are interested in the period starting from June 16 2015, as it is the day when Donald Trump announced his presidential campaign. Our sample ends in August 20 2019. During this period, there are 17,865 tweets posted from his account in total. As expected, there are various topics covered in these tweets. [12]

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 bi-term topic modelling approach.[13] 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 foreign exchange 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 macroeconomics outlook, trade policy, and exchange rate categories. Term sets in this dictionary are constructed by careful audit and validation with a large sample of newspapers 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]

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

[12] 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").

[13] 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.

intended (false positives). We are left with a sample of 458 tweets.[14] In particular, there are 218 tweets about trade, 247 tweets about macroeconomics outlook, and 6 tweets about exchange rates. A sample of tweets can be found in Table B in the Appendix.

4.1.2 Bi-term topic modelling (BTM) approach

BTM is a topic modelling approach developed by Yan et al. (2013) to address shortcomings associated with conventional topic modelling approaches such as LDA and LSI when it comes to discovering content of short texts. To the best of our knowledge, we are the first to employ this method of textual analysis in the finance literature.

Two sets of input are required from BTM approach. The first is the collection of words, which is the corpus. We apply BTM approach on our full sample of tweets after these tweets are properly cleaned with standard text-cleaning procedures, such as lower capitalization, removing numbers and English stop words. The second input required is the number of topics, which we set as 9.[15]

Two sets of output are generated from BTM algorithm. The first set of output includes the list of top keywords in each topic and the respective probabilities of observing each word in the topic. For each topic n, there is a set of vectors $\hat{\beta}_n = [\hat{\beta}_{n,1},..., \hat{\beta}_{n,J}]$', in which $\hat{\beta}_{n,j}$ is the probability that the word j belongs to topic n. A full list of top keywords for all 9 topics can be found in Figure A1 in the Appendix. We summarise the keywords for the two topics we identify as having relevant information content in Figure 2a and 2b. We classify the keywords in Figure 2a as the trade topic, with keywords such as trade, tariff, china, dollar, deal. Similarly, the keywords in Figure 2b refer to the macroeconomic topic. This contains keywords such as job, tax, number, economy, market. These are the 2 out of 9 topics of our interest as they are directly relevant for the FX markets.

[FIGURE 2a and FIGURE 2b ABOUT HERE]

Now that we have identified the keywords in each topic, we use a second set of output 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

[14] Retweets are excluded from the sample

[15] The choice of the optimal number of topics depends on key tradeoffs between interpretation and goodness of fit (Chang, Gerrish, Wang, Boyd-Graber, and Blei, 2009; Hansen, McMahon, and Prat, 2018). For example, in applying probabilistic topic modelling, a lower number of topics increases the interpretation of the topics, whereas a larger number of topics leads to better goodness-of-fit of the model. Our choice of 9 topics is the maximum number of topics which still offers an intuitive interpretation of trade and macroeconomic content.

is a probability associated with Trade or Macroeconomics topics being at least 30%.[16] We then also check all these Tweets to manually to remove false positives, leaving us with a filtered set of 181 Trade and 242 Macroeconomics tweets.

4.1.3 Combined Tweets identified by dictionary approach and BTM approach

We combine all tweets identified by dictionary approach and BTM approach as carrying relevant information for the FX markets. There are occasions when multiple relevant tweets are posted at the same hour. This leaves us with 506 hours with relevant tweets in total. We merge the tweets data at an hourly frequency with FX order flow and indicative quotes data. We summarise the distribution of these tweets across day of the week, and hour of the day based on London time is shown in Panel A and Panel B of Figure 3. In Panel C and Panel D of the same figure, we report these patterns for all tweets posted during the sample period.

[Figure 3 ABOUT HERE]

It can be seen that tweets are distributed relatively equally across all days of the week. It means that a number of tweets are posted during the weekend when the FX market is relatively illiquid and the availability of trading data is also limited. We follow the literature to handle tweets during the weekend by treating all these tweets as if they are posted during the first hour of the next trading week (10pm on Sunday London Time).[17] In terms of hour of the day, most tweets are posted at late afternoon and early morning London Time, which corresponds with morning and evening time based on EST time.

4.2 FX Trading Volume Data

We use the CLS FX volume dataset provided by Quandl. CLS Group handles over 50% of global FX transaction volume (spot, swap, and forward), for up to 16 bilateral currency pairs.[18] The advantage of CLS data is spot FX volume aggregated and delivered at a hourly frequency, in contrast to the BIS Survey. The data records volume of transactions for four groups of market participants, banks, funds, non-bank financial institutions, and

[16]Reducing the threshold to 20% results in many false positives.

[17]We also implement the second approach by removing all tweets during the weekend from the sample. Results are mostly similar and are available upon request.

[18]The currencies included covers bilateral exchange rates of the U.S. with respect to Australia, Canada, Euro Area, Japan, New Zealand, Norway, Sweden, Switzerland, United Kingdom, Hong Kong, Hungary, South Africa, Iceland, Singapore, Mexico and Korea. Denmark's currency is excluded from our sample as it is pegged to the Euro

corporations. Market makers are typically banks, and price takers in the market are divided into three categories, including funds, non-bank financials, and corporates. This gives us four groupings for measuring trading volume: transactions between the bank and funds, bank and non-bank financials, bank and corporates, and bank-bank transactions. Transactions between two market makers (inter-dealer transactions) or two price takers are excluded from this dataset.

As our time period of interest is from when Donald Trump started his presidential campaign on 16th June 2015, this dataset provides us with hourly data of over 4 years. Data is recorded for 5 days a week, with each trading week beginning from 9pm on Sunday and ending at 9pm on Friday (London Time). It therefore covers market transactions between the time when Sydney market opens on Monday morning and New York market closes on Friday evening. The pattern of average hourly spot FX trading volume based on London time is shown in Figure 4.

[Figure 4 ABOUT HERE]

In early morning London time, when only Asian markets are open, trading volume is relatively low. It starts to go up at around 7am as European markets begin their trading day. Trading volume slightly decreases around lunchtime, but it quickly bounces back and reaches its peak of the day at around 1pm. This is when both European and the U.S. markets are active. The trading volume declines gradually after 5pm and reaches its lowest level around 10pm, when only Australian market is open.

FX trading volume for the different groups of market participants are categorized by different groups is plotted in Figure 5. Most of the trading in the spot FX market included in this dataset (around 85%) occurs in inter-bank transactions between a market maker and price taker bank. In contrast, trading between bank and corporates makes up only around 1% of the total volume.

[Figure 5 ABOUT HERE]

We follow the literature (e.g., Krohn and Sushko 2017) to remove data on some holidays when the FX trading volume is relatively thin. Those holidays include Christmas (24th - 26th December), New Years (31st December - 2nd January), July 4th, Good Friday, Easter Monday, Memorial Day, Labour Day, and Thanksgiving and the day after.

4.3 Intraday FX Volatility and Bid Ask Spread

We obtain tick-by-tick high frequency data for spot indicative quotes from Thomson Reuters Tick History. Our sample is from 16th June 2015 to 20th August 2019. This dataset contains indicative quotes sampled at milli-second frequency.

Hourly Volatility: We follow Mueller, Tahbaz-Salehi, and Vedolin (2017) to construct intraday realised volatility. Specifically, we compute spot exchange rate changes sampled at five-minute intervals based on mid price of the quote. Hourly realised variance is the sum of squared changes, and hourly volatility is the square root of realised hourly variance.

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

Hourly Returns: All currencies are quoted against the USD, meaning an increase in s implies an appreciation of the USD. We calculate the exchange rate return as the log difference in the exchange rate over an hour:

$$\Delta s_{t+1} = s_{t+1} - s_t \tag{26}$$

where s_t is the log midpoint of the last quote at hour t.

5 Empirical analysis

In this section, we discover the effects of tweets on several characteristics of FX market, including trading volume, volatility, bid ask spreads, and returns.

5.1 Panel regressions

We pool all observations from 16 currency pairs and run fixed-effects panel regressions with hourly data. Our fixed-effects panel regression specification is in equation 27.

$$x_{i,t} = \alpha_i + \beta_1 Tweet_t + \beta_2 X_t + \mu_d + \sigma_h + \epsilon_{i,t} \tag{27}$$

The outcome variable $x_{i,t}$ is either the trading volume, realised volatility, bid ask spreads, or returns for currency pair i at time t. $Tweet_t$ is the dummy variable equal 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., Presidency dummy, FOMC dummy, VIX, and TED spread). Specifically, Presidency dummy is a variable equal 1 if date is after 8th November 2016, which is the day when Donald Trump won the election and got elected as the U.S. President. FOMC dummy is equal 1 if during that hour FOMC announcements are announced, and 0 otherwise. VIX is the CBOE Volatility Index, and TED spread is the spread between 3-month LIBOR and 3-month T-Bill. 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.

5.2 Trump tweets and FX Trading Volume

We start by testing the first prediction of the model which suggests a link between FX trading volume and Trump tweets with relevant content. To control for persistence in FX volume, we follow Cespa et al. 2021 in constructing a measure of abnormal FX trading volume. We construct our abnormal volume measure for currency pair i at time t is the log deviation from the moving average of FX trading volume at the same hour over the last 21 trading days. Regression results for the panel specification with FX spot trading volume are reported in Table 2.

[TABLE 2 ABOUT HERE]

The regression results shown in the first column suggest a negatively significant link between the presence of a Tweet and spot FX trading volume during that hour. The coefficient of Tweet hour dummy is -0.631, with a *t*-statistic of -3.71. This negative coefficient for Tweet hour dummy implies that during an hour when there is a Trump Tweet relevant for the foreign exchange market, there is a decrease in abnormal spot FX trading volume of approximately 0.63 per cent. To capture a time trend since Trump's presidency, the second column controls for presidency dummy and it still gives us a negatively significant Tweet hour dummy's coefficient. The presidency dummy in this regression is significant, meaning that since Donald Trump won his presidency on 8th November 2016, spot FX trading volume increases. In the third column, we add FOMC dummy into the regression, and Tweets hour dummy remains strongly significant. The FOMC dummy is positive and significant with a *t*-statistic of 2.62. This implies that the release of FOMC announcement is associated with an increase in abnormal spot FX trading volume during that hour. This result is consistent with evidence that FX volume increases following FOMC announcements (Fischer and Ranaldo, 2011). In the fourth column, we add VIX as an additional control, and the coefficient of Tweets hour dummy becomes even stronger, with a *t*-statistic of -4.16. The coefficient of VIX in this regression is positively significant, with a *t*-statistic of 3.65. This finding implies that during a time of higher uncertainty, spot FX trading volume spikes up. In the fifth column, we incorporate TED spread into the specification. When all control variables are included in the regression simultaneously, the coefficient of our variable of interest, which is Tweet hour dummy, remains its negative sign and strongly significant with a *t*-statistic of -4.25. Overall, results from this table suggest that during hour when there is a Trump Tweet containing relevant information for the foreign exchange market, spot FX trading volume decreases.

We now examine if there is variation in the effects on FX volume across the four groups of market participants of banks, funds, non-financial and corporate firms. Regression results for FX volume of each group are reported in Table 3.

[TABLE 3 ABOUT HERE]

In Panel A of the table, we examine the impact of tweets on trading activity between of inter-bank transactions, where one bank is a market maker and the other is a price taker. The coefficient of the Tweet dummy is negative and strongly significant in all specifications. Similar patterns are also observed in the next two panels, where we show the results for trading volume between banks and funds and banks and non-bank financial firms, where the bank acts as the market maker (Panel C). In both panels, when the full set of control variables enters the regression, the coefficient of Twitter dummy remains negative and significant at a 1% level of significance. In panel D, we look at the trading activity between market maker bank and the corporate sector (e.g., multinational firms). The coefficient of Tweet dummy is positive and slightly significant at the first column. However, in the next four columns, this coefficient loses its statistical significance. Therefore we do not find empirical evidence showing clear effects of Tweets on trading volume between the bank and corporate sector. Overall, empirical results from Table 2 and Table 3 suggest that Donald Trump's Tweets decrease overall trading volume in the spot FX market in line with the first prediction of the model. When we break down the trading volume by different market participants, this result holds for three groups of informed market participants. In contrast, we do not find evidence for this effect for uninformed group of market participants, i.e., corporate sector.[19]

5.3 Trump Tweets and FX Volatility

We now test the second prediction of the model, which states that volatility declines for informative Trump tweets.[20] We address the persistence of volatility by using innovations to realised intra-day volatility as the relevant outcome variable. The regression results are reported in Table 4. In the first column, when day of the week and hour of the day dummies are the only control variables in the regression, the coefficient of Tweet dummy is negative and strongly significant with a t-statistic of -5.07. It implies that Tweets reduce FX realised volatility. When more variables are controlled for in the next columns, the magnitude of Tweet dummy's coefficient slightly decreases, however, it remains its statistical significance. In the last column, when the full set of control variables is included in the regression, the coefficient of our interest is negative with a a t-statistic of -2.90. These empirical findings provide strong evidence suggesting that tweets reduce the realised volatility in the FX market.

[TABLE 4 ABOUT HERE]

5.3.1 Trump Tweets and FX Bid-Ask Spreads

The reduction in volatility is consistent with a reduction in asymmetric information, and this should also have an impact on market makers ability to quote smaller bid-ask spreads.

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

[20] In the context of the model, we classify an informative Trump tweet as having a higher precision than private information.

[21] To investigate the effects of tweets on bid-ask spreads, following Krohn and Sushko (2017), we measure bid-ask spreads using price quotes by big banks based on the 2016 G-SIB Classification as these banks provide quotes across most pairs of currency in our sample. Results showing the link between Tweets and bid-ask spreads are reported in Table 5. In the first column, the coefficient of Tweet dummy is negative with a *t*-statistic of -3.11, and the relationship is robust to adding controls. The reduction in bid-ask spreads during Trump Tweet hours, suggesting a reduction in information asymmetry due to trading on the common public signal.[22]

[TABLE 5 ABOUT HERE]

5.4 Trump Tweets and FX Spot Returns

Testing the third prediction of the model, we examine the impact of Trump tweets on FX spot returns. Theoretically, spot returns arise due to a bias between the expectations of public and private information. If Trump tweets are more optimistic about the U.S. economy, or more protectionist about trade relations than speculators, there is a bias in the expectation of future macroeconomic fundamentals. Regression results are reported in Table 6.

[TABLE 6 ABOUT HERE]

The positive coefficient of Tweet dummy in the first column suggests Trump tweets lead to an appreciation of the U.S. dollar. Our estimates suggest that the USD appreciates by an average of 0.5 per cent during Trump tweet hours against a basket of currencies.[23] The results are robust to adding additional controls, such as the Presidency, FOMC meetings, and the VIX. These results support the model prediction that FX returns reflect Trump's optimistic view on the U.S. economy.

[21] While we do not explicitly model bid-ask spreads, adoption of the public signal by speculators reduces the information advantage of informed trading. A market maker needs to be compensated less for taking the other side of informed trades, leading to lower bid-ask spreads.

[22] While bid-ask spreads can also reflect changes in liquidity, we attribute the decline in bid-ask spreads due to a decline in information asymmetry due to the decline in trading during these periods. If bid-ask spreads declined due to increased liquidity, we may expect an increase in trading volume during Tweet hours.

[23] 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.

5.4.1 Macro versus Trade Tweets

We now test if the appreciation of the USD is specific to tweets about trade or macroeconomic content. Effects of presidential tweets on spot returns have been found in Benton and Philips (2018), which shows that trade relations between Mexico and the U.S. lead to an appreciation of the USD/Peso. We report results for the subset of trade and macro tweets in Table 7. In another study that uses textual analysis of Presidential tweets on the China-US trade dispute, Ferrari et al. (2021) find that trade tensions between China and the U.S lead to an appreciation of emerging markets.

[TABLE 7 ABOUT HERE]

In Panels A and B, we show results for regressions with trade and macro tweets respectively. In all specifications, the coefficient of the trade tweet is positive, implying that hours with trade tweets are linked with appreciation of the USD. However, this effect is rather weak as the statistical power is just 10%. In Panel B, we replace trade tweets with macro tweets in the regressions. The coefficient of Macro tweet is positive and strongly significant in all specifications. With the full set of control variables in the last column, the coefficient of Macro tweet is 0.005 (0.5 per cent) with a *t*-statistic of 4.21. This is similar to the unconditional effect of Trump tweets on spot returns, suggesting that the appreciation of the USD against the panel of currencies is driven more by tweets with macro content. This confirms the model prediction that spot returns are related to the bias in Trump's expectation of future macroeconomic fundamentals.

5.4.2 Sentiment analysis of Trump tweets

We can also consider measuring the direction of tweets based on a sentiment analysis. For example, the bias between Trump tweets and private information are conditional on whether Trump's tweets are optimistic or pessimistic regarding the future growth of the U.S. economy. To measure the direction of sentiment, we classify tweets into positive and negative tone based on the dictionary developed by Liu and Hu (2004). Regressions showing the link between positive and negative tweets and currency returns are reported in Table 8.

[TABLE 8 ABOUT HERE]

In Panel A, we run regressions with independent variable of interest being positive tweet. The coefficient of positive tweet is positive and strongly significant in all regressions.

In the last column with the full set of control variable, the coefficient of positive tweet is 0.005 with a t-statistic of 5.22. This result implies that relevant Trump tweets with positive sentiment are associated with USD's appreciation. In Panel B, we examine tweets with negative sentiment, and in line with our hypothesis, the coefficient on the tweet dummy is negative and strongly significant. In the last column, the coefficient of this variable is -0.008 with t-statistic of -5.07. The analysis suggests that the sentiment of tweets matters for currency returns. Positive tweets are linked with USD's appreciation, whereas negative tweets are linked with USD's depreciation. This is consistent with our model prediction on the bias between Trump expectations and private information. Examining the distribution of sentiment, we find two thirds of the sample are classified as positive sentiment, which explains why the unconditional effects of Trump tweets are to cause a USD appreciation in the hour of the tweet.

5.4.3 Trump tweets and media coverage of the Mueller's investigation

We investigate whether Trump tweets are used as a distraction strategy by testing the link between tweets and media coverage of the Mueller's investigation in the New York Times. We use the dataset for media coverage of the Mueller's investigation provided in Lewandowsky et al. (2020). Logit regressions are implemented to examine as to whether media coverage of the Mueller's investigation the probability of Trump tweeting in the next hour. Results are shown in Table 9.

[TABLE 9 ABOUT HERE]

In Panel A, we show the link between informative tweets and media coverage of the 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 increases the probability of him posting an informative tweets in the next hour. Informative tweets are then classified into positive and negative tone as in the previous subsection. In Panel B, the independent variable of interest maintains the same sign as in Panel A. This indicates the positive link between media coverage of the Mueller's investigation and tweets with positive tone. We replicate the logit regressions with negative tweets in Panel C. The coefficient of the independent variable of interest loses its statistical significance. Overall, results from this table provide suggestive evidence that tweets are used as a distraction strategy. In particular, when there is media coverage of harmful topics, Trump is likely to post informative tweets, especially those with positive sentiment.

5.4.4 Intra-hour impacts of Tweets on currency returns

The results so far are based on hourly spot returns. We now investigate the impact of Trump tweets on spot returns within the hour. In particular, we implement an event study at the minute level and show the cumulative returns for the average returns of 16 currency pairs (Panel A) and the USD ETF (Panel B) in Figure 7, following a similar methodology of investigating minute-level ETF returns on the stock market in Abdi et al. (2021) and the analysis of intra-day volatility and liquidity in Scharnowski (2021). Consistent with our panel specification, we find a cumulative USD appreciation for both the average returns of 16 currency pairs and the USD ETF, the post-event cumulative returns (60 minutes after a tweet is posted) are both statistically significant, whereas the corresponding figures in the pre-event period are not statistically significant.

[FIGURE 7 ABOUT HERE]

5.4.5 Trading Strategy: Event Study

To test if the impact of Trump tweets on spot returns persist over the trading day, we implement the following trading strategy based on tweet hours. Currencies are sorted into terciles based on its spot changes during the tweet hours, with portfolio 3 containing currencies with the highest positive spot changes during tweet hours and portfolio 1 containing currencies with the most negative spot changes during tweet hours. Figure 8 shows the average returns of the high minus low (HML) portfolio of going long in Portfolio 1 and going short in Portfolio 3 around the hour of Trump tweets.

[FIGURE 8 ABOUT HERE]

A striking feature observed from Figure 8 is that the average returns of the HML portfolio decreases significantly during the tweet hours, but it immediately bounces back the hour after the tweet occurs. The results suggest that returns from the tradable strategy are short-lived and corrected in the hour following the Trump tweet.[24]

[24] While the effect of Trump tweets on FX spot returns is short-lived from the perspective of long-term investors, one can argue that one hour is a relatively long window for a market populated by algorithmic traders (e.g., Chaboud, Chiquoine, Hjalmarsson, and Vega (2014)).

5.5 Robustness Exercises

5.5.1 Trump Tweets and Macro 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 are echoing 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 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.[25]

We control for the omitted variable by including dummies for macroeconomic releases on output, employment and trading activity. In particular, we add an additional control that is a dummy variable which is equal to 1 if there is at least one macro announcement on that day and 0 otherwise. The list of macro releases are 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. To address the concern that the coefficient estimates on the tweet hour dummy would capture the effect of Trump tweets independent of macro announcements, we control for macro announcements in the regressions. Results of baseline regressions with this new dummy variable are shown in Table 10. The coefficient on the tweet hour dummy is robust to including a variable that captures macroeconomic releases, with significant declines in volatility and FX volume, a decline in bid-ask spreads and an appreciation in spot returns.

[TABLE 10 ABOUT HERE]

5.5.2 Placebo Test: Uninformative tweets and the FX market

Our analysis has used a set of tweets on the macroeconomic outlook and trade, which we perceive as tweets that have relevant information content for exchange rates. We hypothesize that a set of uninformative tweets should not have any information relevant for FX trading. To select a placebo group, we define a set of uninformative tweets as a

[25] While tweets with macroeconomic content can follow a macroeconomic release, there is research that shows that Trump tweets on macroeconomic issues as a diversion to political coverage on the Mueller report and other political news during the presidency (Lewandowsky et al., 2020). Tweeting on macroeconomic topics as a diversion is more consistent with our story of the timing of Trump signals being plausibly exogenous.

complementary set that satisfies two criteria. First, these tweets have the lowest probability of belonging to the trade and macroeconomics topics based on the BTM method.[26] Second, we choose a number of uninformative tweets to match the number of informative tweets. We then replicate the panel regressions with the independent variable being the uninformative tweet hour dummy. Results are reported in Table 11.

[TABLE 11 ABOUT HERE]

In the first column of this table, we can see that uninformative tweets hour is negatively linked with FX trading volume. Although the coefficient of uninformative tweet hour dummy is statistically significant, the magnitude of this coefficient is -0.05, which is an order of magnitude smaller than the coefficient of the informative tweet hour dummy shown in Table 2. The marginal negative effect of FX volume can be due to two reasons. First, errors in classifying tweets as informative or uninformative through the BTM algorithm can create false negatives. Second, the model framework suggests that if the set of irrational agents, "Trump followers", adopt uninformative tweets for FX trading, the model predicts a decline in FX volume. In the next three columns, the estimates of uninformative tweets on volatility, bid-ask spread, and returns are statistically insignificant, suggesting that there is no evidence of uninformative tweets affecting FX volatility, the bid-ask spread, and returns. The results are broadly consistent with our hypothesis that only tweets that have relevant information for FX trading will impact trading, volatility and spot returns. This highlights the importance of implementing textual analysis to filter the informative tweets carrying relevant information for the FX market. Our results are consistent with related work in Abdi et al. (2021) on the effects of Trump tweets on the stock market. The authors find evidence that Trump tweets are responding to information earlier in the day. They do however find evidence of information effects for Trump tweets on the NAFTA trade agreement and the US China trade war, which is consistent with our hypothesis that Trump tweets with macroeconomic and trade content are more informative.

[26]Formally, the BTM method gives us a set of weights that measures the proportion of topics for each tweet. For example, for each tweet, the following vector $\hat{\gamma}_{t,n}$ measures the proportion of tweet t that is made up of topic n. Based on the weight vector, we select tweets with the lowest weights for topics with macroeconomic or trade content.

5.6 Tweets and Disagreement in the FX market

We have shown a decline in volume, volatility and a bias in spot returns. The channel we put forward in the model is that the Trump tweet acts as a common public signal which reduces the dispersion of speculator expectations of the future spot rate. Therefore, we expect a decline in investor disagreement following the Trump tweet. In order to test this channel we construct a proxy for investors' disagreement using FX options. Following Salomé 2020, we use the moneyness ratio of option prices as a proxy for investor disagreement in the options market. We focus on put options for EUR/USD currency pair.[27] The moneyness of an option is provided in equation 28, which is defined as follows:

$$Moneyness = \frac{\ln(\frac{K}{S})}{\sigma\sqrt{\tau}} \tag{28}$$

In the above equation, the numerator expresses the ratio of strike price (K) to underlying price (S). The denominator is the multiplication of yearly volatility of an option (σ) and time to expiration in years (τ). Therefore, the absolute value of moneyness can be considered as a proxy for disagreement as it captures the dispersion between the strike price and the current spot price, after adjusting for the time to expiry and implied volatility of the EUR/USD returns. We examine the link between Tweets and disagreement among investors by running the following time-series regressions:

$$x_{i,t} = \alpha_i + \beta_1 Tweet_t + \beta_2 X_t + \mu_d + \sigma_h + \epsilon_{i,t} \tag{29}$$

in which x_t is the absolute value of moneyness for EUR/USD currency pair put options. We use a similar set of controls X_t to the panel specification in equation 27. Regression results are shown in Table 12.

[TABLE 12 ABOUT HERE]

In the first column, the coefficient of Tweet hour dummy is negative and statistically significant with a *t*-statistic of -2.41. The negative relationship between Trump tweet hours and the absolute value of moneyness suggests disagreement among investors decreases during hours of Trump tweets. In the next three columns, when we add more control variables, the statistical power of Tweet hour dummy remains mostly unchanged. In the last column with full set of control variables, the coefficient of our variable of interest is still significantly negative with a *t*-statistic of -2.15. These empirical findings suggest that the

[27] We clean the data by removing trades with bid price being larger than ask price, and those with ask price and ask size being zero.

potential channel through which Trump tweets reduce volume and volatility in the market is through a reduction in investor disagreement.

6 Conclusion

In this paper, we combine two approaches of textual analysis, the dictionary approach and bi-term topic modelling approach, to identify the information content of tweets posted by Donald Trump. We hypothesize that Trump tweets about the macroeconomics outlook, trade policy, and FX policy are relevant for trading in the foreign exchange market. Through a model, we show that Trump tweets act as a common public signal in a market of heterogeneous private information. A common public signal with sufficient information content reduces investor disagreement on expectations of the future spot rate, and a decline in trading volume and intra-day volatility. 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, FX volume and price data for up to 15 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 decline in the volume of trading during Trump tweets with macro and trade content, both in the aggregate and for specific market participants (banks, funds and non-financial firms). We find a decline in exchange rate volatility, and a decline in asymmetric information in the FX market as dealers quote narrower bid-ask spreads during tweet hours. Turning to spot returns, we find Trump tweets on average lead to an appreciation of the USD reflecting the generally optimistic views of Trump on the U.S. economy. Finally, using the options market to construct a proxy for investor disagreement, we find evidence that the decline in trading volume and volatility is associated with a decline in investor disagreement in the currency market.

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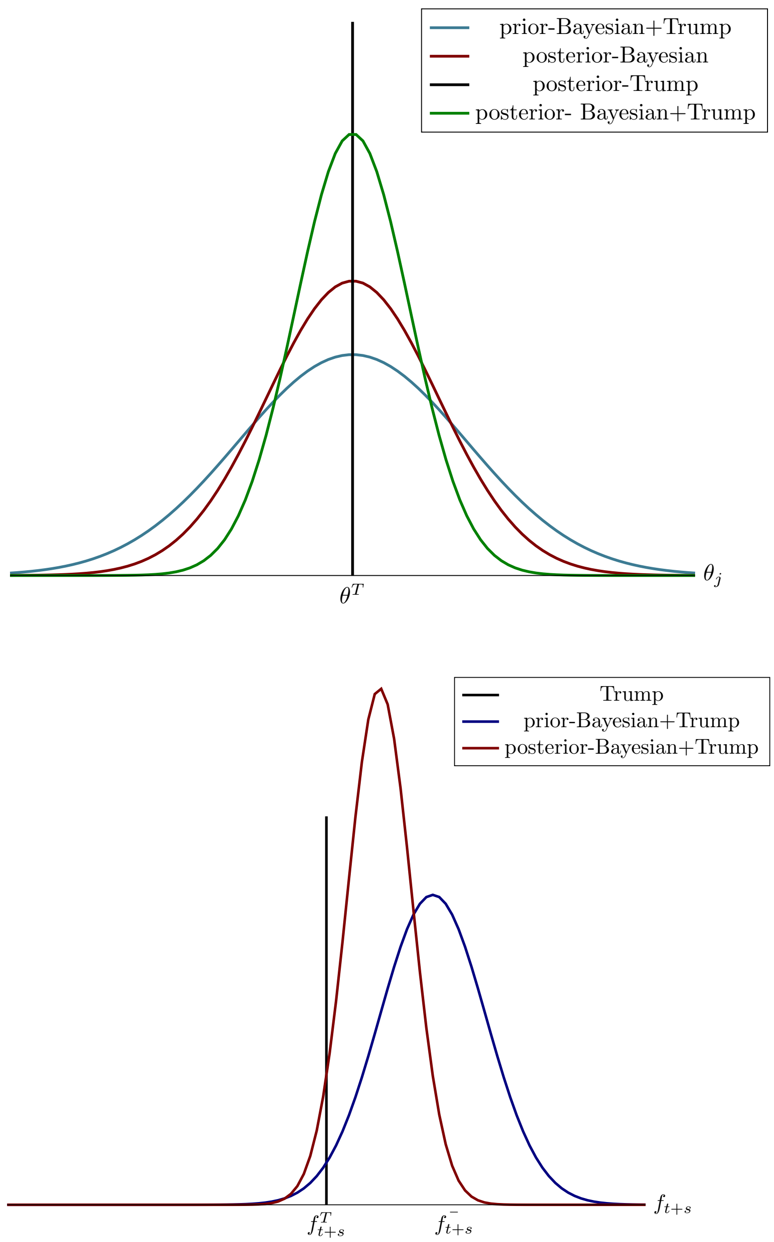
Figure 1. Top: Prior and Posterior Distributions following Trump Tweet, Bottom: Bias between Trump and other agents on expectations of future fundamentals



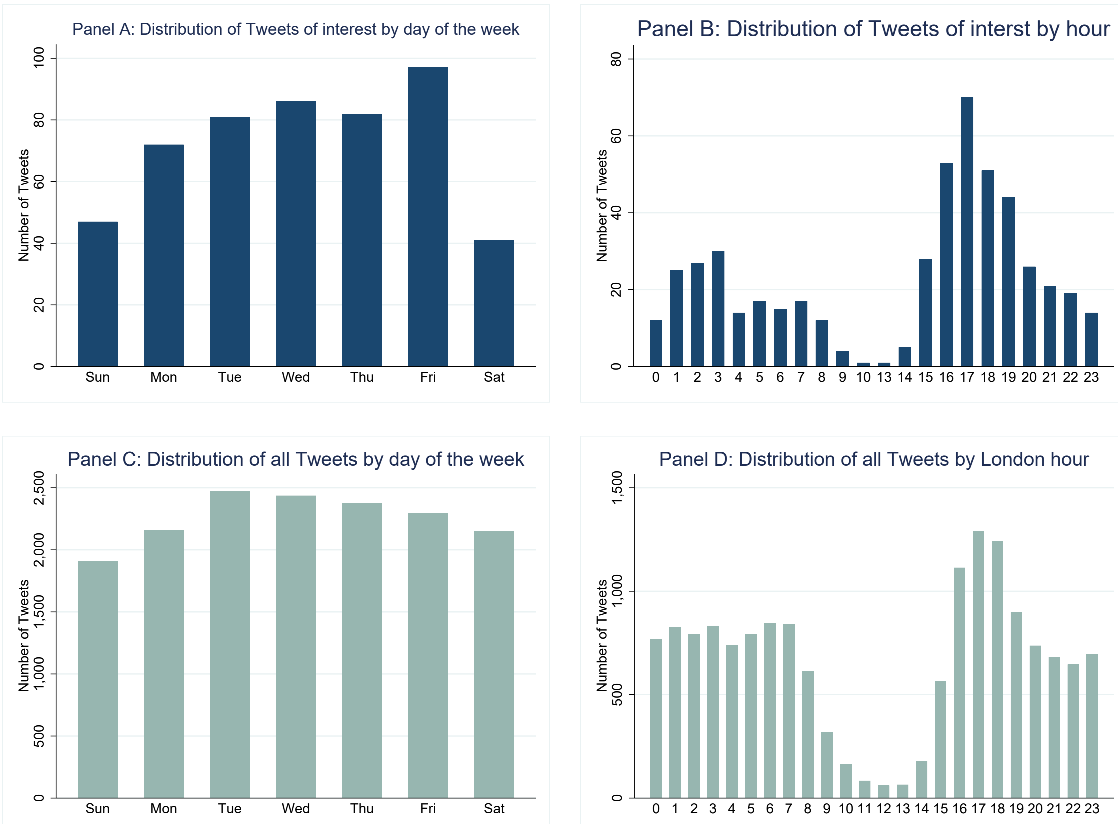
Top: The figure shows the prior and posterior distributions of agent expectations of the future spot rate. Bayesian agents update their prior to give a positive weight to the Trump tweet, which is centered at θ^T. Trump followers adopt the public signal completely, causing a reduction in the dispersion of investor expectations. Bottom: Trump expectations of future fundamentals differ from agent expectations. Bayesian agents update their signal, causing spot returns to change that is proportional to the bias.

Figure 2. trade and macroeconomics Topics from BTM

(a) Trade Topic

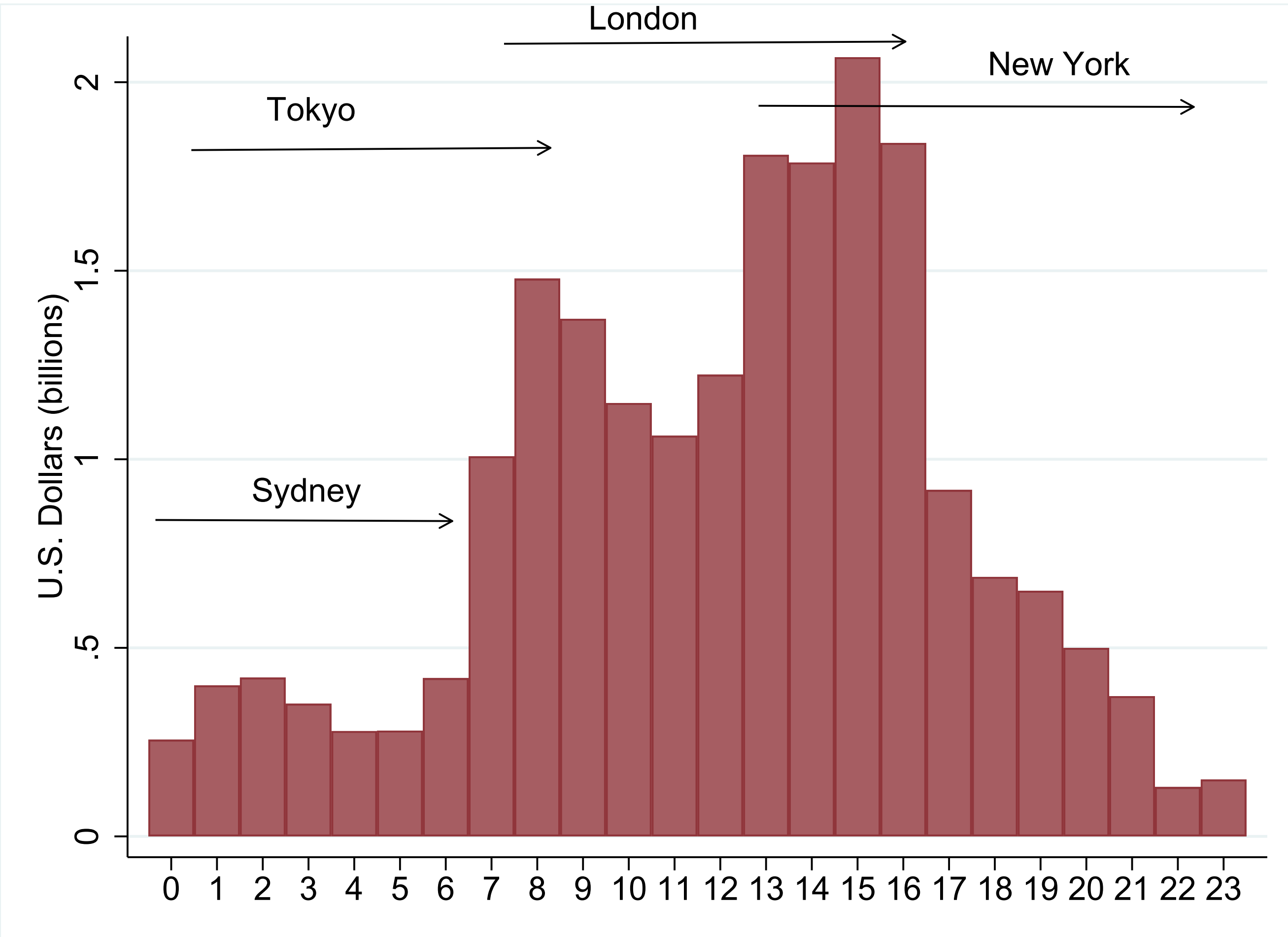
(b) Macroeconomics Topic

Figure 3. Time distribution of Tweets



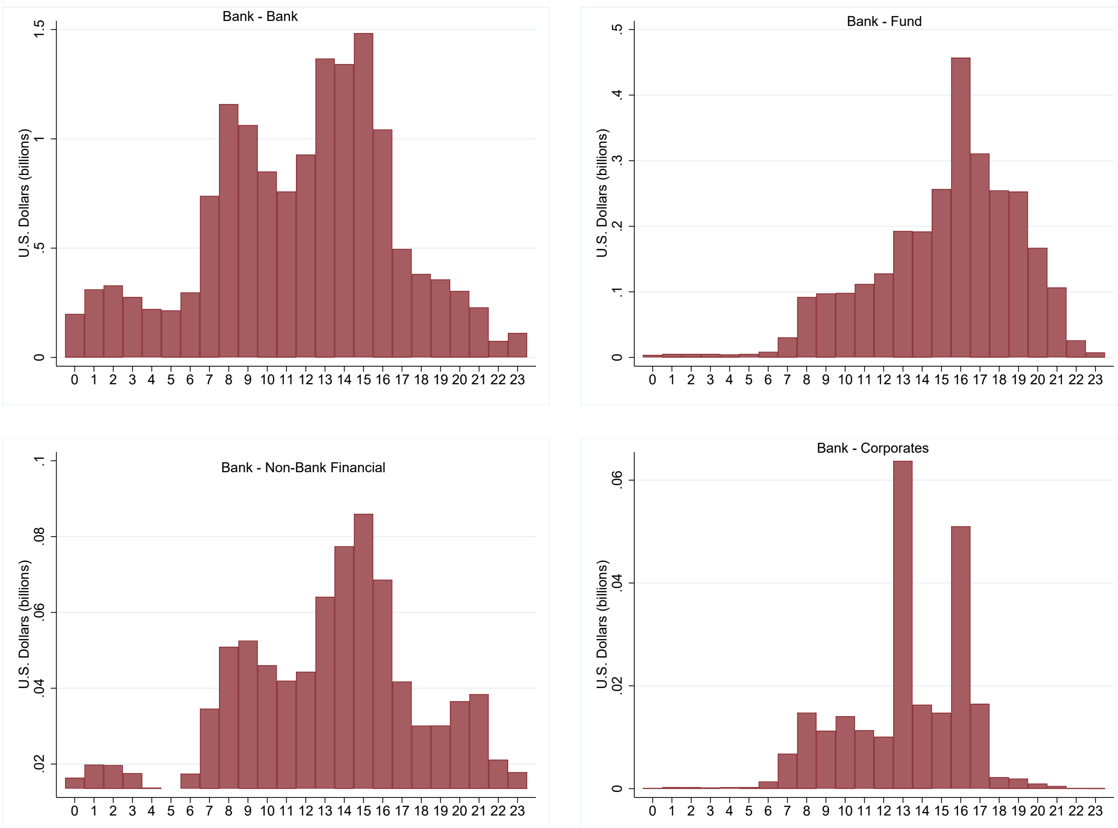
The figure shows time distribution of Tweets belonging to Macroeconomics, Trade Policy, and Exchange Rate categories in Panel A and Panel B. Time distribution of all Tweets is shown in Panel C and Panel D. The number shown on the x-axis is the closing time based on London time. The data are between 16th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

Figure 4. Spot FX Trading Volume



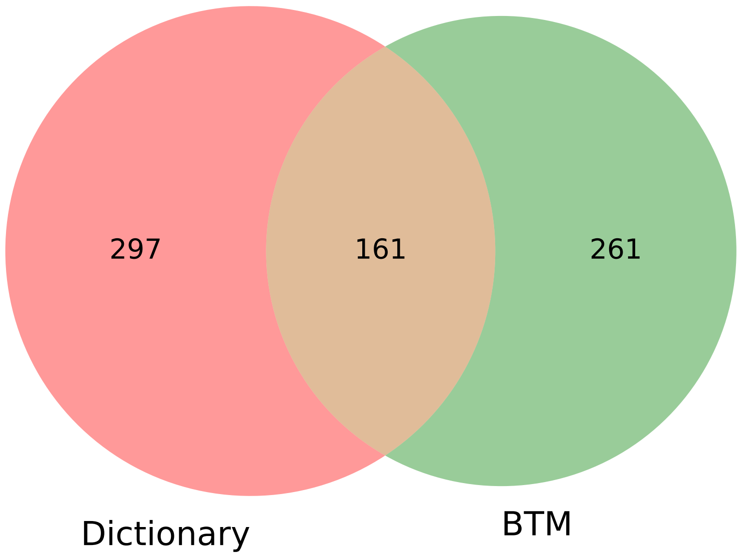
The figure reports the average hourly FX spot volume (in USDs) throughout a business trading day (London Time). The average is constructed across all trading days in our sample, from 16th June 2015 to 20th August 2019. Volume is the sum of 15 pairs of currency included in our sample. The number shown 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).

Figure 5. Spot FX Trading Volume by participants



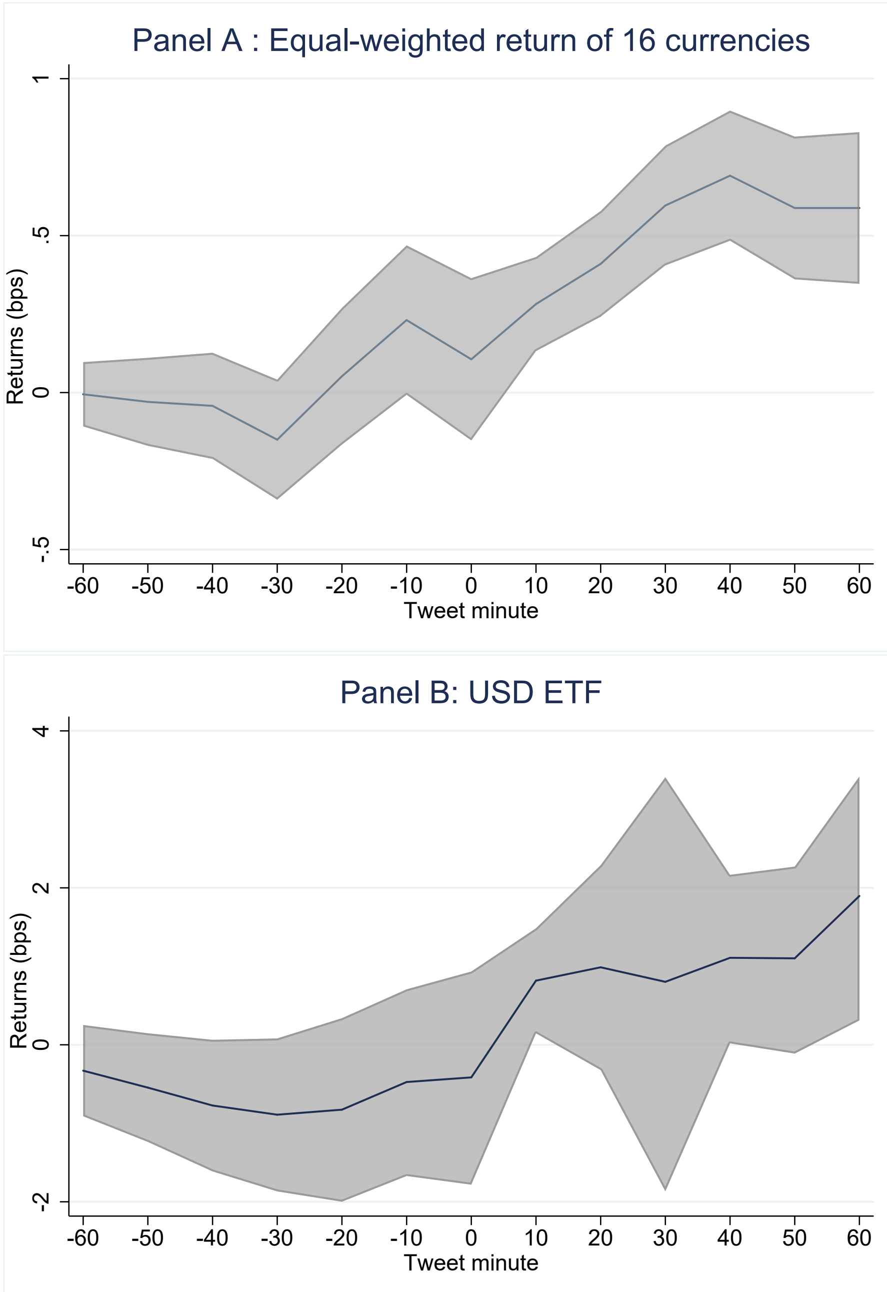
The figure reports the average hourly FX spot volume (in USDs) throughout a business trading day (London Time) by different groups of market participant. The average is constructed across all trading days in our sample, from 16th June 2015 to 20th August 2019. Volume is the sum of 15 pairs of currency included in our sample. The number shown on the x-axis is the closing time based on London time.

Figure 6. Tweets identified by Dictionary approach and BTM approach



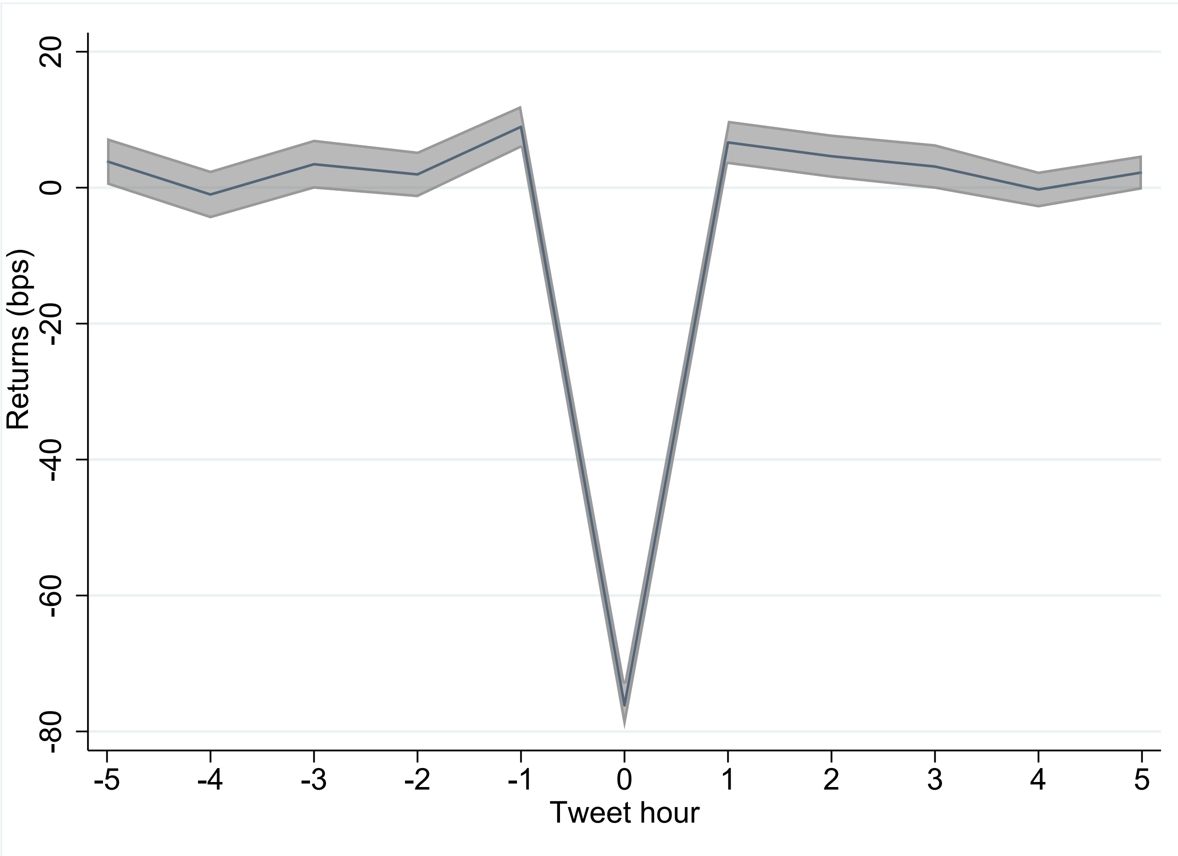
The figure reports the number of relevant Tweets (trade, macro, and FX tweets) identified by dictionary and bi-term topic modelling (BTM) approach.

Figure 7. 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 16 currencies (Panel A) and the USD ETF (Panel B). The shaded area shows 95% confidence interval. The y-axis shows the minutes during the event, with 0 being the minute in which a tweet is posted. The negative values in the y-axis are the number of minutes before tweets.

Figure 8. Event study of spot returns around the Tweet hours



This graph shows the average spot returns in bps around the tweet hours for HML portfolio going long currencies in Portfolio 1 and going short currencies in Portfolio 3. We carry out this strategy for all tweets with relevant content (trade and macro tweets). The shaded area shows 95% confidence interval. Currencies are sorted based on the magnitude of its spot returns during tweet hours, with Portfolio 3 containing currencies with highest spot returns. The y-axis shows the hours during the event, with 0 being the end of the hour in which a tweet is posted. The negative values in the y-axis are the number of hours before tweets.

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, macro 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 Spot FX Trading Volume (Total Sell Side - Total Buy Side)

This table reports panel regressions results for the estimation of Tweets hour dummy on FX Trading Volume. The control variables are presidency dummy, FOMC dummy, VIX, and TED Spread. 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 16th June 2015 and 20th August 2019.

	Dependent variable: Trading Volume between Sell Side and Buy Side				
	(1)	(2)	(3)	(4)	(5)
Tweet hour	-0.647***	-0.710***	-0.711***	-0.712***	-0.715***
	[-4.12]	[-4.10]	[-4.10]	[-4.16]	[-4.25]
$Presidency$		0.283***	0.283***	0.343***	0.332***
		[3.16]	[3.16]	[3.41]	[3.36]
$FOMC$			0.231***	0.244***	0.246***
			[2.62]	[2.87]	[2.92]
VIX				0.023***	0.021***
				[3.65]	[3.54]
TED Spread					-0.327**
					[-2.44]
Country FE	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Obs	367,168	367,168	367,168	363,350	357,423
R^2	3.65%	3.67%	3.67%	3.78%	3.78%

Table 3. 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 presidency dummy, FOMC dummy, VIX, and TED Spread. Hour-of-the-day and day-of-the-week dummies are included in all regressions. In Panel A, dependent variable is trading volume between market maker bank and price taker bank. In Panel B, dependent variable is trading volume between market maker bank and price taker fund. In Panel C, dependent variable is trading volume between market maker bank and price taker non-bank financials. In Panel D, dependent variable is trading volume between market maker bank 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 16th June 2015 and 20th August 2019.

	Panel A. Dependent variable: Bank - Bank Trading Volume					*Panel B. Dependent variable*: Bank - Fund Volume				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Tweet hour	-0.711***	-0.768***	-0.768***	-0.767***	-0.771**	-0.631***	-0.779***	-0.779***	-0.803***	-0.839***
	[-3.70]	[-3.71]	[-3.71]	[-3.73]	[-3.80]	[-3.71]	[-5.06]	[-5.07]	[-5.48]	[-5.75]
Presidency		0.247***	0.247***	0.318***	0.309***		0.642***	0.642***	0.718**	0.711***
		[3.16]	[3.16]	[3.43]	[3.41]		[4.88]	[4.89]	[5.30]	[5.35]
FOMC			0.105**8	0.121**	0.362			0.364	0.370	0.368
			[2.02]	[2.38]	[2.41]			[1.39]	[1.46]	[1.47]
VIX				0.025***	0.024***				0.031***	0.030***
				[3.50]	[3.41]				[5.69]	[5.75]
TED Spread					-0.302**					-0.040
					[-2.06]					[-0.11]
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	310,724	310,724	310,724	307,507	302,395	291,342	291,342	291,342	288,319	283,640
R^2	3.91%	3.89%	3.89%	4.00%	4.00%	22.63%	22.76%	22.76%	22.97%	23.07%

	Panel C. Dependent variable: Bank - Non-Bank Trading Volume					*Panel D. Dependent variable*: Bank - Corporate Volume				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Tweet hour	-0.422***	-0.866***	-0.866***	-0.868***	-0.871***	0.342**	0.174	0.174	0.135	0.098
	[-3.14]	[-6.65]	[-6.66]	[-6.98]	[-7.10]	[2.09]	[1.38]	[1.38]	[1.09]	[0.79]
Presidency		2.002***	2.002***	2.085***	2.049***		0.865***	0.865***	1.032***	0.943***
		[5.99]	[5.99]	[6.19]	[6.08]		[2.94]	[2.94]	[3.06]	[2.80]
FOMC			0.389	0.405	0.409			-0.122	-0.0918	-0.073
			[1.41]	[1.48]	[1.50]			[-0.14]	[-0.10]	[-0.08]
VIX				0.034***	0.034***				0.069***	0.068***
				[5.00]	[4.92]				[3.41]	[3.36]
TED Spread					-0.601**					-1.915***
					[-2.26]					[-2.59]
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	299,828	299,828	299,828	296,758	291,885	102,917	102,917	102,917	101,901	100,292
R^2	2.76%	4.97%	4.97%	5.01%	4.98%	0.99%	1.15%	1.15%	1.25%	1.30%

Table 4. Tweets and FX Hourly Realised Volatility

This table reports panel regressions results for the estimation of Tweets hour dummy on FX hourly realised volatility. The control variables are presidency dummy, FOMC dummy, VIX, and TED Spread. 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 16th June 2015 and 20th August 2019.

	Dependent variable: Realised Volatility				
	(1)	(2)	(3)	(4)	(5)
Tweet hour	-0.006***	-0.003***	-0.003***	-0.003***	-0.003***
	[-5.07]	[-2.77]	[-2.75]	[-3.60]	[-2.90]
Presidency		-0.014***	-0.014***	-0.012***	-0.011***
		[-7.05]	[-7.05]	[-6.38]	[-5.93]
FOMC			0.070***	0.070***	0.070***
			[8.82]	[8.82]	[8.81]
VIX				0.001***	0.001***
				[8.39]	[10.99]
TED Spread					0.017***
					[3.49]
Country FE	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Obs	397,708	397,708	397,708	393,251	387,708
R^2	6.17%	7.22%	7.38%	7.64%	7.77%

Table 5. Tweets and FX Hourly Bid-Ask Spreads

This table reports panel regressions results for the estimation of Tweets hour dummy on FX hourly bid-ask spreads quoted by big banks based on the 2016 G-SIB Classification. The control variables are presidency dummy, FOMC dummy, VIX, and TED Spread. 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 16th June 2015 and 20th August 2019.

	Dependent variable: Bid-Ask Spreads				
	(1)	(2)	(3)	(4)	(5)
Tweet hour	-0.372***	-0.137***	-0.137***	-0.148***	-0.144***
	[-3.11]	[-2.62]	[-2.62]	[-2.75]	[-2.72]
Presidency		-1.022***	-1.022***	-1.012***	-1.010***
		[-2.79]	[-2.79]	[-2.89]	[-2.77]
FOMC			0.261*	0.266*	0.260*
			[1.74]	[1.78]	[1.77]
VIX				0.003	0.003
				[0.45]	[0.47]
TED Spread					0.009
					[0.13]
Country FE	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Obs	382,894	382,894	382,894	378,715	372,638
R^2	0.62%	1.86%	1.86%	1.85%	1.85%

Table 6. Tweets and FX Hourly Returns

This table reports panel regressions results for the estimation of Tweets hour dummy on FX hourly returns. The control variables are presidency dummy, FOMC dummy, VIX, and TED Spread. 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 16th June 2015 and 20th August 2019.

	Dependent variable: Returns				
	(1)	(2)	(3)	(4)	(5)
Tweet hour	0.005***	0.005***	0.005***	0.005***	0.005***
	[3.45]	[3.42]	[3.42]	[3.53]	[3.69]
Presidency		-0.000	-0.000	0.000	0.000
		[-0.23]	[-0.24]	[1.42]	[0.63]
FOMC			-0.023***	-0.023***	-0.023***
			[-4.79]	[-4.77]	[-4.76]
VIX				0.000*	0.000*
				[1.85]	[1.68]
TED Spread					-0.001
					[-1.09]
Country FE	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Obs	401,864	401,864	401,864	397,266	390,806
R^2	0.06%	0.06%	0.07%	0.07%	0.07%

Table 7. Tweets and FX Hourly Returns

This table reports panel regressions results for the estimation of Tweets hour dummy on FX hourly returns. The control variables are presidency dummy, FOMC dummy, VIX, and TED Spread. Hour-of-the-day and day-of-the-week dummies are included in all regressions. In Panel A, independent variable of interest is Trade Tweet. In Panel B, independent variable of interest is Macro 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 16th June 2015 and 20th August 2019.

Panel A: Trade Tweet

Dependent variable: Returns

	(1)	(2)	(3)	(4)	(5)
Trade Tweet	0.003*	0.003*	0.003*	0.003	0.003*
	[1.67]	[1.64]	[1.61]	[1.62]	[1.67]
Presidency		-0.000	-0.000	0.000	0.000
		[-0.01]	[-0.02]	[1.61]	[0.85]
FOMC			-0.023***	-0.023***	-0.023***
			[-4.77]	[-4.75]	[-4.75]
VIX				0.000*	0.000*
				[1.86]	[1.69]
TED Spread					-0.001
					[-1.22]
Country FE	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Obs	401,864	401,864	401,864	397,266	390,806
R^2	0.06%	0.06%	0.07%	0.07%	0.07%

Panel B: Macro Tweet

Dependent variable: Returns

	(1)	(2)	(3)	(4)	(5)
Macro Tweet	0.005***	0.005***	0.005***	0.005***	0.005***
	[3.91]	[3.94]	[3.94]	[3.94]	[4.19]
Presidency		-0.000	-0.000	0.000	0.000
		[-0.24]	[-0.25]	[1.46]	[0.67]
FOMC			-0.023***	-0.023***	-0.023***
			[-4.79]	[-4.77]	[-4.76]
VIX				0.000*	0.000
				[1.88]	[1.71]
TED Spread					-0.001
					[-1.04]
Country FE	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Obs	401,864	401,864	401,864	397,266	390,806
R^2	0.06%	0.06%	0.07%	0.07%	0.07%

Table 8. Tweets and FX Hourly Returns

This table reports panel regressions results for the estimation of Tweets hour dummy on FX hourly returns. The control variables are presidency dummy, FOMC dummy, VIX, and TED Spread. Hour-of-the-day and day-of-the-week dummies are included in all regressions. In Panel A, independent variable of interest is Positive Tweet. In Panel B, independent variable of interest is 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 16th June 2015 and 20th August 2019.

Panel A: Positive Tweet
Dependent variable: Returns

	(1)	(2)	(3)	(4)	(5)
Positive Tweet	0.005***	0.005***	0.005***	0.005***	0.005***
	[4.58]	[4.46]	[4.43]	[4.84]	[5.21]
Presidency		-0.000	-0.000	0.000	0.000
		[-0.29]	[-0.29]	[1.32]	[0.55]
FOMC			-0.023***	-0.023***	-0.023***
			[-4.77]	[-4.75]	[-4.75]
VIX				0.000*	0.000
				[1.85]	[1.68]
TED Spread					-0.001
					[-1.07]
Country FE	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Obs	401,864	401,864	401,864	397,266	390,806
R^2	0.06%	0.06%	0.07%	0.07%	0.00%

Panel B: Negative Tweet
Dependent variable: Returns

	(1)	(2)	(3)	(4)	(5)
Negative Tweet	-0.006***	-0.006***	-0.006***	-0.008***	-0.008***
	[-2.94]	[-2.91]	[-2.93]	[-4.16]	[-5.07]
Presidency		0.000	0.000	0.001*	0.000
		[0.12]	[0.11]	[1.81]	[1.05]
FOMC			-0.023***	-0.023***	-0.023***
			[-4.79]	[-4.78]	[-4.77]
VIX				0.000*	0.000
				[1.90]	[1.74]
TED Spread					-0.001
					[-1.30]
Country FE	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Obs	401,864	401,864	401,864	397,266	390,806
R^2	0.06%	0.06%	0.07%	0.07%	0.07%

Table 9. Tweets and Newspapers Articles about Mueller's investigation report

This table reports logit regressions results showing the link between the probability of Tweets and the publication of newspapers articles about Mueller's investigation in the previous hour. The independent variable of interest is the Lagged articles dummy, which takes the value of 1 if there is publication of newspapers articles about Mueller's investigation in the previous hour and 0 otherwise. The control variables are FOMC dummy, VIX, and TED Spread. Day-of-the-week dummies are included in all regressions. In Panel A, dependent variable of interest is Informative Tweet. In Panel B, dependent variable of interest is Positive Tweet. In Panel B, dependent variable of interest is Positive Tweet. In Panel C, dependent variable of interest is Negative Tweet. 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 17th May 2017 and 6th February 2019.

Panel A: Informative Tweet
Dependent variable: Informative Tweet dummy

	(1)	(2)	(3)	(4)
Lagged articles dummy	1.543***	1.532***	1.516***	1.483***
	[2.95]	[2.90]	[2.80]	[2.64]
$FOMC$		2.016***	2.163***	2.004*
		[1.84]	[2.00]	[1.77]
VIX			0.995	0.979
			[-0.35]	[-1.31]
TED Spread				4.397**
				[2.04]
Day FE	Yes	Yes	Yes	Yes
Obs	10,368	10,368	10,224	10,080
R^2	0.08%	0.11%	0.09%	0.12%

Panel B: Positive Tweet
Dependent variable: Positive Tweet dummy

	(1)	(2)	(3)	(4)
Lagged articles dummy	1.789***	1.782***	1.772***	1.682***
	[2.68]	[2.67]	[2.64]	[2.40]
$FOMC$		1.679*	1.595	1.444
		[0.84]	[0.75]	[0.58]
VIX			1.027*	1.007
			[1.76]	[0.39]
TED Spread				8.796**
Day FE	Yes	Yes	Yes	Yes
Obs	10,368	10,368	10,224	10,080
R^2	0.06%	0.06%	0.07%	0.10%

Panel C: Negative Tweet
Dependent variable: Negative Tweet dummy

	(1)	(2)	(3)	(4)
Lagged articles dummy	1.952	1.924	1.813	1.762
	[1.58]	[1.54]	[1.38]	[1.31]
$FOMC$		2.515	2.361	1.940
		[1.16]	[1.09]	[0.83]
VIX			0.998	0.000*
			[-0.04]	[1.90]
TED Spread				62.230***
				[2.52]
Day FE	Yes	Yes	Yes	Yes
Obs	10,368	10,368	10,224	397,266
R^2	0.01%	0.02%	0.07%	0.07%

Table 10. Tweets and FX market controlling for macro announcements

This table reports panel regressions results for the estimation of Tweets hour dummy on FX market characteristics. Dependent variables in regressions (1), (2), (3), and (4) and hourly total trading volume, hourly volatility, hourly bid-ask spread, and hourly returns respectively. The control variables are presidency dummy, FOMC dummy, VIX, and TED Spread. Macro Announcements is a dummy variable which is equal to 1 if there is at least one macro announcement on that day 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 16th June 2015 and 20th August 2019.

Dependent variable: FX market characteristics				
	(1)	(2)	(3)	(4)
	Volume	Volatility	Bid-Ask Spread	Returns
Tweet hour	-0.752***	-0.003***	-0.142***	0.005***
	[-4.66]	[-2.94]	[-2.70]	[3.70]
$Presidency$	0.368***	-0.012***	-0.996***	0.000
	[3.54]	[-6.15]	[-2.80]	[1.47]
$FOMC$	0.251***	0.070***	0.264*	-0.023***
	[3.19]	[8.81]	[1.79]	[-4.75]
VIX	0.021***	0.001***	0.004	0.000*
	[3.69]	[8.78]	[0.53]	[1.81]
TED Spread	-0.286**	0.017***	0.133	-0.000
	[-1.96]	[3.62]	[0.20]	[-0.32]
Macro Announcements	0.108***	0.001	-0.128	-0.003***
	[4.65]	[1.11]	[-0.98]	[-5.37]
Country FE	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Obs	379,188	387,074	372,638	390,806
R^2	4.80%	7.77%	1.86%	0.07%

Table 11. Uninformative Tweets and FX market

This table reports panel regressions results for the estimation of uninformative Tweets hour dummy on FX market characteristics. Dependent variables in regressions (1), (2), (3), and (4) and hourly total trading volume, hourly volatility, hourly bid-ask spread, and hourly returns respectively. The control variables are presidency dummy, FOMC dummy, VIX, and TED Spread. 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 16th June 2015 and 20th August 2019.

Dependent variable: FX market characteristics				
	(1) Volume	(2) Volatility	(3) Bid-Ask Spread	(4) Returns
Uninformative Tweet hour	-0.058***	0.001	0.098	0.002
	[-3.87]	[1.05]	[1.38]	[1.60]
Presidency	0.326***	-0.011***	-1.011***	0.000
	[3.38]	[-5.94]	[-2.77]	[0.98]
FOMC	0.181***	0.070***	0.261*	-0.023***
	[2.25]	[8.81]	[1.78]	[-4.43]
VIX	0.022***	0.001***	0.003	0.000
	[3.57]	[8.81]	[0.46]	[1.53]
TED Spread	-0.285**	0.017***	0.098	0.017
	[-2.25]	[3.51]	[0.14]	[0.97]
Country FE	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Obs	358,016	387,074	372,638	366,474
R^2	3.82%	7.77%	1.85%	0.07%

Table 12. Tweets and FX Options Moneyness

This table reports time series regressions results for the estimation of Tweets hour dummy on FX options moneyness. The control variables are presidency dummy, FOMC dummy, VIX, and TED Spread. Hour-of-the-day and day-of-the-week dummies are included in all regressions. Standard errors are adjusted by Newey-West with number of lags based on AIC. 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 16th June 2015 and 20th August 2019.

	Dependent variable: Moneyness				
	(1)	(2)	(3)	(4)	(5)
Tweet hour	-0.142**	-0.148**	-0.148**	-0.146**	-0.139**
	[-2.41]	[-2.38]	[-2.38]	[-2.36]	[-2.15]
Presidency		0.067	0.067	0.060	-0.008
		[1.10]	[1.10]	[1.04]	[-0.28]
FOMC			-0.019	-0.179	-0.022
			[-0.26]	[-0.24]	[-0.28]
VIX				-0.003	-0.003
				[-0.62]	[-0.80]
TED Spread					-0.725*
					[-1.71]
Hour FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Obs	9,855	9,855	9,855	9,541	9,378
R^2	0.10%	0.09%	0.08%	0.02%	0.00%

Internet Appendix to

"The Information Content of Trump Tweets and the Currency Market"

by

ILIAS FILIPPOU ARIE GOZLUKLU MY T. NGUYEN GANESH VISWANATH-NATRAJ

(Not for publication)

Appendix A: Model Solution

Solution of optimal weight and bond holdings

Bayesian Agent

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

subject to:

$$W_t^j = \rho_t^j b_t^j$$

We can rewrite the maximization problem as follows:

$$\max_{b_t^j} \qquad L = \mathbb{E}[\rho_t^j] b_t^j - \frac{\gamma}{2} b_t^{j2} (\omega_j^{B2} \sigma_T^2 + (1-\omega_j^B)^2 \sigma_j^2)$$

Taking first order conditions:

FOC w.r.t b_t^j

$$E[\rho_t^j] - \gamma b_t^j [\omega_j^{B2} \sigma_T^2 + (1-\omega_j^B)^2 \sigma_j^2] = 0$$

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

$$b_t^j = \frac{\omega_j^B \theta^T + (1-\omega_j^B)\theta^j - s_t + i_t^* - i_t}{\gamma(\omega_j^{B2} \sigma_T^2 + (1-\omega_j^B)^2 \sigma_j^2)}$$

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:

$$W_t^j = \rho_t^j b_t^j$$

We can rewrite the maximization problem as follows:

$$\max_{b_t^j} \qquad L = \mathbb{E}[\rho_t^j]b_t^j - \frac{\gamma}{2} b_t^{j2} \sigma_T^2$$

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 bond holdings, using the fact that $E[\rho_t^j] = \theta^T - s_t + i_t^* - i_t$

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

Proof of Prediction 1

Bayesian Agent

The market clearing exchange rate is given by:

$$s_t = \theta^T + i_t^* - i_t$$

The excess return for a bayesian agent,

$$\begin{aligned}
\mathbb{E}_t[\rho_t^j] &= \omega_j^B \theta^T + (1-\omega_j^B)\theta^j - s_t + i_t^* - i_t \\
&= \omega_j^B \theta^T + (1-\omega_j^B)\theta^j - (\theta^T + i_t^* - i_t) + i_t^* - i_t \\
&= (1-\omega_j^B)(\theta_j - \theta^T)
\end{aligned}$$

Therefore we can write the bond holdings of investor j of the Bayesian agent (conditioning on public to private information) as follows:

$$\begin{aligned}
b_t^j | I_j, I_T &= \frac{(1-\omega_j^B)(\theta^j - \theta^T)}{\gamma(\omega_j^{B^2}\sigma_T^2 + (1-\omega_j^B)^2\sigma_j^2)} \\
&= \frac{(1-\omega_j^B)(\theta^j - \theta^T)}{\gamma(\omega_j^{B^2}(\sigma_T^2 + \sigma_j^2) + \sigma_j^2 - 2\omega_j^B\sigma_j^2)} \\
&= \frac{\theta^j - \theta^T}{\gamma\sigma_j^2} \times \frac{(1-\omega_j^B)}{\omega_j^{B^2}\frac{\sigma_T^2+\sigma_j^2}{\sigma_j^2} + 1 - 2\omega_j^B}
\end{aligned}$$

Using the fact that bond holdings of investor j conditional on private information is $b_t^j | I_j = \frac{\theta^j - \theta^T}{\gamma\sigma_j^2}$, and $\omega_j^B = \frac{\sigma_j^2}{\sigma_T^2+\sigma_j^2}$, simplifies the bond holdings of investor j to be the same as bond holdings without the Trump tweet (i.e. conditioned only on private information).

$$
\begin{aligned}
b_t^j | I_j, I_T &= \frac{\theta^j - \theta^T}{\gamma \sigma_j^2} \times \frac{(1-\omega_j^B)}{1-\omega_j^B} \\
&= \frac{\theta^j - \theta^T}{\gamma \sigma_j^2} = b_t^j | I_j
\end{aligned}
$$

Trump Follower

The excess return for a bayesian agent,

$$
\begin{aligned}
\mathbb{E}_t[\rho_t^j] &= \theta^T - s_t + i_t^* - i_t \\
&= \theta^T - (\theta^T + i_t^* - i_t) + i_t^* - i_t \\
&= 0
\end{aligned}
$$

Therefore, as expected excess returns of a Trump follower is zero, optimal bond holdings are zero.

Total Volume Traded

The total volume traded is given by $V_{FX} = \frac{1}{2}\sum_{j=1}^{N} |b_t^j|$. We have shown that bond holdings of Bayesian agents are unchanged relative to an equilibrium without public information. Trump followers, on the other hand, do not trade conditional on public information as they earn zero excess returns in equilibrium. Based on this information, we can compute the ratio of trading with the public signal to the original equilibrium as follows:

$$
\begin{aligned}
\frac{V_{FX}|I_j, I_T}{V_{FX}|I_j} &= \frac{\frac{1}{2}\sum_{j \in N_B} |b_t^j|}{\frac{1}{2}\left(\sum_{j \in N_B} |b_t^j| + \sum_{j \in N_B} |b_t^j|\right)} \\
&= \frac{\sum_{j \in N_B} |\frac{\theta^j - \theta^T}{\sigma_j^2}|}{\sum_{j \in N_B} |\frac{\theta^j - \theta^T}{\sigma_j^2}| + \sum_{j \in N_T} |\frac{\theta^j - \theta^T}{\sigma_j^2}|} < 1
\end{aligned}
$$

Proof of Prediction 2

$$
\begin{aligned}
var(s_{t+1|I_j,I_T}) &= \frac{\sum_{j=1}^{N} var(s_{t+1}^{j})}{N} \\
&= \frac{\sum_{j\in N_B} var(s_{t+1}^{j}) + \sum_{j\in N_T} var(s_{t+1}^{j})}{N} \\
&= \frac{N_B}{N}(\omega_j^{B2}\sigma_T^2 + (1-\omega_j^B)\sigma_j^2) + \frac{N_T}{N}\sigma_T^2 \\
&= \frac{N_B}{N}(1-\omega_{j\,\sigma\,j}^{B\ \ 2} + (1-\frac{N_B}{N})\sigma_T^2 \\
&= \sigma_T^2 + \frac{N_B}{N}\left((1-\omega_j^B)\sigma_j^2 + \sigma_T^2\right)
\end{aligned}
$$

Using the fact that the variance conditional on private information is $var(s_{t+1|I_j}) = \sigma_j^2$, the ratio of variance with the public signal to the equilibrium without the public signal is, using $R = \frac{\sigma_T^2}{\sigma_j^2}$

$$
\begin{aligned}
\frac{var(s_{t+1|I_j,I_T})}{var(s_{t+1|I_j})} &= \frac{\sigma_T^2}{\sigma_j^2} + \frac{N_B}{N}\left(1-\omega_j^B - \frac{\sigma_T^2}{\sigma_j^2}\right) \\
&= R + \frac{N_B}{N}\left(\frac{R}{1+R} - R\right) \\
&= R\left(1 + \frac{N_B}{N}\left(\frac{1}{1+R} - 1\right)\right) \\
&= R\left(1 - \frac{N_B}{N}\frac{R}{1+R}\right)
\end{aligned}
$$

For a decline in the volatility conditional on public information, we require $\frac{var(s_{t+1|I_j,I_T})}{var(s_{t+1|I_j})} < 1$, this imposes the following restriction on the share of Bayesian agents.

$$
\begin{aligned}
R\left(1 - \frac{N_B}{N}\frac{R}{1+R}\right) &< 1 \\
\frac{N_B}{N}\frac{R}{1+R} &> 1 - \frac{1}{R} \\
\frac{N_B}{N} &> \frac{R^2-1}{R^2} \implies \frac{var(s_{t+1|I_j,I_T})}{var(s_{t+1|I_j})} < 1
\end{aligned}
$$

Proof of Prediction 3

Using an asset pricing view of the exchange rate to link it to macroeconomic fundamentals, the spot exchange rate conditional on private information is given by (where $f_t = \frac{m_t - m_t^*}{1+\alpha} - \frac{\eta(y_t - y_t^*)}{1+\alpha}$

$$s_t|I_j = f_t + \sum_{s=1}^{\infty}\left(\frac{\alpha}{1+\alpha}\right)^s \frac{1}{N}\sum_{j=1}^{N}\mathbb{E}_t[f_{t+s}^j]$$

The spot exchange rate conditional on public and private information is given by

$$\begin{aligned}
s_t|I_j, I_T &= f_t + \sum_{s=1}^{\infty}\left(\frac{\alpha}{1+\alpha}\right)^s \frac{1}{N}\left(\sum_{j\in N_B}^{N}\left(\omega_B E[f_{t+s}^T] + (1-\omega_B)E[f_{t+s}^j]\right) + \sum_{j\in N_T}^{N} E[f_{t+s}^T]\right) \\
&= f_t + \sum_{s=1}^{\infty}\left(\frac{\alpha}{1+\alpha}\right)^s \left(\frac{\omega_B N_B + N_T}{N} E[f_{t+s}^T] + (1-\omega_B)\frac{1}{N}\sum_{j\in N_B} E[f_{t+s}^j]\right)
\end{aligned}$$

Taking the difference between the spot rate conditional on public information and the spot rate in the equilibrium without the public signal,

$$s_t|I_j, I_T - s_t|I_j = \sum_{s=1}^{\infty}\left(\frac{\alpha}{1+\alpha}\right)^s \left(\frac{\omega_B N_B + N_T}{N} E[f_{t+s}^T] + (1-\omega_B)\frac{1}{N}\sum_{j\in N_B} E[f_{t+s}^j]\right) - \frac{1}{N}\sum_{j=1}^{N}\mathbb{E}_t[f_{t+s}^j]$$

Assuming that $\frac{1}{N_B}\sum_{j\in N_B} E[f_{t+s}^j] = \frac{1}{N}\sum_{j\in N} E[f_{t+s}^j]$, we can simplify the above expression as follows:

$$
\begin{aligned}
s_t|I_j, I_T - s_t|I_j &= \sum_{s=1}^{\infty}\left(\frac{\alpha}{1+\alpha}\right)^s\left(\frac{\omega_B N_B + N_T}{N}E[f_{t+s}^T] + \frac{N_B}{N}\omega_B\sum_{j=1}^{N}E[f_{t+s}^j]\right)\\
&= \sum_{s=1}^{\infty}\left(\frac{\alpha}{1+\alpha}\right)^s\left(\frac{\omega_B N_B + N_T}{N}E[f_{t+s}^T] + \left((1-\omega_B)\frac{N_B}{N} - 1\right)\sum_{j=1}^{N}E[f_{t+s}^j]\right)\\
&= \sum_{s=1}^{\infty}\left(\frac{\alpha}{1+\alpha}\right)^s\left(\frac{\omega_B N_B + N_T}{N}E[f_{t+s}^T] - \frac{\omega_B N_B + N_T}{N}\frac{1}{N}\sum_{j=1}^{N}E[f_{t+s}^j]\right)\\
&= \frac{\omega_B N_B + N_T}{N}\sum_{s=1}^{\infty}\left(\frac{\alpha}{1+\alpha}\right)^s\left(E[f_{t+s}^T] - \frac{1}{N}\sum_{j=1}^{N}E[f_{t+s}^j]\right)
\end{aligned}
$$

Appendix B: Sample of Tweets

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

Macroeconomics Outlook

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

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

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

Trade Policy

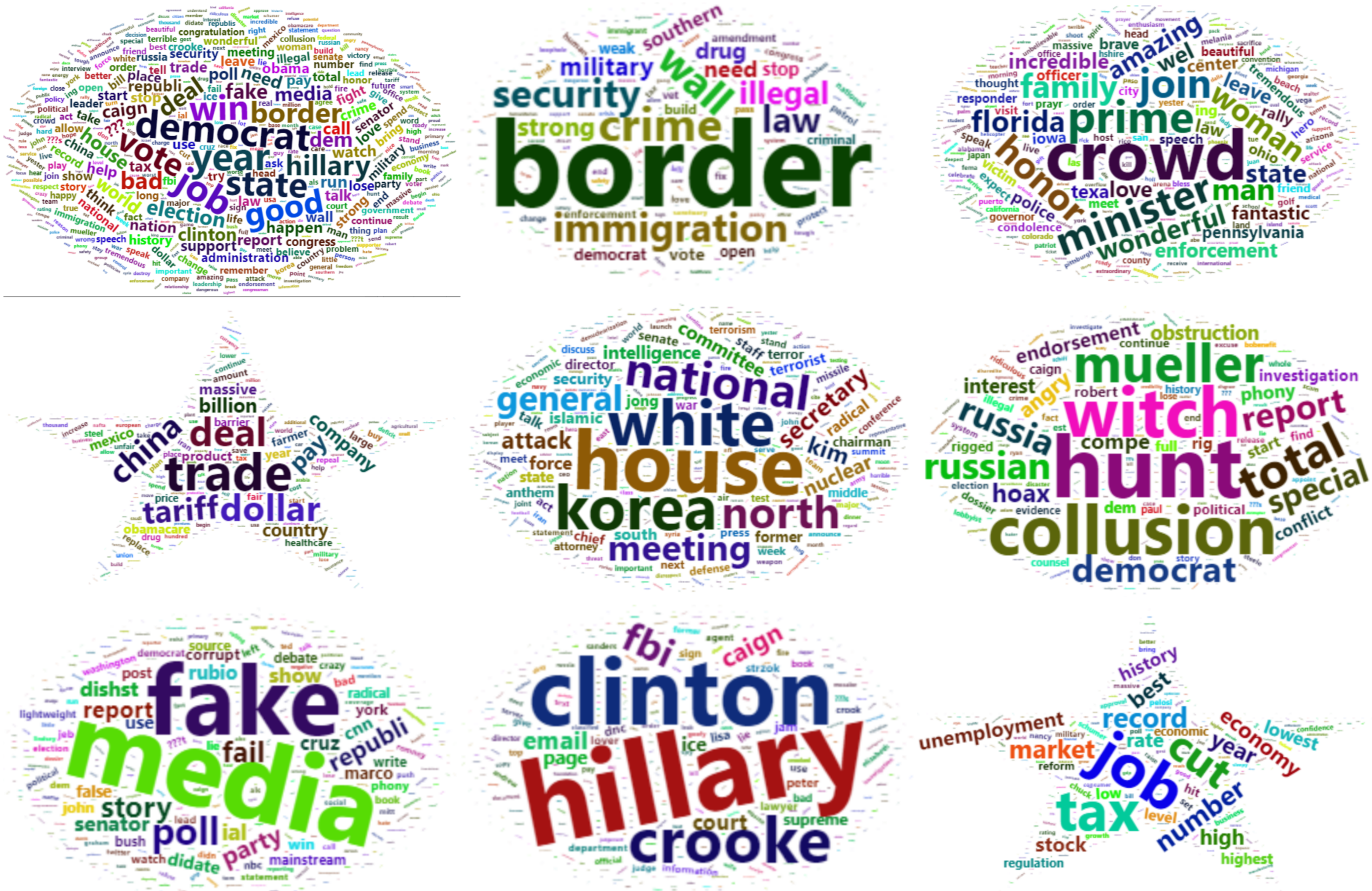
"*I am pleased to inform you that The United States of America has reached a signed agreement with Mexico. The Tariffs scheduled to be implemented by the U.S. on Monday, against Mexico, are hereby indefinitely suspended,*"

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

Exchange Rate

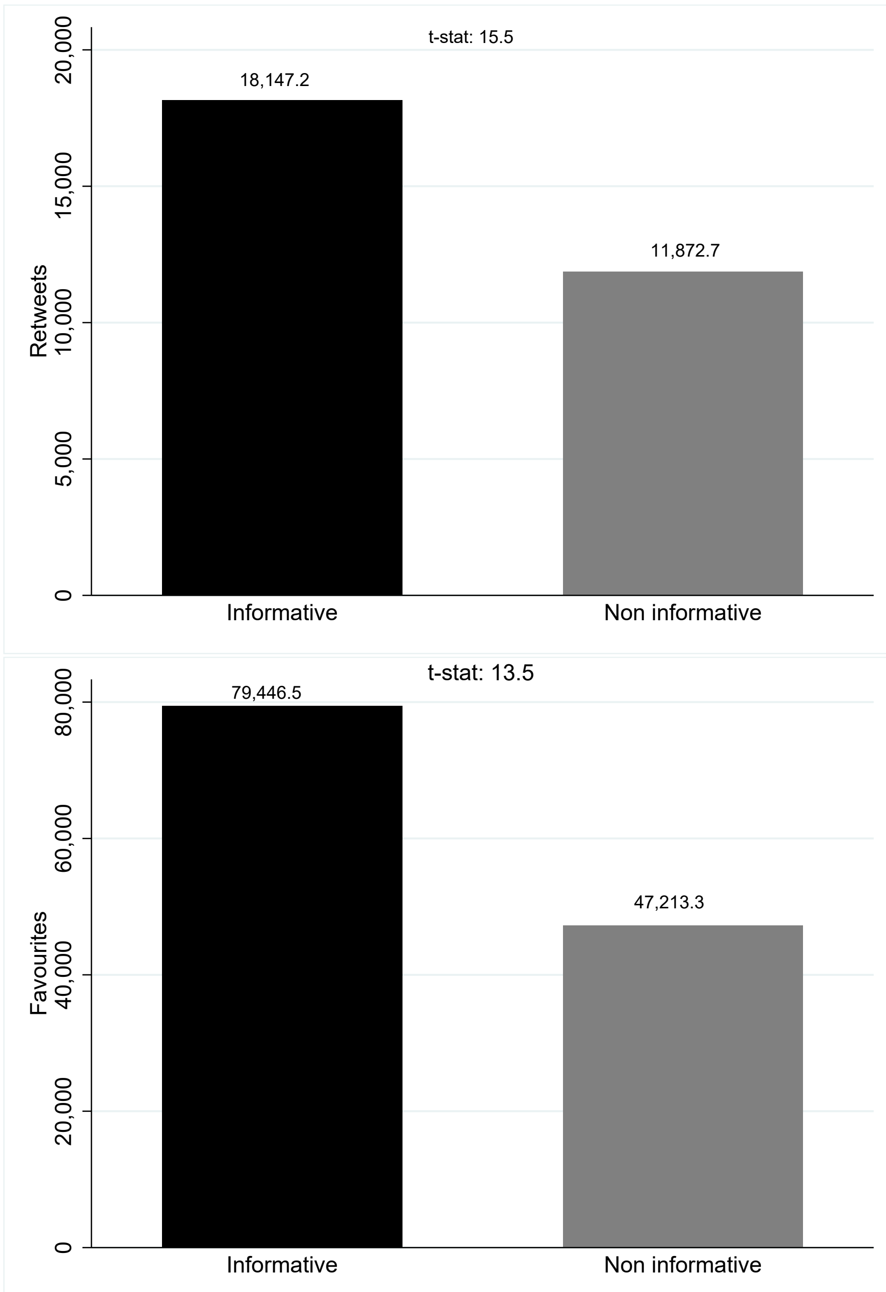
"*Based on the historic currency manipulation by China, it is now even more obvious to everyone that Americans are not paying for the Tariffs – they are being paid for compliments of China, and the U.S. is taking in tens of Billions of Dollars! China has always....*"

Figure A1. BTM Topic Keywords



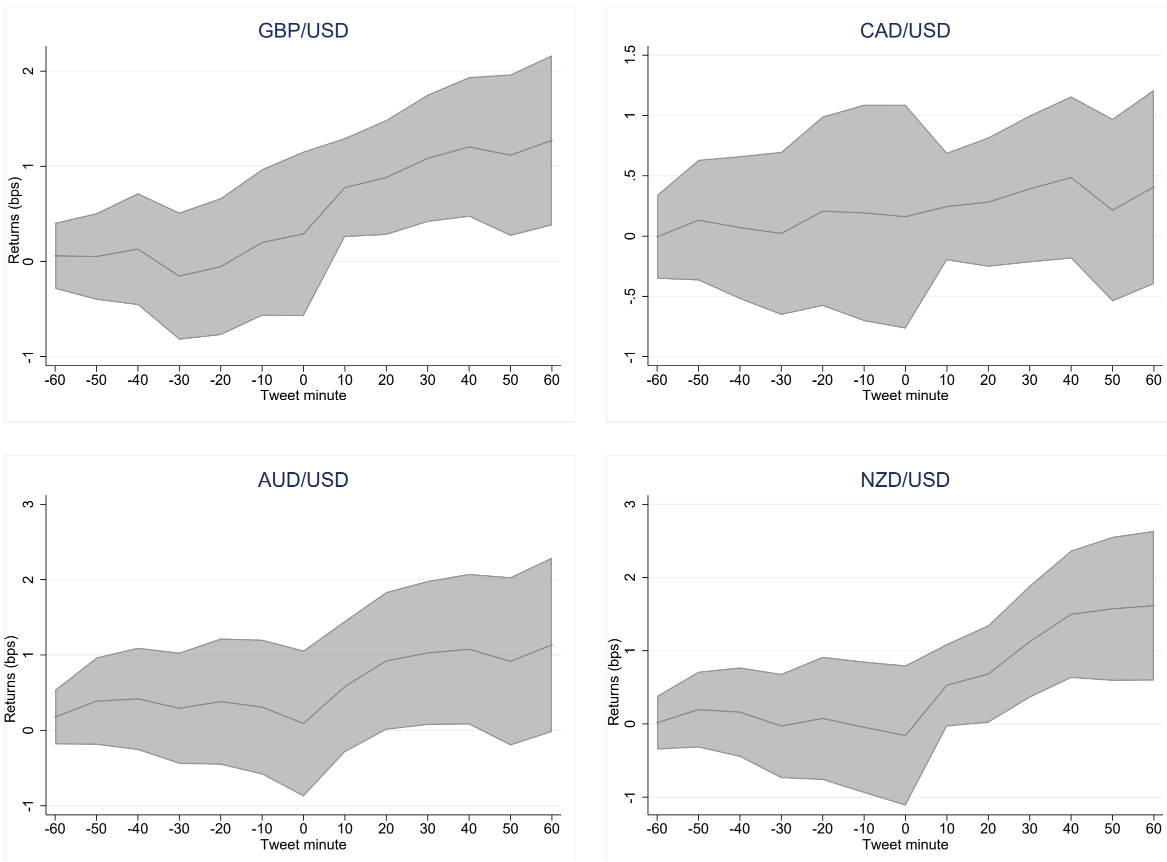
The graph reports results from BTM implemented on Tweets. For each topic, the top keywords are reported.

Figure A2. Informative Tweets and Non-informative Tweets



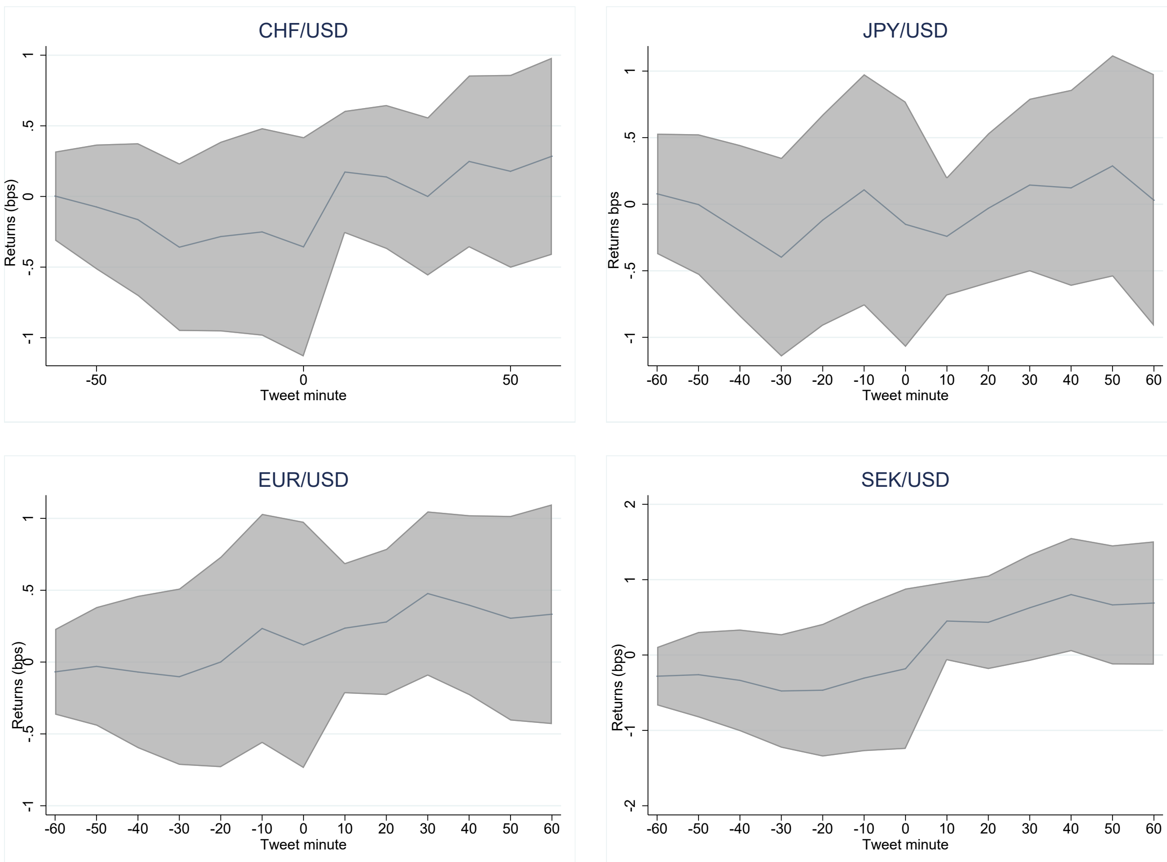
The figure shows the average number of Retweets (Panel A) and favorite (Panel B) for Informative Tweets and Non-informative Tweets. Informative Tweets and Non-informative Tweets are matched by VIX Index and hour-of-day. The data is between 16th June 2015 and 20th August 2019.

Figure A3. Event study: Cumulative returns by currency



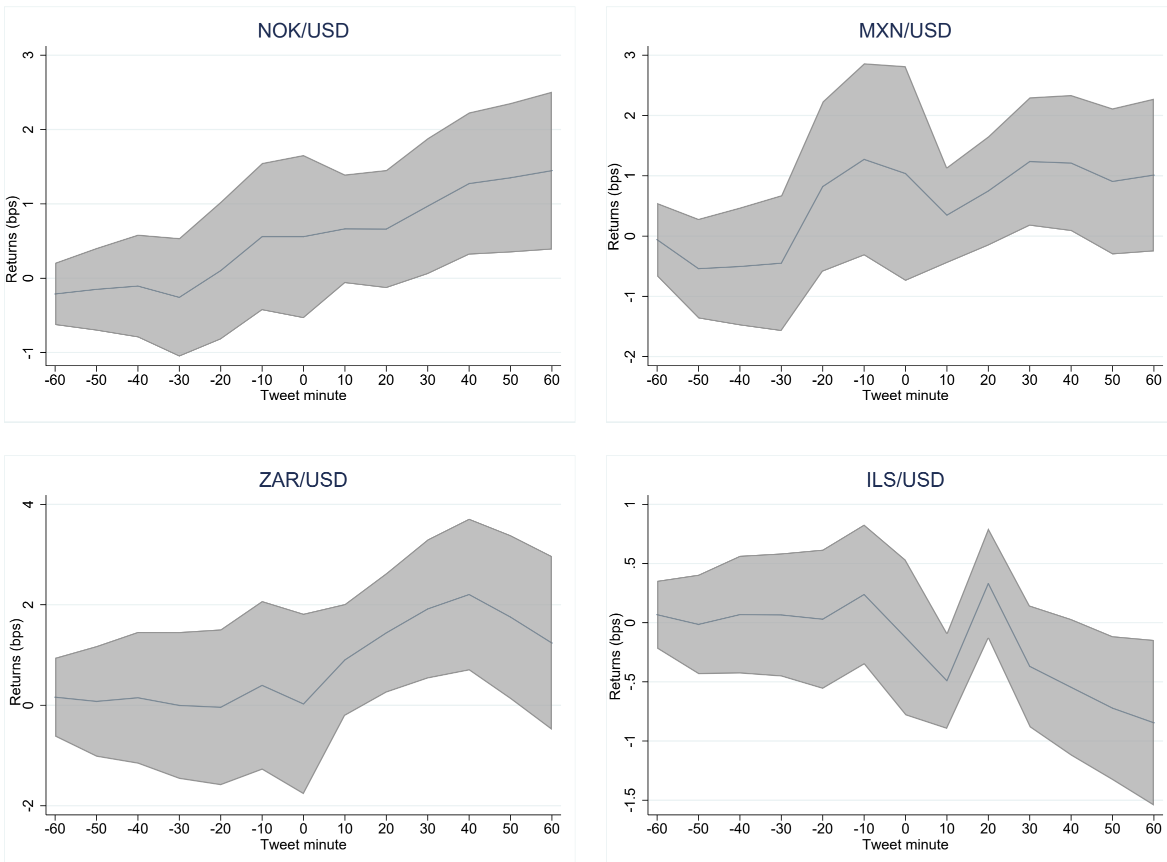
The figure reports the cumulative returns for individual currencies. The y-axis shows the minutes during the event, with 0 being the minute in which a tweet is posted. The negative values in the y-axis are the number of minutes before tweets. The shaded area shows 95% confidence interval

Figure A4. Event study: Cumulative returns by currency



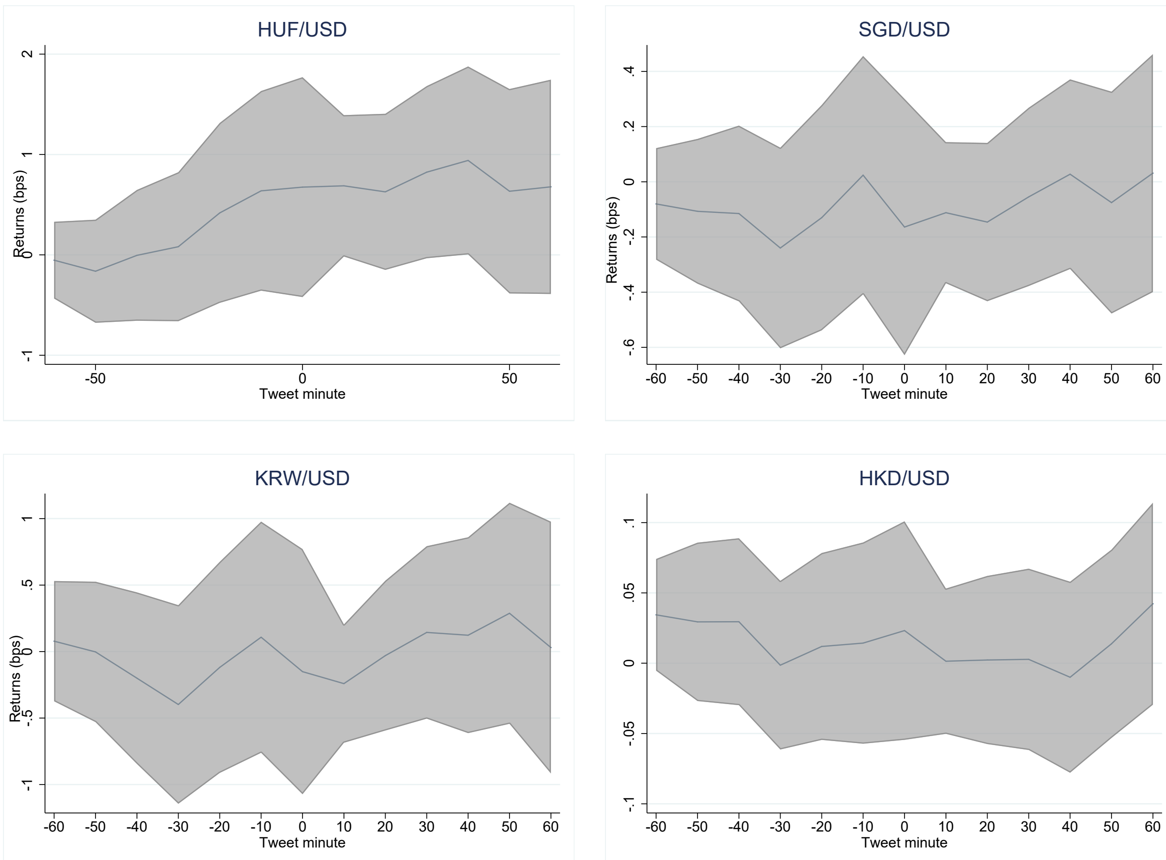
The figure reports the cumulative returns for individual currencies. The y-axis shows the minutes during the event, with 0 being the minute in which a tweet is posted. The negative values in the y-axis are the number of minutes before tweets. The shaded area shows 95% confidence interval

Figure A5. 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 in the y-axis are the number of minutes before tweets. The shaded area shows 95% confidence interval

Figure A6. 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 in the y-axis are the number of minutes before tweets. The shaded area shows 95% confidence interval

Table A1. Tweets (based on dictionary method) and Spot FX Trading Volume (Total Sell Side - Total Buy Side)

This table reports panel regressions results for the estimation of Tweets hour dummy on FX Trading Volume The control variables are presidency dummy, FOMC dummy, VIX, and TED Spread. 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 16th June 2015 and 20th August 2019.

	Dependent variable: Trading Volume between Sell Side and Buy Side				
	(1)	(2)	(3)	(4)	(5)
Tweet hour	-0.645***	-0.709***	-0.709***	-0.738***	-0.743***
	[-4.34]	[-4.30]	[-4.29]	[-4.38]	[-4.51]
Presidency		0.289***	0.289***	0.350***	0.340***
		[3.20]	[3.20]	[3.44]	[3.41]
FOMC			0.167*	0.180**	0.182**
			[1.93]	[2.16]	[2.21]
VIX				0.023***	0.022***
				[3.67]	[3.56]
TED Spread					-0.297**
					[-2.36]
Country FE	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Obs	367,333	367,333	367,333	363,515	357,588
R^2	4.57%	4.64%	4.64%	4.76%	4.75%

Table A2. Tweets (based on dictionary method) 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 presidency dummy, FOMC dummy, VIX, and TED Spread. Hour-of-the-day and day-of-the-week dummies are included in all regressions. In Panel A, dependent variable is trading volume between market maker bank and price taker bank. In Panel B, dependent variable is trading volume between market maker bank and price taker fund. In Panel C, dependent variable is trading volume between market maker bank and price taker non-bank financials. In Panel D, dependent variable is trading volume between market maker bank 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 16th June 2015 and 20th August 2019.

	Panel A. Dependent variable: Bank - Bank Trading Volume					*Panel B. Dependent variable*: Bank - Fund Volume				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Tweet hour	-0.702***	-0.760***	-0.760***	-0.792***	-0.795**	-0.618***	-0.769***	-0.769***	-0.835***	-0.860***
	[-3.85]	[-3.86]	[-3.86]	[-3.94]	[-4.04]	[-3.72]	[-5.07]	[-5.06]	[-5.68]	[-5.80]
Presidency		0.253***	0.253***	0.326***	0.317***		0.666***	0.667***	0.746***	0.742***
		[3.20]	[3.20]	[3.45]	[3.45]		[4.99]	[4.99]	[5.44]	[5.49]
FOMC			0.0408	0.056	0.058			0.186	0.192	0.190
			[0.80]	[1.14]	[1.18]			[0.85]	[0.91]	[0.91]
VIX				0.026***	0.024***				0.033***	0.031***
				[3.51]	[3.42]				[6.00]	[6.10]
TED Spread					-0.269**					0.048
					[-1.96]					[0.13]
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	310,888	310,888	310,888	307,671	302,559	291,541	291,541	291,541	288,518	283,839
R^2	4.80%	4.81%	4.81%	4.94%	4.93%	22.06%	22.23%	22.23%	22.46%	22.55%

	Panel C. Dependent variable: Bank - Non-Bank Trading Volume					*Panel D. Dependent variable*: Bank - Corporate Volume				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Tweet hour	-0.436***	-0.875***	-0.875***	-0.918***	-0.926***	0.083	-0.078	-0.078	-0.151	-0.220
	[-3.79]	[-8.02]	[-8.02]	[-8.92]	[-8.77]	[0.41]	[-0.47]	[-0.47]	[-1.01]	[-1.49]
Presidency		2.019***	2.019***	2.105***	2.072***		0.900***	0.900***	1.068***	0.988***
		[6.05]	[6.05]	[6.27]	[6.17]		[3.16]	[3.15]	[3.27]	[3.04]
FOMC			0.161	0.176	0.179			-0.164	-0.1308	-0.125
			[0.64]	[0.71]	[0.72]			[-0.20]	[-0.16]	[-0.15]
VIX				0.036***	0.035***				0.070***	0.069***
				[5.13]	[5.05]				[3.50]	[3.46]
TED Spread					-0.537**					-1.83***
					[-2.00]					[-2.55]
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	300,093	300,093	300,093	297,023	292,150	103,508	103,508	103,508	102,492	100,883
R^2	2.32%	4.28%	4.28%	4.31%	4.27%	0.95%	1.11%	1.14%	1.24%	1.30%

Table A3. Tweets (based on dictionary method) and FX Hourly Realised Volatility

This table reports panel regressions results for the estimation of Tweets hour dummy on FX hourly realised volatility. The control variables are presidency dummy, FOMC dummy, VIX, and TED Spread. 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 16th June 2015 and 20th August 2019.

	Dependent variable: Realised Volatility				
	(1)	(2)	(3)	(4)	(5)
Tweet hour	-0.006***	-0.003***	-0.003***	-0.004***	-0.003***
	[-5.36]	[-3.20]	[-3.03]	[-3.49]	[-2.93]
Presidency		-0.014***	-0.014***	-0.012***	-0.011***
		[-7.06]	[-7.06]	[-6.38]	[-5.94]
FOMC			0.070***	0.070***	0.069***
			[8.81]	[8.81]	[8.80]
VIX				0.001***	0.001***
				[8.81]	[8.82]
TED Spread					0.017***
					[3.49]
Country FE	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Obs	397,708	397,708	397,708	393,251	387,708
R^2	6.17%	7.22%	7.38%	7.64%	7.77%

Table A4. Tweets (based on dictionary method) and FX Hourly Bid-Ask Spreads

This table reports panel regressions results for the estimation of Tweets hour dummy on FX hourly bid-ask spreads. The control variables are presidency dummy, FOMC dummy, VIX, and TED Spread. 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 16th June 2015 and 20th August 2019.

	Dependent variable: Bid-Ask Spreads				
	(1)	(2)	(3)	(4)	(5)
Tweet hour	-0.439***	-0.208***	-0.208***	-0.210***	-0.202***
	[-3.49]	[-3.51]	[-3.51]	[-3.56]	[-3.51]
Presidency		-1.022***	-1.022***	-1.012***	-1.010***
		[-2.79]	[-2.79]	[-2.89]	[-2.77]
FOMC			0.257*	0.262*	0.256*
			[1.72]	[1.76]	[1.75]
VIX				0.003	0.003
				[0.45]	[0.47]
TED Spread					0.094
					[0.13]
Country FE	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Obs	382,894	382,894	382,894	378,715	372,638
R^2	1.58%	3.32%	3.33%	3.34%	3.45%

Table A5. Tweets (based on dictionary method) and FX Hourly Returns

This table reports panel regressions results for the estimation of Tweets hour dummy on FX hourly returns. The control variables are presidency dummy, FOMC dummy, VIX, and TED Spread. 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 16th June 2015 and 20th August 2019.

	Dependent variable: Returns				
	(1)	(2)	(3)	(4)	(5)
Tweet hour	0.006***	0.006***	0.006***	0.005***	0.006***
	[4.16]	[4.08]	[4.05]	[3.96]	[4.21]
Presidency		-0.000	-0.000	0.000	0.000
		[-0.19]	[-0.20]	[1.31]	[0.65]
FOMC			-0.023***	-0.023***	-0.023***
			[-4.43]	[-4.42]	[-4.41]
VIX				0.000*	0.000
				[1.64]	[1.50]
TED Spread					-0.001
					[-0.85]
Country FE	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Obs	376,850	376,850	376,850	372,534	366,474
R^2	0.07%	0.07%	0.07%	0.07%	0.07%

Table A6. Tweets (based on dictionary method) and FX Hourly Returns

This table reports panel regressions results for the estimation of Tweets hour dummy on FX hourly returns. The control variables are presidency dummy, FOMC dummy, VIX, and TED Spread. Hour-of-the-day and day-of-the-week dummies are included in all regressions. In Panel A, independent variable of interest is Trade Tweet. In Panel B, independent variable of interest is Macro 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 16th June 2015 and 20th August 2019.

Panel A: Trade Tweet
Dependent variable: Returns

	(1)	(2)	(3)	(4)	(5)
Trade Tweet	0.003*	0.003	0.003	0.002	0.003
	[0.98]	[0.97]	[0.95]	[0.78]	[0.97]
Presidency		-0.000	-0.000	0.000	0.000
		[-0.00]	[-0.01]	[1.47]	[0.83]
FOMC			-0.023***	-0.023***	-0.023***
			[-4.45]	[-4.43]	[-4.42]
VIX				0.000*	0.000
				[1.66]	[1.51]
TED Spread					-0.001
					[-0.95]
Country FE	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Obs	376,850	376,850	376,850	372,534	366,474
R^2	0.06%	0.06%	0.07%	0.07%	0.07%

Panel B: Macro Tweet
Dependent variable: Returns

	(1)	(2)	(3)	(4)	(5)
Macro Tweet	0.007***	0.007***	0.007***	0.007***	0.008***
	[4.60]	[4.62]	[4.60]	[4.38]	[4.69]
Presidency		-0.000	-0.000	0.000	0.000
		[-0.19]	[-0.20]	[1.34]	[0.68]
FOMC			-0.023***	-0.023***	-0.023***
			[-4.44]	[-4.43]	[-4.42]
VIX				0.000*	0.000
				[1.66]	[1.51]
TED Spread					-0.001
					[-0.86]
Country FE	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Obs	376,850	376,850	376,850	372,534	366,474
R^2	0.07%	0.07%	0.07%	0.07%	0.07%

Table A7. Tweets (based on dictionary method) and FX Hourly Returns

This table reports panel regressions results for the estimation of Tweets hour dummy on FX hourly returns. The control variables are presidency dummy, FOMC dummy, VIX, and TED Spread. Hour-of-the-day and day-of-the-week dummies are included in all regressions. In Panel A, independent variable of interest is Positive Tweet. In Panel B, independent variable of interest is 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 16th June 2015 and 20th August 2019.

Panel A: Positive Tweet
Dependent variable: Returns

	(1)	(2)	(3)	(4)	(5)
Positive Tweet	0.013***	0.013***	0.013***	0.013***	0.013***
	[5.61]	[5.59]	[5.57]	[5.63]	[5.85]
Presidency		-0.000	-0.000	0.000	0.000
		[-0.31]	[-0.32]	[1.18]	[0.52]
FOMC			-0.023***	-0.023***	-0.023***
			[-4.44]	[-4.42]	[-4.42]
VIX				0.000*	0.000
				[1.67]	[1.53]
TED Spread					-0.001
					[-0.99]
Country FE	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Obs	376,850	376,850	376,850	372,534	366,474
R^2	0.07%	0.07%	0.08%	0.08%	0.07%

Panel B: Negative Tweet
Dependent variable: Returns

	(1)	(2)	(3)	(4)	(5)
Negative Tweet	-0.006***	-0.006***	-0.006***	-0.006***	-0.006***
	[-3.03]	[-3.02]	[-3.04]	[-3.17]	[-3.17]
Presidency		0.000	0.000	0.001	0.000
		[0.04]	[0.03]	[1.56]	[0.91]
FOMC			-0.023***	-0.023***	-0.023***
			[-4.46]	[-4.44]	[-4.43]
VIX				0.000*	0.000
				[1.69]	[1.54]
TED Spread					-0.001
					[-1.00]
Country FE	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Obs	376,850	376,850	376,850	372,534	366,474
R^2	0.06%	0.07%	0.07%	0.07%	0.07%

Table A8. Tweets (based on dictionary method) and FX Options Moneyness

This table reports time series regressions results for the estimation of Tweets hour dummy on FX options moneyness. The control variables are presidency dummy, FOMC dummy, VIX, and TED Spread. Hour-of-the-day and day-of-the-week dummies are included in all regressions. Standard errors are adjusted by Newey-West with number of lags based on AIC. 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 16th June 2015 and 20th August 2019.

	Dependent variable: Moneyness				
	(1)	(2)	(3)	(4)	(5)
Tweet hour	-0.178***	-0.184***	-0.184***	-0.178***	-0.179***
	[-3.25]	[-3.21]	[-3.21]	[-3.24]	[-2.96]
Presidency		0.066	0.066	0.059	-0.010
		[1.09]	[1.09]	[1.03]	[-0.21]
FOMC			-0.024	-0.023	-0.027
			[-0.33]	[-0.31]	[-0.35]
VIX				-0.003	-0.004
				[-0.62]	[-0.80]
TED Spread					-0.728*
					[-1.72]
Country FE	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Obs	9,855	9,855	9,855	9,541	9,378
R^2	0.10%	0.09%	0.08%	0.02%	0.00%

Table A9. Tweets (based on BTM method) and Spot FX Trading Volume (Total Sell Side - Total Buy Side)

This table reports panel regressions results for the estimation of Tweets hour dummy on FX Trading Volume The control variables are presidency dummy, FOMC dummy, VIX, and TED Spread. 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 16th June 2015 and 20th August 2019.

Dependent variable: Trading Volume between Sell Side and Buy Side					
	(1)	(2)	(3)	(4)	(5)
Tweet hour	-0.737***	-0.819***	-0.819***	-0.809***	-0.801***
	[-3.95]	[-3.97]	[-3.97]	[-4.00]	[-4.10]
Presidency		0.293***	0.293***	0.353***	0.343***
		[3.22]	[3.22]	[3.45]	[3.42]
FOMC			0.200**	0.214**	0.216***
			[2.26]	[2.49]	[2.54]
VIX				0.023***	0.021***
				[3.63]	[3.52]
TED Spread					-0.295**
					[-2.36]
Country FE	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Obs	367,333	367,333	367,333	363,515	357,588
R^2	4.59%	4.65%	4.65%	4.76%	4.75%

Table A10. Tweets (based on BTM method) 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 presidency dummy, FOMC dummy, VIX, and TED Spread. Hour-of-the-day and day-of-the-week dummies are included in all regressions. In Panel A, dependent variable is trading volume between market maker bank and price taker bank. In Panel B, dependent variable is trading volume between market maker bank and price taker fund. In Panel C, dependent variable is trading volume between market maker bank and price taker non-bank financials. In Panel D, dependent variable is trading volume between market maker bank 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 16th June 2015 and 20th August 2019.

	Panel A. Dependent variable: Bank - Bank Trading Volume					*Panel B. Dependent variable*: Bank - Fund Volume				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Tweet hour	-0.813***	-0.889***	-0.889***	-0.874***	-0.864**	-0.745***	-0.941***	-0.941***	-0.952***	-0.976***
	[-3.55]	[-3.06]	[-3.60]	[-3.57]	[-3.61]	[-3.73]	[-5.36]	[-5.36]	[-5.70]	[-6.05]
Presidency		0.257***	0.257***	0.329***	0.321***		0.672***	0.672***	0.750***	0.747***
		[3.22]	[3.22]	[3.46]	[3.46]		[5.07]	[5.07]	[5.50]	[5.56]
FOMC			0.0818*	0.097**	0.098**			0.222	0.230	0.228
			[1.70]	[2.05]	[2.09]			[1.03]	[1.10]	[1.11]
VIX				0.025***	0.024***				0.032***	0.031***
				[3.47]	[3.38]				[5.92]	[6.02]
TED Spread					-0.267**					0.050
					[-1.96]					[0.13]
Obs	310,888	310,888	310,888	307,671	302,559	291,541	291,541	291,541	288,518	283,839
R^2	4.81%	4.83%	4.83%	4.94%	4.93%	22.07%	22.24%	22.24%	22.47%	22.55%

	Panel C. Dependent variable: Bank - Non-Bank Trading Volume					*Panel D. Dependent variable*: Bank - Corporate Volume				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Tweet hour	-0.517***	-1.078***	-1.079***	-1.069***	-1.048***	0.517***	0.286**	0.287**	0.279**	0.270*
	[-3.02]	[-6.17]	[-6.18]	[-6.23]	[-6.34]	[4.79]	[2.07]	[2.06]	[2.13]	[1.92]
Presidency		2.025***	2.025***	2.109***	2.076***		0.896***	0.895***	1.063***	0.983***
		[6.06]	[6.06]	[6.27]	[6.17]		[3.11]	[3.11]	[3.23]	[3.00]
FOMC			0.213	0.229	0.231			-0.172	-0.1358	-0.128
			[0.84]	[0.92]	[0.93]			[-0.21]	[-0.17]	[-0.16]
VIX				0.035***	0.034***				0.070***	0.069***
				[5.05]	[4.97]				[3.49]	[3.45]
TED Spread					-0.537**					-1.83***
					[-2.00]					[-2.53]
Obs	300,093	300,093	300,093	297,023	292,150	103,508	103,508	103,508	102,492	100,883
R^2	2.33%	4.29%	4.29%	4.32%	4.28%	0.96%	1.14%	1.14%	1.24%	1.30%

Table A11. Tweets (based on BTM method) and FX Hourly Realised Volatility

This table reports panel regressions results for the estimation of Tweets hour dummy on FX hourly realised volatility. The control variables are presidency dummy, FOMC dummy, VIX, and TED Spread. 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 16th June 2015 and 20th August 2019.

	Dependent variable: Realised Volatility				
	(1)	(2)	(3)	(4)	(5)
Tweet hour	-0.007***	-0.003***	-0.003***	-0.004***	-0.003***
	[-5.24]	[-2.55]	[-2.60]	[-3.45]	[-2.59]
Presidency		-0.014***	-0.014***	-0.012***	-0.011***
		[-7.05]	[-7.04]	[-6.37]	[-5.93]
FOMC			0.070***	0.070***	0.069***
			[8.81]	[8.81]	[8.80]
VIX				0.001***	0.001***
				[8.81]	[8.82]
TED Spread					0.017***
					[3.49]
Country FE	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Obs	397,708	397,708	397,708	393,251	387,708
R^2	6.17%	7.22%	7.38%	7.64%	7.77%

Table A12. Tweets (based on BTM method) and FX Hourly Bid-Ask Spreads

This table reports panel regressions results for the estimation of Tweets hour dummy on FX hourly bid-ask spreads. The control variables are presidency dummy, FOMC dummy, VIX, and TED Spread. 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 16th June 2015 and 20th August 2019.

Dependent variable: Bid-Ask Spreads					
	(1)	(2)	(3)	(4)	(5)
Tweet hour	-0.406***	-0.111**	-0.111**	-0.126**	-0.124**
	[-2.91]	[-2.07]	[-2.07]	[-2.21]	[-2.28]
Presidency		-1.023***	-1.023***	-1.013***	-1.010***
		[-2.79]	[-2.79]	[-2.89]	[-2.77]
FOMC			0.263*	0.268*	0.262*
			[1.75]	[1.79]	[1.78]
VIX				0.003	0.003
				[0.44]	[0.46]
TED Spread					0.096
					[0.14]
Country FE	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Obs	382,894	382,894	382,894	378,715	372,638
R^2	1.57%	3.32%	3.33%	3.34%	3.45%

Table A13. Tweets (based on BTM method) and FX Hourly Returns

This table reports panel regressions results for the estimation of Tweets hour dummy on FX hourly returns. The control variables are presidency dummy, FOMC dummy, VIX, and TED Spread. 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 16th June 2015 and 20th August 2019.

	Dependent variable: Returns				
	(1)	(2)	(3)	(4)	(5)
Tweet hour	0.006***	0.006***	0.006***	0.007***	0.007***
	[4.08]	[4.07]	[4.08]	[4.21]	[4.18]
Presidency		-0.000	-0.000	0.000	0.000
		[-0.27]	[-0.29]	[1.23]	[0.57]
FOMC			-0.023***	-0.023***	-0.023***
			[-4.47]	[-4.45]	[-4.44]
VIX				0.000*	0.000
				[1.67]	[1.52]
TED Spread					-0.001
					[-0.86]
Country FE	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Obs	376,850	376,850	376,850	372,534	366,474
R^2	0.07%	0.07%	0.07%	0.07%	0.07%

Table A14. Tweets (based on BTM method) and FX Hourly Returns

This table reports panel regressions results for the estimation of Tweets hour dummy on FX hourly returns. The control variables are presidency dummy, FOMC dummy, VIX, and TED Spread. Hour-of-the-day and day-of-the-week dummies are included in all regressions. In Panel A, independent variable of interest is Trade Tweet. In Panel B, independent variable of interest is Macro 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 16th June 2015 and 20th August 2019.

Panel A: Trade Tweet

Dependent variable: Returns

	(1)	(2)	(3)	(4)	(5)
Trade Tweet	0.004***	0.004***	0.004***	0.005***	0.004***
	[2.74]	[2.69]	[2.65]	[2.80]	[2.65]
Presidency		-0.000	-0.000	0.000	0.000
		[-0.06]	[-0.07]	[1.42]	[0.78]
FOMC			-0.023***	-0.023***	-0.023***
			[-4.45]	[-4.43]	[-4.43]
VIX				0.000*	0.000
				[1.65]	[1.51]
TED Spread					-0.001
					[-0.98]
Country FE	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Obs	376,850	376,850	376,850	372,534	366,474
R^2	0.06%	0.06%	0.07%	0.07%	0.07%

Panel B: Macro Tweet

Dependent variable: Returns

	(1)	(2)	(3)	(4)	(5)
Macro Tweet	0.007***	0.007***	0.007***	0.007***	0.008***
	[3.68]	[3.71]	[3.74]	[3.77]	[3.78]
Presidency		-0.000	-0.000	0.000	0.000
		[-0.17]	[-0.19]	[1.38]	[0.72]
FOMC			-0.023***	-0.023***	-0.023***
			[-4.48]	[-4.46]	[-4.45]
VIX				0.000*	0.000
				[1.70]	[1.55]
TED Spread					-0.001
					[-0.82]
Country FE	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Obs	376,850	376,850	376,850	372,534	366,474
R^2	0.07%	0.07%	0.07%	0.07%	0.07%

Table A15. Tweets (based on BTM method) and FX Hourly Returns

This table reports panel regressions results for the estimation of Tweets hour dummy on FX hourly returns. The control variables are presidency dummy, FOMC dummy, VIX, and TED Spread. Hour-of-the-day and day-of-the-week dummies are included in all regressions. In Panel A, independent variable of interest is Positive Tweet. In Panel B, independent variable of interest is 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 16th June 2015 and 20th August 2019.

Panel A: Positive Tweet
Dependent variable: Returns

	(1)	(2)	(3)	(4)	(5)
Positive Tweet	-0.000	-0.000	-0.000	0.000	0.000
	[-0.32]	[-0.31]	[-0.32]	[0.05]	[0.19]
Presidency		0.000	0.000	0.000	0.000
		[0.05]	[0.04]	[1.49]	[0.86]
FOMC			-0.023***	-0.023***	-0.023***
			[-4.46]	[-4.44]	[-4.43]
VIX				0.000*	0.000
				[1.67]	[1.53]
TED Spread					-0.001
					[-0.96]
Country FE	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Obs	376,850	376,850	376,850	372,534	366,474
R^2	0.06%	0.06%	0.07%	0.07%	0.07%

Panel B: Negative Tweet
Dependent variable: Returns

	(1)	(2)	(3)	(4)	(5)
Negative Tweet	-0.005*	-0.005*	-0.005*	-0.009***	-0.010***
	[-1.78]	[-1.77]	[-1.78]	[-3.64]	[-4.30]
Presidency		0.000	0.000	0.001	0.000
		[0.08]	[0.07]	[1.63]	[0.99]
FOMC			-0.023***	-0.023***	-0.023***
			[-4.46]	[-4.44]	[-4.44]
VIX				0.000*	0.000
				[1.68]	[1.54]
TED Spread					-0.001
					[-1.00]
Country FE	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Obs	376,850	376,850	376,850	372,534	366,474
R^2	0.06%	0.06%	0.07%	0.07%	0.07%

Table A16. Tweets (based on BTM method) and FX Options Moneyness

This table reports time series regressions results for the estimation of Tweets hour dummy on FX options moneyness. The control variables are presidency dummy, FOMC dummy, VIX, and TED Spread. Hour-of-the-day and day-of-the-week dummies are included in all regressions. Standard errors are adjusted by Newey-West with number of lags based on AIC. 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 16th June 2015 and 20th August 2019.

	Dependent variable: Moneyness				
	(1)	(2)	(3)	(4)	(5)
Tweet hour	-0.089	-0.098	-0.098	-0.099	-0.089
	[-1.39]	[-1.42]	[-1.42]	[-1.43]	[-1.29]
$Presidency$		0.065	0.065	0.059	-0.010
		[1.08]	[1.08]	[1.01]	[-0.21]
$FOMC$			-0.019	-0.018	-0.022
			[-0.26]	[-0.24]	[-0.28]
VIX				-0.003	-0.004
				[-0.64]	[-0.82]
TED Spread					-0.724*
					[-1.72]
Country FE	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Obs	9,855	9,855	9,855	9,541	9,378
R^2	0.10%	0.09%	0.08%	0.02%	0.00%

Table A17. Tweets and FX Hourly Returns

This table reports time series regressions results for the estimation of Tweets hour dummy on FX hourly returns. The control variables are presidency dummy, FOMC dummy, VIX, and TED Spread. Hour-of-the-day and day-of-the-week dummies are included in all regressions. Standard errors are adjusted by Newey-West standard error. Number of lags is chosen based on AIC. 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 16th June 2015 and 20th August 2019.

	Dependent variable: Returns				
	Tweet hour (1)	Trade Tweet (2)	Macro Tweet (3)	Negative Tweet (4)	Positive Tweet (5)
USDGBP	0.007	0.009	0.006	-0.006	0.004
	[1.51]	[1.37]	[1.10]	[-0.67]	[0.60]
USDCHF	0.000	0.000	0.002	-0.014*	0.004
	[0.06]	[0.03]	[0.36]	[-1.78]	[0.98]
USDJPY	-0.004	-0.004	-0.001	-0.014	0.004
	[-0.97]	[-0.61]	[-0.21]	[-1.29]	[-0.90]
USDCAD	0.005	0.004	0.004	-0.004	0.007
	[1.31]	[0.73]	[0.89]	[-0.52]	[1.37]
USDAUD	0.006	0.004	0.006	-0.006	0.004
	[1.22]	[0.58]	[1.13]	[-0.74]	[0.70]
USDNZD	0.008	0.002	0.008	-0.010	0.002
	[1.48]	[0.31]	[1.26]	[-1.14]	[0.37]
USDEUR	0.009*	0.006	0.012**	-0.008	0.007
	[1.93]	[0.83]	[2.02]	[-0.69]	[1.43]
USDMXN	0.014*	0.027**	0.010	0.008	0.011
	[1.67]	[2.14]	[0.93]	[0.63]	[1.36]
USDSEK	0.004	0.004	0.003	-0.007	0.013**
	[0.51]	[0.42]	[0.30]	[-0.58]	[2.26]
USDNOK	0.014***	0.007	0.018***	-0.007	0.008
	[2.59]	[0.80]	[2.68]	[-0.64]	[1.25]
USDHKD	0.000	0.000	0.000	0.001	0.000
	[0.33]	[0.40]	[0.13]	[0.77]	[0.39]
USDHUF	0.009	0.005	0.013	-0.013	0.011*
	[1.44]	[0.61]	[1.51]	[-1.21]	[1.69]
USDZAR	0.011	-0.001	0.016	-0.013	0.010
	[1.10]	[-0.07]	[1.25]	[-0.68]	[0.94]
USDILS	-0.004	-0.007	-0.002	-0.008	-0.003
	[-1.06]	[-1.36]	[-0.30]	[-1.22]	[-0.61]
USDSGD	0.003	0.003	0.002	-0.010**	0.004
	[1.21]	[0.73]	[0.59]	[-2.08]	[1.59]
USDKRW	0.001	-0.003	0.000	-0.001	0.003
	[0.12]	[-0.45]	[0.00]	[-0.14]	[0.62]

Table A18. Log ReTweets and Spot FX Trading Volume (Total Sell Side - Total Buy Side)

This table reports panel regressions results for the estimation of Tweets hour dummy on FX Trading Volume The control variables are presidency dummy, FOMC dummy, VIX, and TED Spread. 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 16th June 2015 and 20th August 2019.

Dependent variable: Trading Volume between Sell Side and Buy Side					
	(1)	(2)	(3)	(4)	(5)
Log Retweets	-0.068***	-0.076***	-0.076***	-0.076***	-0.076***
	[-4.18]	[-4.16]	[-4.16]	[-4.23]	[-4.32]
$Presidency$		0.298***	0.299***	0.360***	0.350***
		[3.25]	[3.25]	[3.49]	[3.46]
$FOMC$			0.184**	0.198**	0.201***
			[2.16]	[2.39]	[2.44]
VIX				0.024***	0.022***
				[3.66]	[3.55]
TED Spread					-0.305**
					[-2.41]
Country FE	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Obs	367,333	367,333	367,333	369,492	358,013
R^2	4.59%	4.66%	4.66%	4.77%	4.77%

Table A19. Log ReTweets and FX Hourly Returns

This table reports panel regressions results for the estimation of Tweets hour dummy on FX hourly returns. The control variables are presidency dummy, FOMC dummy, VIX, and TED Spread. 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 16th June 2015 and 20th August 2019.

	Dependent variable: Returns				
	(1)	(2)	(3)	(4)	(5)
Log ReTweets	0.001***	0.001***	0.001***	0.001***	0.001***
	[3.64]	[3.60]	[3.60]	[3.65]	[3.74]
Presidency		-0.000	-0.000	0.000	0.000
		[-0.29]	[-0.30]	[1.21]	[0.53]
FOMC			-0.029***	-0.028***	-0.023***
			[-4.46]	[-4.44]	[-4.43]
VIX				0.000*	0.000
				[1.65]	[1.52]
TED Spread					-0.001
					[-0.84]
Country FE	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Obs	376,850	376,850	376,850	372,534	366,474
R^2	0.07%	0.07%	0.07%	0.07%	0.07%

Table A20. Log ReTweets and FX Hourly Realised Volatility

This table reports panel regressions results for the estimation of Tweets hour dummy on FX hourly realised volatility. The control variables are presidency dummy, FOMC dummy, VIX, and TED Spread. 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 16th June 2015 and 20th August 2019.

	Dependent variable: Realised Volatility				
	(1)	(2)	(3)	(4)	(5)
Log Retweets	-0.001***	-0.000***	-0.000***	-0.000***	-0.000***
	[-5.04]	[-2.62]	[-2.59]	[-3.36]	[-2.68]
Presidency		-0.014***	-0.014***	-0.012***	-0.011***
		[-7.06]	[-7.05]	[-6.38]	[-5.93]
FOMC			0.070***	0.070***	0.070***
			[8.82]	[8.82]	[8.81]
VIX				0.001***	0.001***
				[8.81]	[8.82]
TED Spread					0.017***
					[3.49]
Country FE	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Obs	397,708	397,708	397,708	393,251	387,708
R^2	6.18%	7.22%	7.38%	7.64%	7.77%

Table A21. Log ReTweets and FX Options Moneyness

This table reports time series regressions results for the estimation of Tweets hour dummy on FX options moneyness. The control variables are presidency dummy, FOMC dummy, VIX, and TED Spread. Hour-of-the-day and day-of-the-week dummies are included in all regressions. Standard errors are adjusted by Newey-West with number of lags based on AIC. 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 16th June 2015 and 20th August 2019.

	Dependent variable: Moneyness				
	(1)	(2)	(3)	(4)	(5)
Log Retweets	-0.013**	-0.014**	-0.014**	-0.014**	-0.013*
	[-2.18]	[-2.16]	[-2.16]	[-2.14]	[-1.93]
Presidency		0.066	0.066	0.059	-0.009
		[1.09]	[1.09]	[1.03]	[-0.20]
FOMC			-0.019	-0.019	-0.023
			[-0.27]	[-0.26]	[-0.29]
VIX				-0.003	-0.004
				[-0.63]	[-0.81]
TED Spread					-0.727*
					[-1.72]
Country FE	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Obs	9,855	9,855	9,855	9,541	9,378
R^2	0.10%	0.09%	0.08%	0.02%	0.00%