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Abstract

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JEL Classification: E40, E50, D72

Keywords: central bank independence, monetary policy, Twitter, fed funds target, High-Frequency Identification

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Threats to Central Bank Independence: High-Frequency Identification with Twitter

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July 2021§

We use a high-frequency approach to analyze the effects of President Trump's tweets that criticize the Federal Reserve on financial markets. Identification exploits a short time window around the precise timestamp for each tweet. The average effect on the expected fed funds rate is negative and statistically significant, with the magnitude growing by horizon. The tweets also lead to an increase in the stock market, breakeven inflation, and spreads linked to the risk of financial instability. VAR evidence shows that the tweets had an important impact on actual monetary policy, the stock market, bond premia, and the macroeconomy.

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1 Introduction

Central bank independence has evolved significantly over time and across countries, often with the changing political and economic landscape.[1] A motive for strengthening central bank autonomy is to curb political incentives for expansionary monetary policy arising from electoral reasons. Cross-country evidence finds that a monetary authority with greater autonomy is associated with lower and more stable inflation.[2] In the 1960s and 1970s, the Johnson and Nixon administrations pressured the Federal Reserve chairman to keep interest rates low, eschewing price stability.[3] This extended period of expansionary monetary policy contributed to the Great Inflation of the 1970s. To fight inflation, greater independence was established in the late 1970s by defining a dual mandate of price stability and maximum employment followed by the creation of an arms-length relationship that insulated the Fed from interference by the executive branch. The enhanced autonomy for instrument setting allowed the Fed to aggressively target and stabilize inflation in the ensuing three decades.

The global financial crisis in 2008 significantly weakened public confidence in central banks around the world.[4] The unconventional policies implemented in the aftermath of the financial crisis further increased scrutiny on central banks. The widespread public criticism of central banks around the world threatens the autonomy established in the previous decades. Among the most notable critics, President Trump was voracious in his frequent attacks on Fed policy. On April 18, 2018, President Trump launched his first attack on Fed policy by tweeting, "Russia and China are playing the Currency Devaluation game as the U.S. keeps raising interest rates. Not acceptable!" The panel in the upper-right corner of Figure 1 illustrates the impact of the message on the expected fed funds rate (FFR) implied by fed funds futures (FFF) prices in a 30-minute window. The FFF contracts are stratified based on the number of FOMC announcements occurring before the corresponding expiration month. The change in expected rates is measured in basis points. The expected fed funds rate decreases noticeably across all three groups of contracts, with an increasing magnitude with respect to maturity, indicating that market participants expect that the President impacts monetary policy persistently.

The left column of Figure 1 shows all of the jumps in the expected FFR over narrow event windows associated with President Trump's tweets criticizing the Federal Reserve. The jumps are reported as a cumulative sum to convey both their average effect and relative sizes. It is immediate to see that the tweets had a predominantly negative effect on the

[1] Crowe and Meade (2007) provide a survey of the evolution of central bank independence across countries.

[2] Some examples include Alesina and Summers (1993) and Grilli, Masciandaro, and Tabellini (1991).

[3] Fessenden (1965) details instances of Fed interference by Presidents Johnson and Nixon.

[4] Kohn (2013) discusses the erosion of confidence in the Fed in the aftermath of the financial crisis measured by public polls.

expected FFR, with some of them producing large revisions in expectations. The second and third panels in the right column of Figure 1 focus on the effects on the FFF contracts around two of the most relevant tweets with the corresponding text. These tweets generate a sharp drop in the expected fed funds rate, especially at longer horizons.

We systematically investigate market perceptions of threats to central bank independence during the Trump presidency with a high-frequency event study approach that exploits his extensive use of Twitter as a primary tool of public communication. We scrape his account for tweets that exclusively relate to the Federal Reserve which unequivocally advocate looser monetary policy, hearkening back to the political pressure exerted on the Fed during the Johnson and Nixon administrations. The impact of these tweets on expectations of the fed funds rate is examined by using tick-by-tick data on FFF contracts. The key insight is that if financial markets perceived the Fed as immune from political pressure, these tweets should not have any effect on market expectations about future monetary policy.

Our identification scheme exploits a small time window around a single second precision time-stamp on the tweets. The payoff of these FFF contracts depends on the average FFR computed in the final month before expiry. As the fed funds target rate is set at the eight predetermined FOMC meetings per year, we classify FFF contracts of different maturities based on the number of future meetings that precede the computation of the payoff (i.e., final month of the contract). For each contract classification, we estimate the average impact of the tweets by running a linear regression of the change in the expected FFR, implied by the futures price, on an intercept. For the contracts whose payoffs occur strictly after one or more future meetings, the tweets have a negative and statistically significant impact on the expected fed funds target.

The average effect of the tweets across all contracts is around -0.26 bps per tweet. This effect grows with the time horizon, with a peak of -0.55 bps at the longest horizon, which is sizable considering that the typical change in the target rate at each FOMC meeting is ± 25 bps. To fix ideas, consider a scenario in which agents are considering the possibility of either a 25 bps interest rate cut or no change. A -0.55 bps revision in expectations implies that each tweet, on average, leads to a 2.2% *per tweet* increase in the probability of an interest rate cut over the next year.[5] Similar results obtain when inferring short rate expectations using Eurodollar futures (EDF), including at longer horizons. The high-frequency evidence with the FFF and EDF contracts illustrate how markets believe that the President can influence the conduct of monetary policy in a persistent way.[6]

[5]The results can also be interpreted in an analogous way if we assume that the two scenarios are a "25 bps increase" or "No change." In this example, the results would be interpreted as a 2.2% increase in the probability of no change.

[6]As the target rate is only changed during the FOMC meetings, outstanding short maturity futures

Foreign exchange (forex) data is used to estimate the impact of the tweets on interest rates across different maturities using covered interest rate parity (CIP) with our high-frequency identification approach. CIP is an arbitrage relation that links the forward premium to interest rate differentials. We use intraday data of forex futures and spot prices between the US dollar and four other currencies (JPY, EUR, GBP, CHF) for contract maturities of one to seven quarters. We find that average changes in interest rate differentials between the US and the four other foreign regions fall in response to the tweets at each maturity, consistent with the notion that President Trump's threats on the Fed are influencing the expected time path of US monetary policy.

Our baseline results focus on the average effect of a tweet and treat all tweets equally. However, it is entirely possible that some tweets convey more information than others. For example, the first tweet in which President Trump tweeted against the Federal Reserve might have revealed to the public his discontent with the conduct of monetary policy, but also his willingness to openly criticize the Federal Reserve. At the same time, some criticism of the Federal Reserve might have occurred under different circumstances and using different media outlets. In light of these considerations, we extend our baseline analysis in two directions. First, we select the tweets that were more newsworthy among the ones considered in our baseline analysis by conditioning on the number of replies to each tweet. Second, we identify other instances during which President Trump openly criticized the Federal Reserve through other media outlets distinct from our set of tweets. These two sets of events are merged into what we refer to as big news.

Our baseline estimates with FFF and EDF contracts are strengthened using big news. For example, the average effect on FFR expectations pooled across horizons increases in magnitude from -0.256 bps to -0.333, confirming that we are identifying more newsworthy events about Fed independence jointly with President Trump's preferred stance about monetary policy. Hence, our benchmark estimates using all tweets provide conservative estimates on the effects of President Trump's tweets. Some of the tweets about the Fed might have had negligible effects because they are repetitive or less forceful in criticizing the Federal Reserve. As a consequence, we find significantly stronger effects when the analysis is repeated using big news.

The big news can also help us to identify effects with noisier data (e.g., ETF data) or in noisier settings (e.g., longer event windows). For example, high-frequency changes in the stock market index and volatility along with breakeven inflation can be inferred from using

contracts that expire before the next FOMC announcement provide a control group for microstructure and liquidity effects that are potentially correlated with the tweets. The estimated reactions from the tweets implied by these untreated contracts are negligible and not statistically significant.

the intraday price data of ETFs tracking these variables. Using the high-frequency approach, we find that the stock market level increases significantly around the big news, while the volatility decreases. The level stock market response is consistent with the evidence from Bernanke and Kuttner (2005) which documents how stock market valuation increases in response to an interest rate cut. We also find evidence that breakeven inflation increases around the big news, consistent with President Trump's pressure for more expansionary monetary policy.

The big news is also used to identify the impact of President Trump's threats on the Fed using data that are sampled at a daily frequency, requiring a longer event window than our high-frequency analysis. We show that daily changes in treasury yields and instantaneous forward rates fall in response to the big news at each maturity up to five years, with the peak effects around two to three years. These estimates support the notion that President Trump's attacks on the Fed generate persistent downward revisions short rate expectations. Finally, we show that daily changes in measures of financial stability, the LIBOR-OIS and TED spreads, increase around the big news. This result could be reflecting how market participants are also interpreting the attacks on the Fed as a signal of further deregulation of the banking sector that could weaken Fed oversight of banks, like in the Crapo bill signed by President Trump on May 2018. In addition, pressure for lower interest rates could induce further expected bank risk-taking. In short, the big news helps us to identify the effects of President Trump's attacks on the Fed in different markets.

The high frequency approach used in this paper leverages the unique circumstances of a President openly criticizing the central bank via social media. A high frequency analysis allows a clean identification of the events of interest under the assumption that over such a short period of time, no other relevant news arrive. Two important related questions are whether the effects of these tweets persist over time and if the tweets affect the actual path of the FFR. To address these questions, we follow the recent literature that combines high-frequency identification strategies with VAR analysis. These papers use movement in FFF rates around FOMC announcements to identify the effects of monetary policy shocks. Similarly, we use the revision in expectations around the tweet as instrument for a "tweet shock." This approach allows us to assess if the effects of the tweets persist over time, but also whether the tweets had an actual effect on the path of the FFR. This second aspect of the analysis has important additional ramifications, as we are not only checking if markets perceive the Federal Reserve as fully independent, but also if the Federal Reserve was affected in its decisions by the tweets.

We find evidence that monetary policy changed course following these tweets. Our conclusions are based on a Bayesian VAR that includes macro and financial variables, augmented with Twitter news, constructed by adding up the intraday surprises occurring within a month in response to the tweets criticizing the Federal Reserve. Our VAR includes five variables: the shadow FFR as a policy rate, the log of the S&P500, the log of real GDP, the log of the GDP deflator, and the excess bond premium (EBP) as an indicator of financial conditions, and is estimated with Bayesian methods following Jarociński and Karadi (2020).

As a first step, we compute the impulse responses to a tweet shock. All macro and financial variables are allowed to respond on impact to the shock. A negative tweet shock is followed by a drop in the shadow FFR and the EBP, and an increase in the stock market. The effect on the shadow FFR is an order of magnitude larger than the initial high-frequency shock, while the effect on the stock market is an order of magnitude larger compared to the decline in the shadow FFR and the EBP. Inflation and GDP do not move on impact, while they tend to increase afterwards, in line with the decline in the shadow FFR and the EBP. The fact that the macro variables do not respond on impact and move upward afterwards mitigates the concern that the decline in the shadow FFR and the high frequency results documented above are driven by a "news effect," i.e. the idea that President Trump's tweets reveal bad news about the future that in turn lead to a downward revision in expectations about the future FFR.

We then ask what the effect of the tweets has been on the actual path of the FFR and the other variables. In order to address this question, we construct a counterfactual simulation that removes the tweet shocks and computes the corresponding path of the macro and financial variables. These estimates arguably represent a lower bound of the overall effect of political interference as they only capture the effects of the tweets over a short window of time, while they cannot capture other forms of moral suasion. Both the shadow FFR and the EBP rate are found to be around 1% lower than what they would have been without the tweets. Under the assumption that unconventional monetary policy acts through both the shadow rate and the EBP, the large decline in these two variables suggests that the tweets might have in fact induced a change in the current and expected monetary policy stance. The effect on the stock market is also estimated to be very large, suggesting that large part of the run-up in the stock market towards the end of the sample can be attributed to a reversal of the monetary policy stance. The effects on the real economy are also estimated to be important. Real GDP at the end of the period is found to be 1.6% higher than it would have been without the tweets and the associated policy reversal.

In the last part of the paper, we study historical antecedents and examine corroborating evidence for our main results using external data sources. Previous Presidents have generally refrained from *publicly* criticizing the Federal Reserve. This is what makes President Trump's attacks unique. Nevertheless, we consider three instances in which past administrations publicly interfered with the work of the Federal Reserve. We found that President Johnson and President Reagan publicly criticized the Fed, while President H.W. Bush expressed his discontent via his Deputy Secretary of the Treasury, John Robson. The first two cases led to a sizable decline in interest rates. In the last example involving President H.W. Bush and John Robson, the political pressure did not result in any visible change in the course of monetary policy. We explain that this might be due in part to a desire of the Fed to outwardly exhibit independence to enhance credibility, as revealed by the FOMC transcripts.

In summary, we find strong evidence that the consistent pressure applied by President Trump to pursue more expansionary monetary policy is manifested in market expectations of a lower target rate, implying a steady erosion in central bank independence over the course of his presidency. Our findings that market participants do not perceive the Federal Reserve as fully independent from the executive branch has indirect, but important, consequences for the actual autonomy of the central bank. Evidence that the Fed closely monitors and is affected by market expectations of its own actions (e.g., Faust (2016) and Vissing-Jorgensen (2019)) implies that even if President Trump did not directly influence Fed decisions, his political pressure might still have affected policy indirectly by changing market expectations and public opinion regarding the Fed.

The methodological approach of our paper relates to the literature identifying monetary policy shocks using high-frequency data (e.g., Kuttner (2001), Cochrane and Piazzesi (2002), Faust, Swanson, and Wright (2004), Gürkaynak, Sack, and Swanson (2007), and Nakamura and Steinsson (2018)) and papers studying the effect of these shocks on interest rates using a high-frequency approach (e.g., Gürkaynak, Sack, and Swanson (2005a), Gürkaynak, Sack, and Swanson (2005b), Beechey and Wright (2009), Swanson (2011), Hanson and Stein (2015), Gertler and Karadi (2015), Krishnamurthy and Vissing-Jorgensen (2011), Swanson (2017), Gilchrist, Yue, and Zakrajšek (2019)). We follow a similar methodology as these papers, but the objective of our paper is to identify and to quantify the effects of violations of central bank independence. Like these papers we measure expectations of the fed funds target using high-frequency futures prices. The unique approach of our paper is to use tweets by President Trump that pressure the Fed to lower interest rates as the news component.

Alesina (1988), Grilli, Masciandaro, and Tabellini (1991), Cukierman, Web, and Neyapti (1992), Alesina and Summers (1993), Acemoglu, Johnson, Querubin, and Robinson (2008), and Binder (2021) are examples of papers constructing indices of central bank independence across countries that capture different forms of autonomy (e.g., legal, operational, or economic). This aforementioned literature examines the impact of the degree of independence on macroeconomic outcomes. We differ from this literature in that we identify threats to central bank independence using high-frequency financial data and messages from the social media account of the President.

Our findings complement the literature examining the effect of informal communication of policymakers between FOMC meetings on equity markets. Lucca and Moench (2015) document a pre-announcement drift in stock returns Cieslak, Morse, and Vissing-Jorgensen (2018) study returns over the FOMC cycle, and Ai and Bansal (2018) provide a revealed preference theory for explaining the equity premium around the announcements. The focal point of our paper is to identify particular instances of how direct pressure from the President affects expected policy decisions in future FOMC meetings.

The paper is structured as follows. Section 2 describes the data used in our analysis. Section 3 characterizes the high-frequency identification procedure and presents the baseline estimates. Section 4 presents the results for the most newsworthy tweets and related statements and interviews. Section 5 studies the impact of the tweets on actual monetary policy, financial markets, and the macroeconomy. In Section 6, we examine past episodes of political interference and corroborating evidence for our main results. Section 7 concludes.

2 Data Description

Our main empirical analysis is based on tweets and comments by President Trump and their impact on different asset prices. The set of tweets are collected from the personal Twitter account of President Trump (`@realDonaldTrump`). Each observation includes the text, the accurate to the second timestamp, and the number of replies and likes. We focus on tweets by the President which are directed at the Fed and advocate lower interest rates. To this end, the following selection criteria are implemented. First, tweets with at least one of the following keywords are selected: 'fed', 'reserve', 'interest', 'rate', 'jerome', 'jay', 'powell'. Word extensions stemming from the keywords are also included (e.g., 'federal' and 'rates'). Second, the following filters are applied to the selected tweets. Tweets unrelated to the conduct of monetary policy (e.g., appointment of Fed board members) are eliminated. In addition, tweets which occur within the narrow event window of other related news are dropped to avoid potential contamination. The Online Appendix provides additional details of the tweet selection criteria and reports all tweets used in the analysis.

In addition, we consider instances in which President Trump criticized the Federal Reserve in public statements outside Twitter based on a Bloomberg article (Condon (2019)) which lists related events. The associated second accurate timestamp is obtained by identifying the first appearance of each event on the Bloomberg terminal.

Past and future FOMC meeting days are obtained from the website of the Federal Reserve Bank. The precise timestamps of past FOMC announcements are obtained by the earliest report on the Terminal News Ticker from Bloomberg on the federal funds rate decision.

Following the methodology of Gürkaynak, Sack, and Swanson (2005b) and Nakamura and Steinsson (2018), market expectations of the future fed funds rate at different horizons are inferred by using tick-by-tick trade data of 30-day federal funds futures and eurodollar futures on the Chicago Board of Trade Exchange (XCBT) obtained from the CBE. Price, volume, contract expiration, entry date, second precision time-stamps of trades, and the trading sequence are observed. Observations with zero volume, indicating that the trade was canceled, are dropped from the sample. If there are multiple trades of the same contract within the same second, the trade with the lowest sequence number is used (i.e., the earliest trade within that particular second).

Forex data is used to measure intraday interest rate differentials between the US and four other countries using covered interest rate parity (CIP). The second-by-second bid and ask spot rates for the four currency pairs GBP/USD, YEN/USD, CHF/USD, and EUR/USD are obtained from Dukascopy. The tick-by-tick data for the corresponding FX futures are obtained from Refinitiv. The raw data is cleaned following Barndorff-Nielsen, Hansen, Lunde, and Shephard (2008) and Bollerslev, Li, and Xue (2018).

Intraday series for the stock market index is inferred from the SPDR S&P 500 ETF (ticker: SPY), breakeven inflation is from the ProShares Inflation Expectations ETF (ticker: RINF), and the VIX index is from the iPath Series B S&P500 VIX Short Term Futures ETN (ticker: VXX). All series are obtained from the Trade and Quote (TAQ) database. The raw data is cleaned following the same procedure as the Forex data. Our sample period starts on the announcement day of the presidential campaign of Donald Trump (June 16, 2015) and ends on the inauguration day of Biden (January 20, 2021).

Daily data on zero coupon nominal yields and instantaneous forward rates constructed based on the methodology from Gürkaynak, Sack, and Swanson (2007) for maturities longer than one year are obtained from the Federal Reserve Board. Daily data for the three month, six month, one year treasury yields, and the TED spread are from FRED. We obtain the daily LIBOR-OIS spread (i.e. the difference between the three-month US LIBOR rate and the overnight index swap) from the Bloomberg Terminal.

3 Threats to Central Bank Independence

This section identifies how critical tweets by President Trump directed at the Fed advocating lower interest rates affect *market expectations* of the future path of monetary policy.

3.1 High-Frequency Identification

We begin by presenting the high-frequency identification strategy that exploits the accurate to the second time-stamp of each tweet and the tick-by-tick federal funds and eurodollar futures prices across varying maturities. The fed funds futures (FFF) are used to infer market expectations about the fed funds rate (FFR) and we classify each contract by their exposure to the number of FOMC meetings. The eurodollar futures (EDF) are used to back out market expectations of the US three-month LIBOR interest rate and we organize each contract by the maturity. We next describe the link between the FFF prices and the expected FFR.

Market expectations of the FFR are extracted from the traded price of the FFF contracts. FFF are contracts that reflect the market opinion of what the average FFR will be in the future. The price quotation for this type of contract is 100 minus the arithmetic average of the daily effective FFR during the expiration month. FFF contracts are financially settled on the first business day following the last trading day. For an expiring contract, the last trading day corresponds to the last business day in the delivery month of the futures contract. The corresponding daily federal funds overnight rate is provided by the Federal Reserve Bank of New York. On weekends or holidays, this rate is equal to the previous reported rate on a business day. The effective FFR is the weighted average of all transactions for a group of federal funds brokers.

The FFF rate associated with a contract that expires in month i in the future can be decomposed into two components:

$$FFF_{t,i} = E_t\overline{FFR}_i + \alpha_{t,i},$$

where $FFF_{t,i}$ is the month i FFF rate at time t, E_t denotes the expectation conditional on all the available information up to time t, $\overline{FFR}_i$ is the average of the daily effective federal funds rate for each day of month i, and $\alpha_{t,i}$ is a bias term that varies with the forecast horizon. The bias term can capture risk premia and variations in the effective FFR due to regulation requirements.

We are interested in measuring the revision of expectations about the Fed interest rate policy following a tweet or other relevant information, as opposed to expectations themselves. Our focus is on the fed funds target, FFT, the component that is directly under the control of the Federal Reserve. The futures rate, $FFF_{t,i}$, depends on the average Federal Funds target rate and the discrepancy between the average target and the average effective FFR in the final month of the futures contract:

$$FFF_{t,i} = E_t\left[\overline{FFT}_i\right] + E_t\left[\overline{FFR}_i - \overline{FFT}_i\right] + \alpha_{t,i}. \tag{1}$$

Following the methodology of Gürkaynak, Sack, and Swanson (2005b) and Nakamura and

Steinsson (2018), the baseline results assume that the tweets do not systematically affect covariances between the pricing kernel and the fed funds rates at short horizons and the discrepancy between the effective and target rates. Under these two assumptions, the revision in expectations following a tweet can be obtained from the change in futures interest rates:

$$(E_t - E_{t-\Delta t})\left[\overline{FFT}_i\right] = FFF_{t,i} - FFF_{t-\Delta t,i}, \tag{2}$$

where $(E_t - E_{t-\Delta t})$ denotes the change in expectation of the FFT over the event window Δt. Thus, the FFF prices can be used to recover changes in expectations at different horizons.

Following a similar logic, expectations of the three-month interest rate are obtained from the eurodollar futures (EDF) prices across varying maturities as in Nakamura and Steinsson (2018). The payoff of these contracts are defined as 100 minus the three-month US dollar LIBOR interest rate on the third Wednesday of the contract month. Using this definition, we can similarly back out the implied three-month interest rate using the EDF price. The EDF contracts are available at longer maturities compared to the FFF contracts. The longer maturity contracts allow us to estimate the impact of the tweets on expectations of short-term nominal interest rates at longer horizons.

The identifying assumption of our high-frequency approach is that no other systematic shocks to market expectations about the future short rate occur within a particular time window around the tweet at time 0. Thus, within this window, changes in rates capture the revision in expectations induced by the tweet. Following the literature, we disregard observations which fall into an inner time window $[T_1, T_2]$, with $T_1 < 0 < T_2$, to give time for markets to react. All trades that fall outside an outer window $[T_0, T_3]$, where $t < T_0 < T_1$ and $t > T_3 > T_2$, are also disregarded in order to select observations that are close to the tweet. We then measure the revision in expectations as described in equation (2) by taking the difference between the rate from the post-event time interval $[T_2, T_3]$ which is closest to T_2 and the rate within the pre-event time interval $[T_0, T_1]$ which is closest to T_1. Figure C.1 of the Appendix provides a visual depiction of how the two trade observations are selected.

In the benchmark estimation, the pre-event outer window is between $T_0 = 240$ min and $T_1 = 0.1$ min before the tweet. This ensures that the last observation before the tweet is not impacted by the event itself, but still is as recent as possible. In contrast to other high-frequency studies, there is less concern for confounding information to arrive beforehand, given that tweets are the first-hand source. The post-event outer window starts at $T_2 =$ 5 min, which gives investors time to react and trade on the news. The cutoffs at $T_1 - T_0 =$ 240 min and $T_3 - T_2 = 120$ min ensure that only contracts with recent trades are considered.

We choose a relatively short time window for our benchmark analysis to make sure to isolate the effects of the tweets that we are interested in. President Trump can sometimes engage in a long series of tweets related to different topics. A short time window minimizes the possibility that other tweets fall inside the window. Furthermore, for each tweet, we confirm that no other economic news is released within the time window. To do so, we search the Bloomberg Terminal for important announcements around the event. Here, “important” is defined by Bloomberg’s classification system having at least an asterisk to highlight the event. We also considered longer alternative event windows and found very similar, and in many cases, stronger results. These additional results are reported in the Online Appendix. We prefer the tight time window to avoid confounding effects coming from other news or other tweets, even at the cost of underestimating the market response to the tweets criticizing the Federal Reserve.

3.2 Benchmark estimates

We estimate revisions in expectations of the FFR and the three-month interest rate across different horizons caused by the selected tweets. The FFF contracts are organized based on the number of FOMC meetings a certain contract is exposed to. The EDF contracts are organized based on the contract maturities rather than exposures to FOMC meetings because the EDF maturities are spaced out based on coarser intervals (mainly quarterly increments) compared to FFF contracts (monthly increments). The quarterly spacing makes it difficult to map a particular EDF contract to the number of meeting exposures evenly across bins for each tweet at a given point in time. While the range of EDF contract maturities are coarser, an advantage is that the longer maturity EDF contracts allow us to measure the impact of shocks on longer term expectations. We start by discussing the benchmark estimates with the FFF contracts and then confirming these results using the EDF contracts.

Analyzing the term structure of expectations is an important dimension of our analysis because most of our selected tweets do not coincide with a month in which an FOMC meeting is scheduled after the tweet. The discrete nature of the target rate changes on meeting dates implies that the revisions in expectations caused by a tweet occurring in a month without a scheduled meeting or afterwards would only be reflected in longer maturity contracts that expire after the next meeting and not in shorter maturity contracts. Indeed, we find that the price of short maturity contracts that expire before the next meeting are not materially affected by the tweets. Comparing the changes in expectations at different horizons also provides information on whether the tweets affect the expected timing of a monetary policy change that is already anticipated, or, on the contrary, they lead to a comprehensive revision in the expected course of monetary policy. Overall, we find evidence for the latter hypothesis: President Trump’s tweets lead to a persistent decline in expected target rates with a magnitude that increases with the horizon.

As the federal funds target is set on eight predetermined FOMC meetings per year, we categorize FFF contracts across different maturities based on the number of FOMC meetings between the time of the tweet and the contract expiration.[7] If the tweets move expectations about Fed actions in the next FOMC meeting, this should be reflected in the price of the first contract fully exposed to this meeting. If markets instead do not expect rate changes in the next meeting, but instead believe that downward adjustments will occur in subsequent meetings, then the price of the contracts exposed to multiple FOMC meetings would be expected to decline, while the price of short term contracts would be unchanged. Finally, the average change in the expected FFR across time horizons can be obtained from contracts of varying maturities that are exposed to a different number of FOMC meetings or by pooling all contracts together in the statistical analysis.

A contract classified by exposure number j is selected to simultaneously have the shortest time to expiration and at least the corresponding number of FOMC meetings j scheduled before the beginning of the expiration month. This criterion makes sure that the shortest maturity contract that is exposed to at least j FOMC meetings is selected. Then, for each tweet and maturity, two trades are chosen to measure the change in the expected federal funds rate. The first observation is the last trade five seconds before the tweet and the second observation is the earliest trade five minutes after the tweet. For those trades, the average distance to the pre-event window, T_1, is eight minutes. The average distance between T_2 and the post-event trade is 10 minutes. These statistics highlight that most selected trades occur within a narrow time window, validating the high-frequency approach taken.

For each FOMC meeting exposure j, the event study regresses the revision in expectations of the FFR implied by the FFF prices on a constant around each selected tweet in the event window according to:

$$(E_t - E_{t-\Delta t})[r_j] = \alpha_j + \varepsilon_j, \tag{3}$$

where $(E_t - E_{t-\Delta t})$ denotes the change in the market expectation of the FFR in the event window Δt, α_j is a constant capturing the average effect of President Trump's tweets on the expected fed funds rate of meeting exposure j, and ε_j is the error term.

The regression results for the FFF sorted by contract exposure to the number of FOMC meetings j are reported in Panel A of Table 1. A column labelled j corresponds to the contract with the earliest expiration month that is fully exposed to at least j meetings at each

[7] The dates of the FOMC meetings are obtained from the Federal Reserve Board website. There were no changes of the FFR at meetings without press conferences over the sample used in our analysis. However, it is possible that agents might still have expected such an event to occur. The evidence on the zero FOMC contract presented below suggests otherwise, given that we do not find significant movements in its rate in response to any of the tweets. Furthermore, the analysis below based on EDF contracts of different maturities confirms our findings based on FFF contracts.

point in time. The coefficient of interest, α_j, captures the average revision in expectations of the FFR around each tweet for a particular horizon. The coefficient is negative for all contracts exposed to at least one meeting, with an increasing magnitude as the meeting exposure j rises.

The results for the short maturity contracts exposed to only one FOMC meeting imply that the expected interest rate declines by 0.143 bps following a tweet. The change in the expected interest rate for a contract exposed to ten FOMC meetings (a contract that expires more than one year later), declines by 0.549 bps. Excluding the zero maturity contract, the coefficients are statistically different from zero at the 5% level for nine out of ten contracts. Every coefficient is statistically different from zero at the 10% level, and seven of them are statistically different from zero at the 1% level. Contracts that expire before the next FOMC meeting (zero maturity contracts) provide a useful control group for potential microstructure and liquidity effects that are possibly correlated with the tweets. The estimated coefficient for the zero exposure contract is not statistically different from zero, ruling out potential microstructure effects driving our main results. In summary, these estimates across contract categories provide strong evidence that our selected tweets by President Trump influence market expectations about the future path of interest rates.

To interpret the economic magnitude of these effects, note that the typical change in the fed funds target is ± 25 bps. Consider an example with two possible scenarios: The rates will remain unchanged or they will be cut by 25 bps. Then, a decline of 0.549 bps corresponds to a 2.2% increase in the probability of a 25 bps target cut, which is a relevant change in the probability assigned to an expansionary monetary policy change, once we take into account that the reported coefficient is the average effect of each tweet. Naturally, certain tweets convey more information than others and generate larger revisions in expectations about future interest rate policy, which is explored in Section 4 below.

Panel B of Table 1 runs the same event study regression specified in equation (3) but focusing on the EDF contracts that give us expectations of three-month nominal interest rates across different horizons. As highlighted above, the EDF contracts are organized based on their maturity rather than their exposure to the number of FOMC meetings given the range of maturities are coarser compared to FFF contracts. We consider all EDF contracts with quarterly maturities up to two years along with the three, four, and five year maturities. The EDF contracts provide additional information about the effect of the selected tweets on long-term interest rate expectations.

The results based on EDF contracts are consistent with the results obtained with FFF contracts. A tweet criticizing the Fed has the effect of lowering expected nominal short rates with an effect that grows with the time horizon. Eight out of ten contracts present coefficients that are statistically significant and in all cases have negative values. The magnitudes of the coefficients are also similar between the two contracts, with an average effect around -0.26 bps. The peak effect with the EDF contract occurs at the longest maturity included in our estimation (five year horizon) with an estimated coefficient of -0.56 bps that is statistically significant. Overall, we conclude that the evidence based on EDF contracts reinforce the conclusion that the tweets criticizing the Federal Reserve induce a downward revision in expected interest rates.

The evidence so far shows that across all horizons, the tweets lower expectations of the FFR and nominal short rates with the effect growing as the horizon increases. Table 2 formalizes this result by first measuring the average effect across all horizons (Panel A) and then by estimating the average and horizon effect together (Panel B).

In Panel A of Table 2, we consider the average effect across all horizons by running the same event study regression as in equation (3) but pooling contracts with a nonzero meeting exposure rather than running horizon-specific regressions. The second row of Panel A repeats the same exercise by pooling across all maturities of the EDF contracts considered in Table 1 above, while the last row of Panel A pools together both the FFF and EDF contracts across all maturities. Overall, we find that the average effect is negative in the pooled estimation across all three groups. The average effect implied by the pooling regression is around -0.26 bps and is very similar across the two class of contracts, consistent with the horizon-specific regressions presented in Table 1. Across all specifications, pooling the information contained in different contracts together leads to strongly statistically significant results, as the noise linked to the price variation of the single contracts is attenuated.

Panel B of Table 2 explicitly estimates the "horizon" effect. In particular, we formally estimate the possibility that the effect of the tweets increases with the time horizon. To capture this idea, we run the following regression:

$$(E_t - E_{t-\Delta t})[r] = \alpha + \beta \cdot \texttt{horizon} + \varepsilon$$

where $(E_t - E_{t-\Delta t})$ denotes the revision in expectations around each tweet in the event window specified, α is the intercept relating to the average effect across horizons, `horizon` is the demeaned contract horizon, β is the coefficient measuring the horizon effects of the selected tweets on expectation revisions, and ε is the error term.

FFF and EDF contracts are analyzed separately for the horizon regressions because they differ in terms of how the time horizon is defined. The first row of Panel B considers the horizon regression for the FFF contracts with an exposure to at least one scheduled FOMC meeting with `horizon` measured by the number of FOMC meeting exposures ranging from one to ten (used in our benchmark estimates) and subtracting the mean. The second row of Panel B reports the horizon regression estimates with the EDF contracts that includes the maturities of the contracts with `horizon` measured by the maturities of the contracts used in our benchmark estimates (i.e., quarterly maturities up to two years along with the three, four, and five year maturities) and then subtracting the mean. In both regressions, the intercept α and slope coefficient β are negative and statistically significant. The negative intercept reflects how the tweets lower average short rate expectations across horizons. The negative slope coefficient captures the notion that the effect of the tweets intensifies over the time horizon. The average and horizon regressions across contracts therefore reaffirm the patterns documented in the horizon-specific benchmark estimates from Table 1.

Figure C.3 in the Online Appendix shows that there are no statistically significant pre-trends in the futures prices before the selected tweets and that the effect of the tweets grows larger as the post-event window is extended. When considering changes over 20 minutes and 60 minutes after the tweets, the average effect across all horizons grows from -0.26 bps to -0.52 and -0.70 bps, respectively. Thus, the average effect more than doubles in size. We opt for a narrower event window in our benchmark estimation to minimize the likelihood of confounding events. The Online Appendix also shows that our benchmark results are robust to alternative event windows and tweet selection criteria. We also consider a placebo test with randomly selected tweets from President Trump in our sample period (and excluding the ones used in our benchmark estimation) to confirm that tweets unrelated to monetary policy have no systematic impact on changes in interest rate expectations across horizons.

3.3 Other asset classes

Table 3 reports the impact of President Trump's tweets using high frequency data from other asset classes. Panels A and B considers foreign exchange (forex) rate data and Panel C examines stock market evidence.

Forex data is used to measure intraday interest rate differentials between the US and four other regions using covered interest rate parity (CIP). CIP is an arbitrage relation that relates the forward premium to the interest rate differential:

$$i_{t,n} - i^*_{t,n} = (1/n) * (f_{t,n} - s_t)\,, \tag{4}$$

where f_t is the n-year log forward rate in units of the US dollar (USD) per foreign currency, s_t is the log spot exchange rate in units of USD per foreign currency, $i_{t,n}$ is the n-year riskfree interest rate in USD, and $i^*_{t,n}$ is the n-year riskfree interest rate in the foreign currency. Therefore, using CIP with the intraday forex data gives us a way to measure interest rates of varying maturities at high frequencies. Assuming that President Trump's tweets about the Fed primarily impact the average level of the domestic short rate rather than foreign short rates, term premia, or currency risk premia, the interest rate responses reflect revisions in the average path of future domestic short rates over the maturity of the contracts.

We use spot and future rate data for the USD per Japanese yen (JPY), Euro (EUR), British pound (GBP), and Swiss franc (CHF), which are four of the most liquid currency pairs, to construct interest rate differentials according to equation (4) between the US and the foreign currency. Panel A of Table 3 runs the event study regression with the changes in an equal-weighted portfolio of the interest rate differentials for maturities of one quarter to seven quarters around the tweets in the same event window as the benchmark on a constant:

$$\frac{1}{m}\sum_{c=1}^{m}\Delta(i_{j,t,n}-i^{*}_{j,t,n,c})=\alpha_j+\varepsilon_j, \tag{5}$$

where $\Delta(i_{j,t,n}-i^{*}_{j,t,n,c})\equiv(i_{j,t,n}-i^{*}_{j,t,n,c})-(i_{j,t-\Delta t,n}-i^{*}_{j,t-\Delta t,n,c})$ is the change in the interest rate differential of maturity j with foreign country c implied by CIP around each tweet in the event window, α_j measures the average effect on the interest rate differential across the countries, and ε_j is the error term. We find negative effects on the average interest rate differential at each maturity, with the estimates quoted in bps. These are statistically significant for five out of the seven maturities. Panel B considers the changes in interest rate differentials within each currency pair with the US in the long position and the foreign currency in the short position, but pooling across maturities. The final column of Panel B pools across all currencies and maturities. The average effect is negative for each currency pair with three out of the four being statistically significant. We conclude that the evidence from forex markets is consistent with the notion that the attacks against the Fed are impacting market expectations of Fed interest rate policy.

While there is some evidence of deviations from CIP after 2008 (e.g., Du, Tepper, and Verdelhan (2018)), there is no *a priori* reason to believe that President Trump's attacks on the Fed would primarily induce systematic changes in arbitrage opportunities rather than changes in the interest rate differential. Given the strong evidence above that President Trump's tweets lower interest rate expectations with the FFF and EDF contracts, we interpret our results with forex data as providing additional support for the notion that President Trump had a material impact on expected monetary policy, manifested in lower interest rates across various maturities implied by CIP. In Section 4 below, we provide direct evidence that President Trump's tweets negatively affected nominal Treasury yields of similar maturities.

Panel C of Table 3 contains the estimates of the impact of the tweets on the level and volatility of the stock market index using high-frequency data from the ETFs, SPY and VXX, respectively. We run the event study using the log change in the prices of these two ETFs around the selected tweets using the same event window as our benchmark estimation with the FFF and EDF contracts. The estimates for these stock market regressions are reported in percentages rather than bps. We find that the average impact on the level of the stock market index is positive while the effect is negative for the volatility. The positive response of the stock market to an interest rate cut is consistent with the evidence from Bernanke and Kuttner (2005). Both effects are not statistically significant, in contrast to the significant interest rate responses documented above.

A positive, even if insignificant, stock market reaction helps to alleviate the potential concern that the tweets criticizing the Fed are associated with bad news about the economy, leading to expectations of monetary policy easing through the dependency of the Fed reaction function on output and the stock market (e.g., Rigobon and Sack (2003)), as opposed to market expectations of lower future rates attributed directly to political pressure. In Section 4, we will show that the Bernanke-Kuttner effect gets larger and statistically significant when focusing on the most important tweets and on big news related to President Trump's interference with the conduct of monetary policy.

3.4 Economic Interpretation

Our main results presented in Tables 1 and 2 demonstrate that political pressure from tweets advocating lower rates significantly affect expectations about the fed funds rate. The revision in expectations caused by the tweets is present across all contract horizons with an effect that increases over time. These dynamic effects indicate that the tweets do not simply affect expectations about the timing of changes that markets were already anticipating, but instead move market expectations about the stance of monetary policy.

Suppose that right before the tweet, markets expect that the Fed will cut rates in six months, but not in the near future. If a tweet only induces a change in expectations about the timing of the already anticipated interest rate cut, a revision in expectations would be observed at only short horizons. Panel A of Figure C.2 in the Appendix illustrates this example. Our estimates documenting that the revision in expectations increases with the time horizon indicates that the revision in expectations is more pervasive. Markets are not sure if the Fed will succumb to the political pressure in the immediate future (e.g., during the next FOMC meeting), but they assign an increasing probability to this outcome occurring at some point in the future. Suppose that, as in the previous case, before the tweet, markets expect that the Fed will cut interest rates in six months. If the tweet now generates a decline in expectations both at short and long horizons, we can infer that the tweet does not merely change the timing of an already anticipated decline. Panel B of Figure C.2 in the Appendix provides a visual depiction of this alternative example.

More broadly, our findings suggest that market participants do not perceive the Fed as a fully independent institution immune from political pressure from the executive branch. The fact that market participants may not perceive the Fed as autonomous from the executive branch can in itself influence Fed actions. Faust (2016) and Vissing-Jorgensen (2019) show that the Federal Reserve pays close attention to market expectations about its own actions. FOMC members often discuss the importance of not deviating from such expectations. Indeed, one of the cited reasons behind the interest rate cut in July was that markets were anticipating a cut, and not following through would effectively be a stance of contractionary monetary policy (Timiraos (2019)). Therefore, even if President Trump's threats only have a direct impact on market expectations, they can still indirectly affect policy due to how the Fed factors in market expectations when deciding on monetary policy. In Section 5, we employ a VAR augmented with Twitter news to assess whether the tweets attacking the Federal Reserve were followed by an actual change in the conduct of monetary policy.

4 Big News

The benchmark estimates from the previous section illustrated how President Trump's tweets criticizing the Fed led to a downward revision in expected interest rates across different horizons and contracts. We took a conservative approach in our benchmark analysis by selecting all President Trump's tweets that criticize the Federal Reserve but are not likely to contain other information about the state of the economy. All of these selected tweets are given equal importance in the event studies from the previous section. However, it is possible that some of the selected tweets convey more new information than others. For example, the first instance that President Trump tweeted against the Fed might have revealed to the public his discontent with the conduct of monetary policy and his willingness to openly criticize (and possibly influence) Fed policy. On the other end of the spectrum, some of the selected tweets may be less informative by occurring within a day after another selected tweet. Moreover, some of the important public attacks on the Fed might have occurred outside of the Twitter platform.

In light of these considerations, this section extends our benchmark analysis in two directions. First, we select the tweets that are more newsworthy among the selected tweets used in Section 3. Second, we identify other instances in which President Trump openly criticized the Fed using other news that did not coincide with our selected tweets. These two set of events are merged to form a set of events that we refer to as big news.

4.1 Selecting the newsworthy tweets and related news

In order to select the most newsworthy tweets, we augment the tweet selection criteria described in Section 2 used in our benchmark analysis of Section 3 by also conditioning on the number of Twitter replies for each tweet. This additional selection criterion leverages the novel user-generated content from the Twitter platform in the following steps. First, we rank the set of tweets by President Trump critical of the Fed based on the number of replies.[8] Second, we select the tweets that are above the median with respect to the number of replies and refer to these as the *newsworthy tweets*. These newsworthy tweets are indicated by an asterisk in Table C.1 in the Online Appendix. Our conjecture is that President Trump's tweets that produce more user-generated activity are more likely to be those that contain more new information. This additional selection criteria does not use financial market data to minimize selection bias. We next characterize a few notable examples from our set of newsworthy tweets before moving to a more systematic analysis of these tweets.

As described in the introduction, the left panel of Figure 1 plots the cumulative effect of all President Trump's tweets criticizing the Fed on changes in the expected FFR. The red line corresponds to revisions in FFR expectations inferred from contracts exposed to ten FOMC meeting and the blue line corresponds to the average change in FFR expectations across contracts. It is immediate to see that some tweets have a large negative effect, while others have a negligible impact on expectations. The right panel of Figure 1 zooms in on the change in expectations at different horizons separately for three newsworthy tweets. The top right plot shows the change in FFR expectations around the first tweet by President Trump criticizing the Fed. This tweet had a sizable negative impact compared to the benchmark estimates in Table 1, which makes sense if we consider that this tweet revealed for the first time that President Trump was unhappy with the conduct of monetary policy and was willing to openly criticize the Fed, both aspects that are newsworthy. By publicly criticizing the Fed to lower interest rates, the President arguably generated political pressure on the Fed as an institution.

The first tweet did not have largest effect however. Two other newsworthy tweets plotted below with larger effects highlight some interesting features for understanding why President Trump's tweets produced revisions in market expectations. The tweet, "Now the Fed can show their stuff!" (9:01 AM ET, August 23, 2019) suggesting that the Fed should change the path of monetary policy, occurred on the same morning that Chairman Powell was scheduled to deliver his speech at the Jackson Hole symposium to discuss challenges for monetary policy, and after China had announced new tariffs in response to President Trump's trade policies.

The response to the tweet displayed in the bottom right, "As I predicted, Jay Powell and the Federal Reserve have allowed the Dollar to get so strong, especially relative to ALL other currencies, that our manufacturers are being negatively affected. Fed Rate too high. They are their own worst enemies, they don't have a clue. Pathetic!" (10:34 AM EST, October

[8] We obtain a similar ranking of the tweets using likes instead of replies.

1st, 2019), President Trump attacked the Fed after the weakest US manufacturing data in 10 years. In this case, markets might have inferred that President Trump was shifting blame to the Fed for the poor manufacturing data as opposed to his trade policies, despite the fact that the Fed had already implemented two interest rate cuts over the year. This tweet is also interesting because it highlights another possible channel through which President Trump might influence the Fed: By swaying public opinion and media coverage.

Each of these three newsworthy tweets had significantly larger effects compared to the average effect estimated using all tweets reported in Tables 1 and 2. Focusing on the long horizon (exposure to 10 FOMC meetings), the first tweet by President Trump had a peak effect of -1.5 bps over a 20 minute window after the tweet, while the other two tweets both had a peak effect of -2 bps. Consider again a scenario in which agents are considering the possibility of a 25 bps interest rate cut. These changes imply that the first tweet induced a 6% increase in the probability of an interest rate cut, while the other two tweets led to an 8% increase in the probability of an interest rate cut. As a reference point, the average effect across all tweets using the long horizon contract implied a 2.2% increase in the probability of a rate cut.

In addition to identifying newsworthy tweets, we also consider instances in which President Trump criticized the Federal Reserve through other media outlets. We use a Bloomberg article (Condon (2019)) for such a list of related events that can also be considered newsworthy. In particular, this article reports cases in which President Trump criticized the Fed. The Bloomberg terminal is then used to determine the accurate to the second timestamps for when each article was posted online. In several cases, the article reports the tweets that are already included in our dataset. However, the Bloomberg article also includes 26 additional events related to the confrontation between the President and the Fed Chairman that do not overlap with our set of tweets. These events are reported in the Online Appendix. These distinct Bloomberg events are merged with our 25 newsworthy tweets to a create a set of *big news* about President Trump's attacks on Fed independence along with his preferred stance on future interest rate policy.

A relevant example of these distinct Bloomberg news events occurs on June 18, 2019. President Trump asked lawyers at the White House about the possibility of removing Chairman Powell. This article detailed how people familiar with the matter argued that Powell could not be fired without cause, but that he could be removed as Chairman and remain in the FOMC as a governor. Figure 4 shows the response of expected short rates at different horizons to this news. We observe a decline in rates across all maturities, with a more pronounced effect at longer maturities. At long horizons, the peak effect is around -4 bps, corresponding to a 16% increase in the probability of an interest rate cut.

The observation that longer maturity futures contracts are affected more than shorter maturity ones is consistent with the fact that regardless of the legal feasibility of replacing Powell with a new Chairman, such a decision would take time to be implemented. The fact that markets reacted so strongly to the threat of removing Powell suggests that such an action is potentially a direct channel through which the President can influence monetary policy. While historically a Chairman has never been fired, Chairman Miller had a very short tenure (March 8, 1978 - August 6, 1979) and left the Fed to become secretary of the Treasury under Carter. President Trump is known for challenging institutional norms, so perhaps a strong market reaction is not surprising.

4.2 Effects of Big News

This subsection presents the results as reported in Table 4, organized into three parts. The first set of results focus on the high frequency evidence, similarly to the baseline analysis of Section 3.2. The second set of results focus on the effects on daily interest rates. The third and final set of results relate to the effects of the tweets for financial stability.

High frequency analysis This section revisits the high-frequency evidence from Section 3.2 using the collection of big news rather than the full set of tweets that includes less newsworthy tweets and excludes other news. The first two columns of Panel A in Table 4 run the regressions for the fed funds futures (FFF) and the eurodollar futures (EDF) contracts that consider the average effect pooled across all maturities, respectively. Compared to the similar regressions reported in Panel A of Table 2, the estimated effects are larger in magnitude with increased statistical significance using big news rather than all tweets. The average effect is -0.333 bps with big news compared to -0.256 bps for the pooled FFF regression and -0.285 bps compared to -0.255 bps for the pooled EDF regression. This evidence supports the notion that the big news events reveal a disproportionate amount of information about Trump's impact on Fed independence jointly with his preferred objectives for monetary policy (i.e., lower interest rates).

The fact that the effects of big news on short rate expectations are enhanced (relative to the benchmark estimates) is not mechanical since the big news selection criteria did not use price data. Instead we relied on the intensity of social media engagement to identify newsworthy tweets and searched for related events from other media outlets. The results in Table 4 provide additional evidence supporting that the central bank is not perceived as a fully independent institution and that public attacks from the President affect financial markets. The current analysis with big news suggests that the effects can in fact be large. To put the numbers into perspective, consider again a situation in which markets expect two possible scenarios: No change or a 25 bps cut. A decline of 0.333 bps in expected rates corresponds to a 1.33% increase in the probability of an interest rate cut across maturities. For the tweet with the largest effect, the increase in the probability of an interest cut at long horizons is around 8%. As we will see in Section 5, these movements over a short window of time translate to significant changes at lower frequencies.

The third and fourth columns of Panel A in Table 4 report the effects of the big news on the stock market index (SPY) and stock market volatility (VXX) using the benchmark event window with the estimates in percentages. We find that the stock market increases significantly on average following big news, in line with the evidence from Bernanke and Kuttner (2005) who find that surprise interest rate cuts increase stock market valuations. The estimated effects of the Trump attacks on the stock market are now statistically significant, consistent with the notion that the big news selection criteria is identifying newsworthy events. We also find that the big news lead to a marginally significant decline in stock market volatility. Overall, the stock market evidence is sharpened using big news.

The last column of Panel A considers the impact of big news on breakeven inflation around the benchmark event window with the estimates quoted in percentages. As breakeven inflation is not readily available at high frequencies, we infer intraday variation using the prices of an ETF that tracks breakeven inflation (RINF). We find evidence that the Trump pressure for expansionary monetary policy increases breakeven inflation. This result is consistent with the idea that markets expect political interference to lead to higher inflation in the long run. Overall, the big news selection criterion allows us to obtain sharper identification of the effects of Trump pressure both on interest rates and other asset prices given the more stringent news selection criteria for big news that distinguishes between newsworthy tweets versus those that are plausibly priced-in.

Daily interest rates This section examines the impact of the big news on daily interest rates across various maturities using nominal zero coupon treasury yields and instantaneous forward rates. Maturities of up to five years are included in the analysis, which covers the second term if President Trump had been reelected. This data is sampled at a daily frequency, requiring a wider event window in the event study analysis compared to our benchmark estimation. Given that other economic news are more likely to be released over the course of a day compared to the narrow intraday event windows used in the high-frequency analysis, the big news can potentially help us to identify the effects in such a noisier setting or with noisier data (e.g., stock market and ETF data). The treasury yields and forward rates allow us to trace out the impact of the Trump attacks on expectations about the time path of monetary policy, particularly at longer horizons. Abstracting from bond liquidity and risk premia, nominal yields reflect expectations about the average path of future short rates over the maturity of the bond, while forward rates give us the expectations of the time path of future short rates at different horizons.

Panel B of Table 4 reports the estimates of the regression of daily changes in interest rates and forward rates on a constant term around the big news event, similar to our specification in equation (3) but for a daily event window. We find that the average effect of the big news about Trump pressure lowers treasury yields across maturities of three months to five years, suggesting that Trump pressure inferred from big news generates persistent downward revisions in the average path of short rates. The magnitude of the effects are monotonically increasing from six months to three years before declining slightly at five years. The average effect of the news on the forward rates is also negative for maturities of one to five years, with the effects being similar across maturities of one to three years, before the magnitude declines at five years. Similarly to what we found when using FFF and EDF contracts, an interpretation of this evidence is that markets expect that the Trump attacks will change the course of monetary policy as opposed to just changing the timing of policy changes that were already anticipated.

Financial stability In addition to determining monetary policy, the Federal Reserve also plays an important role in financial stability through bank regulation and supervision. As such, it is possible that financial markets perceive the public attacks against the Fed as a signal of potential future deregulation in the banking sector that could weaken the Fed's oversight of banks. Indeed, on May 24, 2018 (around a month after the first President Trump's tweet attacking the Fed), President Trump signed the Economic Growth, Regulatory Relief and Consumer Protection Act (Crapo bill) that rolled back many bank oversight measures designed to curtail bank risk-taking from the Dodd-Frank act. For example, the Crapo bill increased the threshold from \$50M to \$250M for banks to be considered a Systemically important financial institution (SIFI), thereby requiring periodic stress tests and strict oversight by the Fed. Aside from easing regulation, pressure to keep interest rates low can also further induce additional bank risk-taking (Adrian and Shin (2010)).

Panel C of Table 4 examines if the Trump threats affect two common measures of financial stability, the TED spread and LIBOR-OIS spread. The TED spread is constructed as the difference between the three-month US LIBOR rate and the three-month treasury bill rate. The LIBOR-OIS spread is the difference between the three-month US LIBOR rate and the overnight index swap (OIS) rate. These spreads reflect credit risk in the banking sector and spiked up dramatically during the financial crisis in 2008. As the data on the spreads are sampled at a daily frequency, we estimate the effects with big news using a daily event window. We find that the big news widen both spreads, supporting the narrative that financial markets perceive President Trump's threats as reducing financial stability.

5 Tweets and Monetary Policy Reversal

We have shown above that President Trump's tweets criticizing the Federal Reserve induce changes in expectations about future monetary policy. The analysis has been conducted using a high-frequency approach that leverages the unique circumstances of a President openly criticizing the central bank via social media. A high-frequency analysis allows a clean identification of the events of interest under the assumption that over such short period of time no other relevant news arrive. Two important related considerations are if the effects of these tweets persist over time and if the tweets affect the actual path of the FFR.

To address these questions, we follow the recent literature that combines high-frequency identification strategies with VAR analysis. Specifically, we adopt the approach of Jarociński and Karadi (2020), which uses movement in FFF rates around FOMC announcements to identify the effects of monetary policy shocks. Similarly, we use the revision in expectations around the tweet as instrument for a "tweet shock." This approach allows us to assess whether the effects of the tweets persist over time, but also if the tweets had an actual effect on the path of the FFR. This second aspect of the analysis has important additional ramifications, as we are not only checking if markets perceive the Federal Reserve as fully independent, but also if the Fed was affected in its policy decisions by the tweets. As shown below, we find evidence that monetary policy changed course following President Trump's tweets.

5.1 A VAR Augmented with Tweet Shocks

To understand how the tweets affect the path of macro and financial variables, we fit the following VAR augmented with Twitter news:

$$\begin{pmatrix} m_t \\ y_t \end{pmatrix} = \sum_{p=1}^{P} \begin{pmatrix} 0 & 0 \\ B_{ym}^p & B_{yy}^p \end{pmatrix} \begin{pmatrix} m_{t-p} \\ y_{t-p} \end{pmatrix} + \begin{pmatrix} 0 \\ c_y \end{pmatrix} + \begin{pmatrix} u_{m,t} \\ u_{y,t} \end{pmatrix}, \quad \begin{pmatrix} u_{m,t} \\ u_{y,t} \end{pmatrix} \sim \mathcal{N}(0, \Sigma)$$

where y_t is a vector of N_y macroeconomic and financial variables observed in month t and m_t is a vector of surprises in the FFF rate observed in month t. To construct m_t, we add up the intraday surprises occurring in month t in response to the full set of tweets by President Trump criticizing the Fed considered in Section 3. We use the change in expectations implied by an FFF contract exposed to at least four FOMC meetings. We assume that before President Trump started tweeting about the Fed, this variable was always zero. The vector y_t includes five variables: a policy rate, the log of the S&P500, the log of real GDP, the log of the GDP deflator, and an indicator of financial conditions. Results are similar when adding a commodity price index. The autoregressive coefficients in the equation for m_t are restricted to zero. This restriction is consistent with the assumption that the revision in expectations following a tweet is a surprise.

For the monetary policy rate, we use the shadow FFR constructed by Wu and Xia (2016) that builds on the shadow rate term structure model (SRTSM) first proposed by Black (1995). The model assumes a linear relation between a shadow rate and Gaussian factors driving the term structure of interest rates. The observed short-term interest rate is the maximum of the shadow rate and zero. Wu and Xia (2016) employ an analytical representation as an approximation of bond prices in the multifactor SRTSM and use it to extract the corresponding shadow rate. Using the shadow rate allows us to capture the effects of unconventional monetary policy at the zero lower bound. When the zero lower bound is binding, the shadow FFR can be interpreted as a counterfactual interest rate that captures the overall stance of monetary policy as reflected in the term structure of interest rates. Results based on using 1-year constant Treasury yields are qualitatively similar, but tend to be noisier. The advantage of using the shadow FFR is that when the zero lower bound is not binding the rate tracks the actual FFR very closely. We find this feature desirable to the extent that the FFR is under the direct control of the Federal Reserve while yields of longer maturities are affected by inflation expectations and movements in risk premia.

The stock price index is constructed as the monthly average of the S&P 500 in logs. To obtain a monthly series of real GDP, we follow Jarociński and Karadi (2020) and interpolate real GDP and GDP deflator to a monthly frequency using the methodology described in Stock and Watson (2017). The monthly series is constructed by using a Kalman filter to distribute the quarterly GDP and GDP deflator series across months using a dataset of monthly variables that are closely related to economic activity and prices. Finally, we use the excess bond premium (EBP) as an indicator of financial conditions (EBP, Gilchrist and Zakrajšek (2012)). The EBP corresponds to the average corporate bond spread net of default compensation.

We fit the VAR over the sample 2001:10-2020:2. We choose this sample for two reasons. First, Bianchi, Lettau, and Ludvigson (2016) and Bianchi and Ilut (2017) present evidence of structural breaks in the conduct of monetary policy in the post-millennial period. Second, the focus of the study is on the effects of the tweets that occurred over a short period of time (2017:4-2020:2). We find it more reasonable to analyze the marginal effect of these tweets over a period of time that is as homogenous as possible with respect to the conduct of monetary policy. We include 12 lags and use Bayesian methods to prevent overfitting. We employ standard Bayesian priors for the VAR parameters, following Litterman (1986). Draws from the posterior are generated using a Gibbs sampling algorithm.

5.2 Results

As a first step, we compute the impulse response to a tweet shock. This is obtained by taking a Cholesky decomposition of the covariance matrix with m_t ordered first. This ordering implies that all macro and financial variables are allowed to respond on impact to the shock. To facilitate the interpretation of the results, we consider a negative surprise in FFF.

Figure 2 reports the median together with 68% and 90% credible sets. The negative Tweet shock is followed by a drop in the shadow FFR and the EBP, and an increase in the stock market. The effect on the shadow FFR is an order of magnitude larger than the initial high-frequency shocks, while the effect on the stock market is an order of magnitude larger with respect to the decline in the shadow FFR and the EBP. Inflation and GDP do not move on impact, while they tend to increase afterwards, in line with the decline in the shadow FFR and the EBP. The fact that the macro variables do not respond on impact and move upward afterwards mitigates the concern that the decline in the shadow FFR and the results documented above are driven by a "news effect," (i.e., the idea that President Trump's tweets reveal bad news about the future that in turn lead to a downward revision in expectations about the future FFR).[9]

The credible sets for the impulse responses are relatively wide for the macro variables. This should not be surprising given that we are looking at a series of events that unfolded over a short period of time (unlike when analyzing the effects of monetary policy shocks). However, the credible sets of the impact responses imply a large probability of a decline for the shadow FFR and the EBP, the variables directly linked to monetary policy decisions, suggesting that criticism from President Trump might have had an immediate effect on the choice of the central bank. We also report the response of the sum of the shadow rate and the EBP. Note that this variable is not included in the VAR, but reconstructed *ex-post*. Under the assumption that unconventional monetary policy also affects bond premia, the sum of the two variables can be seen as a proxy for the overall monetary policy stance. There is strong evidence in favor of a decline of this composite variable, with bands that become tighter with respect to the EBP response. Thus, the tweets appear to be followed by easing in financial markets.

In light of these impulse responses, it is interesting to isolate the effects of the tweets on the actual path of the FFR and the other variables. In order to address this question, we construct a counterfactual simulation that removes the tweets and computes the correspond-

[9] We also tried to separate shocks that generate a positive high-frequency commovement between the stock market and the revision in expected interest rates from the shocks that generate a negative commovement between the two variables. The results were inconclusive, arguably because of the small number of observations.

ing path of the macro variables. We then take the difference between the actual path and the counterfactual path. Such difference represents the overall effect of President Trump's tweets, as identified with the high-frequency approach. Note that these estimates likely represent a lower bound of the overall effect of political interference as they only capture the effects of the tweets, while they cannot capture other forms of moral suasion.

Figure 3 reports the results. The overall effect attributed to the tweets is quite large. The shadow FFR and the EBP rate are found to be around 0.7% and 0.9% lower than what they would have been without the tweets. The last panel of the figure also reports the cumulative effect on the sum of EBP and the shadow rate. Under the assumption that unconventional monetary policy acts through both the shadow rate and the EBP, the large decline in the sum of these two variables suggests that the tweets might have in fact contributed to a reversal of the monetary policy stance. The effect on the stock market is also estimated to be very large, with a peak of close to 18%. Such a finding suggests that a large fraction of the run-up in the stock market at the end of the sample can be attributed to a reversal of the monetary policy stance. The effects on the real economy are also estimated to be important. Real GDP at the end of the period is found to be 1.5% higher than it would have been without the tweets and the associated policy reversal. Finally, the effects on inflation are more modest and less precisely estimated, but still positive, in line with what was indicated by the impulse responses.

With respect to the credible sets, it is worth emphasizing that large error bands should be expected given the small number of observations. However, even when accounting for uncertainty, the results are quite strong. For all variables, with the exception of the GDP deflator, we find that the 68% error bands do not include zeros for several periods. Furthermore, for the stock market, the EBP, and the sum of the shadow rate and EBP 90% error bands do not include zeros over several periods. Given that we take a Bayesian approach to inference, it might also be useful to interpret these results in terms of posterior odds ratios. We define the posterior odds ratio for a variable that increases in response to the tweets ($\Delta X_t > 0$) as:

$$Odds\ ratio\,(X) = P\,(\Delta X_t > 0)\,/P\,(\Delta X_t < 0)\,,$$

while for a variable that decreases ($\Delta X_t < 0$) we define it as:

$$Odds\ ratio\,(X) = P\,(\Delta X_t < 0)\,/P\,(\Delta X_t > 0)\,.$$

To fix ideas, consider that if we observe a positive (negative) change in response to the tweet shocks with 68% (90%) credible sets that do not include zero, we can conclude that the posterior odds of an increase (decrease) of the variable of interest is at least 5.25 (19) times more likely than a decrease (increase).

Table 5 reports the peak of the effect of the tweets measured with respect to the posterior median, the value of the posterior odds ratios in favor of a change of the same sign at this peak, and the maximum value of the posterior odds ratios. Thus, the table provides information both about the magnitudes of the responses, but also about the overall statistical evidence in favor of an effect in that direction. For the shadow rate, at the peak, a decline as a result of the tweets is more than 5.5 times more likely than an increase. Furthermore, the posterior odds ratio in favor of a decline in the shadow rate following the tweet reaches a maximum of 18.5. There is also strong evidence that the tweet shocks were followed by a large decline in EBP. Specifically, at the peak, a decline is 23 times more likely than an increase, while the posterior odds ratio in favor of a decline can be as high as 35. The results are even more clear when considering the combined effect on the shadow rate and EBP. At the peak, a decline is more than 70 times more likely than an increase, and at some point the probability assigned to a decline is 400 times larger than the probability assigned to an increase. This last result is very important in light of the fact that expansionary monetary policy also lowers risk premia. The results indicate that the tweets were followed by a drastic reversal in the overall financial market conditions.

The evidence in favor of a large increase in the stock market is also strong, with an increase eventually 80 times more likely than a decline, and the probability of an increase 18 times more likely than a decline at the peak. For GDP, we find that the probability that the tweets had an expansionary effect is 9 times more likely than if they had a negative effect. Even for the GDP deflator, the variable that shows more uncertainty, the probability assigned to an increase is around 4 times larger than the probability assigned to a decrease.

Summarizing, our VAR results show that the tweet shocks had a quantitatively large effect on the economy, financial variables, and the path of monetary policy. The result on the behavior of the stock market is of particular interest. In our high-frequency analysis, we find clear evidence for the Bernanke-Kuttner effect (i.e. a downward revision in the expected path of interest rates is associated with an increase in the stock market), only when focusing on the most newsworthy tweets. However, this pattern clearly emerges when focusing on the VAR analysis that captures the effects of the tweets at business cycle frequencies. One possible explanation for this result is that the tweets criticizing the Fed cause a revision in expectations about the FFR, but also elicit concerns about a possible conflict between the Fed and the executive branch. Thus, on impact, the positive effect of lowering interest rates on the stock market could be partially dampened by concerns about the possibility of an institutional conflict. However, once the conflict does not materialize, the overall effect is the expectation of more dovish monetary policy with an increase in asset valuations and a decline in risk premia.

6 Historical antecedents and corroborating evidence

In this last section, we first examine episodes of political interference from past presidential administrations on the conduct of monetary policy. We then present corroborating evidence for our main results using external data sources.

6.1 Historical antecedents

As described in the introduction, political influence from the executive branch on central bank decision making is not a new phenomenon associated with President Trump. In this section, we analyze events that happen to be particularly relevant and show that, in some cases, had an impact similar to what we found for President Trump's tweets.

A distinguishing feature of the political attacks on the Fed by President Trump is the communication to the general public with the use of social media. Actively conducting political interference through a social media platform such as Twitter is important for our empirical identification strategy in the following ways. First, the political interference is widespread and publicly observable, while interference from past administrations were more likely to occur behind closed doors. For example, during a conversation that occurred on October 23, 1969, just after Burns' nomination to the Fed had been announced, President Nixon invited Burns "to see [him] privately anytime" and suggested communicating through an intermediary in order to preserve "the myth of the autonomous Fed" (Abrams, 2006). Second, the accurate to the second timestamp of the tweets makes it possible to pinpoint the *exact* moment in which political interference was revealed to the public. Third, the use of Twitter implies that all followers of the President immediately become aware of the new information. In addition, the pervasive use of electronic devices to acquire news implies that even market participants who do not follow the President will become quickly aware of the news. Fourth, tweets have the advantage that they are limited in length and often cover only one topic. Previous criticism towards the Fed's policy were made in speeches and interviews which often covered the economy and other topics that could impact expectations of the federal funds rate.

There are a few notable historical antecedents of US Presidents *publicly* criticizing the Federal Reserve. During the State of the Union speech of January 1967, President Johnson claimed that the "[...] greatest disappointment in the economy during 1966 was the excessive rise in interest rates and the tightening of credit" and pledged to "[d]o everything in a President's power to lower interest rates and to ease money in this country" (Johnson, 1967). At the welcoming ceremony to the White House for the newly appointed Chairman Arthur Burns, President Nixon said: "I respect [the Federal Reserve's] independence. On the other hand, I do have the opportunity as President to convey my views to the Chairman of the Federal Reserve in meetings [...]. I hope that independently [Chairman Burns] will conclude that my views are the ones that should be followed," (Nixon, 1970). He ended his remarks telling Burns: "Please give us more money!" (Greene, 2006).

A high-frequency analysis of the market responses to these events is not possible for two reasons. First, data for the FFF contracts are not available around these events. Second, it is substantially harder to pinpoint exactly when the information became known to the public. Nevertheless, we can examine the behavior of interest rates at lower frequencies around these historical events. The first two panels in Figure 6 report the behavior of daily interest rates around these two events. The decline in response to President Johnson speech over a month was between 0.3% and 0.4% depending on the maturity, while it was around 1% following President Nixon's speech. These magnitudes are in line with the estimates from our VAR analysis. Considering the low interest rate environment that the Fed is confronting in the recent period, the decline in interest rates following President Trump's pressure is even more dramatic.

The Volcker disinflation marked a significant change in the relations between the US President and the Fed Chairman, with US Presidents generally refraining from criticizing the Fed. However, in some instances, members of the administration expressed opinions that are arguably in line with the President's views. For example, President H.W. Bush expressed his discontent via his Deputy Secretary of the Treasury, John Robson, in January 1992. In this last case, the political pressure did not result in any visible change in the course of monetary policy. As illustrated in right panel of Figure 6, this episode was not followed by any visible decline in interest rates. In fact, it seems that political interference under the H.W. Bush administration might have backfired, perhaps due in part to a desire of showing independence, as revealed by the transcripts of the June 1992 meeting. In a June 26 article leading up to the June 1992 FOMC meeting, the New York Times notices that "The Administration, worried about rising unemployment rates during an election year, has been keeping up pressure on the Federal Reserve to cut interest rates further. Earlier this week, President Bush publicly called on the Fed to ease credit." This public interference had some interesting effects. During the June 30-July 1 FOMC meeting, Governor Lindsay said "I couldn't imagine a better test for us to establish credibility. We have not only a Presidential statement but [...] [t]hey got everybody together to give background interviews. So it was a pretty public act of pressure on us. We'd clearly establish credibility if we stood tall." Similarly, Governor LaWare said "[...] it is hard for me to see what effect we could expect to have from a further easing of policy. To the contrary, in my view there are some recognizable risks, including [...] the concern that we are pursuing a political course following public jawboning from the Administration." The Federal Reserve decided not to cut rates in that case, with a bias toward easing with rare dissents from LaWare and Melzer.[10]

This last episode is quite important for two reasons. First, it shows that political interference does not always lead to lower interest rates despite still being present. The fact that some of the FOMC members took political pressure into consideration in the decision process still implies a distortion of the natural decision-making process. Second, this last event makes the results presented in this paper even more relevant because it shows that it is not obvious that President Trump's tweets should automatically lead to lower expected rates and lower realized rates. It could be argued that the Fed appeared more independent following the Volcker disinflation. Thus, President Trump's tweets came to perturb an equilibrium that had lasted for around four decades. President Trump's willingness to challenge political and institutional norms might explain the effects of his tweets on expected and actual monetary policy.

6.2 Corroborating Evidence

In this last subsection, we provide corroborating evidence for our main results using information outside of Twitter. The evidence presented here also suggests potential reasons for why markets might not perceive the Fed as completely immune from political pressure.

Figure 5 presents daily prices for a bet offered by the website PredictIt. The bet asks "Will the Senate confirm a new Fed chair in 2019?" The bet pays $1 if a new Chairman is confirmed before the end of 2019. Note that the bet is not about whether Powell will be fired, because that might not be legally possible. However, the President might have other ways to achieve the same goal, like offering Powell a position in the cabinet, demoting him to governor, or putting pressure on his resignation as Chairman. A similar bet did not exist for Powell's predecessor, Chairwoman Janet Yellen.

The price of the contract is positively related to the probability that the betting participants assign to the event that a new Chairman will be confirmed by Congress. This data is only available at a daily frequency, so we cannot conduct the same high-frequency analysis we used for the FFF and EDF contracts. As such, we only use this data to provide suggestive evidence through a narrative account. The price increases after both the March 19-20, 2019 and April 30-May 1, 2019 FOMC meetings, where no rate changes occurred despite frequent complaints by the President advocating lower interest rates on Twitter. Without following through on the rate cuts recommended by the President, these attacks possibly changed bettor perceptions of an increased likelihood that Powell is removed as Chairman.

[10] The following day the employment report showed an increase in unemployment and Chairman Greenspan decided for a 50 bps cut.

The prices spike up again in response to the White House report on June 18th, 2019 that the President was looking into the legal aspects of firing Powell and again in response to a series of tweets on August 23, 2019 in which the President escalated his complaints against the Fed and at Powell.[11] The price naturally trends downward as the end of 2019 approaches given that the bet only pertains to the removal of Powell in 2019.

Finally, we explore how the attitude of President Trump toward monetary policy changed after announcing his Presidential campaign. The President might criticize the Fed because of his particular view of monetary policy as it could be that President Trump is dovish when it comes to the conduct of monetary policy. To this end, all tweets by President Trump before he decided to run for President are analyzed. We select all tweets that comment on the Fed that predate June 16, 2015, the day in which Donald Trump delivered his Presidential Announcement Speech. A total of 17 tweets are identified mentioning the Federal Reserve, spanning the period August 10, 2011 - September 30, 2013. Out of these 17 tweets, 14 tweets contain criticism of the Federal Reserve for being *too dovish*. In particular, Trump was at that time advocating for tighter monetary policy and the end of quantitative easing, expressing concerns for the risk of high inflation and a weak dollar. These 14 tweets cover the period between August 10, 2011 - August 7, 2012, when economic conditions were arguably substantially weaker than in 2018-2019. For example, the unemployment rate was 9% in August 2011, when he was advocating for tighter monetary policy, while it was 3.9% in April 2018, when he started tweeting that the Fed should keep rates low. The remaining three tweets are from August and September 2013 and do not contain any criticism or praise of the Fed.

The fact that President Trump was advocating for more hawkish monetary policy before he decided to run for President while he advocates for more dovish monetary policy starting from April 2018 suggests a shift in his attitude toward monetary policy. One possible reason for his change is the political incentive as the incumbent President for more dovish monetary policy leading up to his re-election campaign. Expansionary monetary policy can generate higher stock market valuations and more robust real activity in the short-term. Another possible reason is that President Trump viewed accommodative monetary policy as part of a broader strategy to compete with other countries. In both cases, it seems fair to infer that his advice to the Fed is not independent of his broader political agenda, akin to episodes of political interference in the past.

[11] The series of tweets includes two tweets that are particular relevant. The first one, "Now the Fed can show their stuff!" (9:01 AM ET, August 23, 2019), suggests that the Fed should change monetary policy course. The second one, "....My only question is, who is our bigger enemy, Jay Powell or Chairman Xi?" (10:57 AM ET, August 23, 2019), presents one of the most direct complaints about Fed Chairman Jerome Powell.

7 Conclusions

In this paper, we use a high-frequency analysis to show that President Trump's tweets criticizing the Fed affected market expectations about future monetary policy. Our high-frequency identification approach relies on a large collection of tweets from President Trump criticizing the conduct of monetary policy in conjunction with tick-by-tick FFF and EDF prices. The average effect on the expected FFF and short rates are negative and statistically significant with the magnitude growing by horizon. The criticism by President Trump also lead to an increase in the stock market index and in breakeven inflation, in line with economic theory about the effects of more dovish monetary policy, but also in spreads linked to financial instability. This last result suggests that markets might have seen the attacks on the Federal Reserve as disruptive or indicative of future changes of the regulatory environment. Our results are stronger when focusing on big news (i.e., newsworthy tweets and important related news from other media outlets). Overall, our findings suggest that financial markets do not perceive the Federal Reserve as being fully independent of the executive branch.

We then combined the high-frequency shocks with a VAR analysis to show that the tweets had a material impact on the conduct of monetary policy, the stock market, bond premia, and the macroeconomy. These effects are not negligible and show that the reversal in the conduct of monetary policy at the beginning of 2019 and the associated run-up in the stock market can be in part explained by the political pressure exercised by President Trump.

References

Abrams, B. A., 2006. How Richard Nixon pressured Arthur Burns: Evidence from the Nixon tapes. Journal of Economic Perspectives 20(4), 177–188.

Acemoglu, D., S. Johnson, P. Querubin, J. A. Robinson, 2008. When does policy reform work? The case of central bank independence. Unpublished working paper. National Bureau of Economic Research.

Adrian, T., H. S. Shin, 2010. Financial intermediaries and monetary economics. Handbook of Monetary Economics vol. 3 pp. 601–650.

Ai, H., R. Bansal, 2018. Risk preferences and the macroeconomic announcement premium. Econometrica 86(4), 1383–1430.

Alesina, A., 1988. Macroeconomics and politics. NBER macroeconomics annual 3, 13–52.

Alesina, A., L. H. Summers, 1993. Central bank independence and macroeconomic performance: some comparative evidence. Journal of Money, credit and Banking 25(2), 151–162.

Barndorff-Nielsen, O. E., P. R. Hansen, A. Lunde, N. Shephard, 2008. Designing realized kernels to measure the ex post variation of equity prices in the presence of noise. Econometrica 76(6), 1481–1536.

Beechey, M. J., J. H. Wright, 2009. The high-frequency impact of news on long-term yields and forward rates: Is it real?. Journal of Monetary Economics 56(4), 535–544.

Bernanke, B. S., K. N. Kuttner, 2005. What explains the stock market's reaction to Federal Reserve policy?. The Journal of Finance 60(3), 1221–1257.

Bianchi, F., C. Ilut, 2017. Monetary/fiscal policy mix and agents' beliefs. Review of economic Dynamics 26, 113–139.

Bianchi, F., M. Lettau, S. C. Ludvigson, 2016. Monetary policy and asset valuation. Unpublished working paper. National Bureau of Economic Research.

Binder, C. C., 2021. Political Pressure on Central Banks. Journal of Money, Credit and Banking 53(4), 715–744.

Black, F., 1995. Interest rates as options. The Journal of Finance 50(5), 1371–1376.

Bollerslev, T., J. Li, Y. Xue, 2018. Volume, volatility, and public news announcements. The Review of Economic Studies 85(4), 2005–2041.

Cieslak, A., A. Morse, A. Vissing-Jorgensen, 2018. Stock returns over the FOMC cycle. The Journal of Finance.

Cochrane, J. H., M. Piazzesi, 2002. The fed and interest rates-a high-frequency identification. American Economic Review 92(2), 90–95.

Condon, C., 2019. Key Trump Quotes on Powell as Fed Remains in the Firing Line. www.bloomberg.com/news/articles/2019-08-22/key-trump-quotes-on-powell-as-fed-remains-in-the-firing-line.

Crowe, C., E. E. Meade, 2007. The evolution of central bank governance around the world. Journal of Economic Perspectives 21(4), 69–90.

Cukierman, A., S. B. Web, B. Neyapti, 1992. Measuring the independence of central banks and its effect on policy outcomes. The world bank economic review 6(3), 353–398.

Du, W., A. Tepper, A. Verdelhan, 2018. Deviations from covered interest rate parity. The Journal of Finance 73(3), 915–957.

Faust, J., 2016. Oh, What a Tangled Web we Weave: Monetary policy transparency in divisive times. Hutchins Center Working Papers.

Faust, J., E. T. Swanson, J. H. Wright, 2004. Identifying VARs based on high frequency futures data. Journal of Monetary Economics 51(6), 1107–1131.

Fessenden, H., 1965. The Year the Fed and LBJ clashed". Federal Reserve Bank of Richmond Econ Focus.

Gertler, M., P. Karadi, 2015. Monetary policy surprises, credit costs, and economic activity. American Economic Journal: Macroeconomics 7(1), 44–76.

Gilchrist, S., V. Yue, E. Zakrajšek, 2019. US monetary policy and international bond markets. Journal of Money, Credit and Banking 51, 127–161.

Gilchrist, S., E. Zakrajšek, 2012. Credit spreads and business cycle fluctuations. American economic review 102(4), 1692–1720.

Greene, J. R., 2006. Presidential profiles: The Nixon-Ford years. Facts on File.

Grilli, V., D. Masciandaro, G. Tabellini, 1991. Political and monetary institutions and public finance policies in the industrial democracies. Economic Policy 13, 341–392.

Gürkaynak, R. S., B. Sack, E. Swanson, 2005a. The sensitivity of long-term interest rates to economic news: Evidence and implications for macroeconomic models. American Economic Review 95(1), 425–436.

Gürkaynak, R. S., B. Sack, E. T. Swanson, 2005b. Do Actions Speak Louder Than Words? The Response of Asset Prices to Monetary Policy Actions and Statements. International Journal of Central Banking.

Gürkaynak, R. S., B. P. Sack, E. T. Swanson, 2007. Market-based measures of monetary policy expectations. Journal of Business & Economic Statistics 25(2), 201–212.

Hanson, S. G., J. C. Stein, 2015. Monetary policy and long-term real rates. Journal of Financial Economics 115(3), 429–448.

January 31, ., 1970. Remarks at the Swearing In of Dr. Arthur F. Burns as Chairman of the Board of Governors of the Federal Reserve System (January 31, 1970). The American Presidency Project, UCSB.

Jarociński, M., P. Karadi, 2020. Deconstructing monetary policy surprises—the role of information shocks. American Economic Journal: Macroeconomics 12(2), 1–43.

Johnson, L. B., 1967. State of the Union Address (January 10, 1967). UVA Miller Center.

Kohn, D., 2013. Federal Reserve independence in the aftermath of the financial crisis: should we be worried?. Business Economics 48(2), 104–107.

Krishnamurthy, A., A. Vissing-Jorgensen, 2011. The effects of quantitative easing on interest rates: channels and implications for policy. Unpublished working paper. National Bureau of Economic Research.

Kuttner, K. N., 2001. Monetary policy surprises and interest rates: Evidence from the Fed funds futures market. Journal of Monetary Economics 47(3), 523–544.

Litterman, R. B., 1986. Forecasting with Bayesian vector autoregressions—five years of experience. Journal of Business & Economic Statistics 4(1), 25–38.

Lucca, D. O., E. Moench, 2015. The pre-FOMC announcement drift. The Journal of Finance 70(1), 329–371.

Nakamura, E., J. Steinsson, 2018. High-frequency identification of monetary non-neutrality: the information effect. The Quarterly Journal of Economics 133(3), 1283–1330.

Rigobon, R., B. Sack, 2003. Measuring the reaction of monetary policy to the stock market. The quarterly journal of Economics 118(2), 639–669.

Stock, J. H., M. W. Watson, 2017. Monthly GDP and GNI-Research Memorandum. manuscript.(2012)"Disentangling the Channels of the 2007–09 Recession," Brookings Papers on Economic Activity 2012, 81–135.

Swanson, E. T., 2011. Let's twist again: a high-frequency event-study analysis of operation twist and its implications for QE2. Brookings Papers on Economic Activity pp. 151–208.

Swanson, E. T., 2017. Measuring the effects of Federal Reserve forward guidance and asset purchases on financial markets. Unpublished working paper. National Bureau of Economic Research.

Timiraos, N., 2019. Fed Readies First Interest-Rate Cut Since 2008. www.wsj.com/articles/fed-readies-first-interest-rate-cut-since-2008-11564563601.

Vissing-Jorgensen, A., 2019. Central Banking with Many Voices: The Communications Arms Race. Unpublished working paper.

Wu, J. C., F. D. Xia, 2016. Measuring the macroeconomic impact of monetary policy at the zero lower bound. Journal of Money, Credit and Banking 48(2-3), 253–291.

Table 1: FFF and EDF Contracts by Horizon

This table estimates the impact of President Trump's tweets criticizing the Fed on changes in expectations of short rates. Panel A infers market expectations of the FFR using fed funds futures (FFF) contracts where horizon j is defined as the number of FOMC meetings a selected FFF contract is exposed to ranging from 0 to 10 meetings. Panel B infers market expectations of the three-month interest rate using eurodollar futures (EDF) contracts where horizon j corresponds to the maturity of the EDF contract ranging from 1 quarter to 5 years. The event study regresses the revision in expectations the short rate r_j of horizon j on a constant around each selected tweet in the event window according to:

$$(E_t - E_{t-\Delta t})[r_j] = \alpha_j + \varepsilon_j,$$

where $(E_t - E_{t-\Delta t})$ denotes the change in the market expectation of the short rate in the event window, α_j is a constant capturing the average effect of President Trump's tweets on the expected fed funds rate of meeting exposure j, and ε_j is the error term. The inner event window is 0.1 minutes before the tweet and five minutes after. The outer event window is four hours before and two hours after. The estimates of α are quoted in bps. Our sample period starts on the announcement day of the presidential campaign of Donald Trump (June 16, 2015) and ends on the inauguration day of Biden (January 20, 2021).

Panel A: FFF											
Expsure to FOMC Meetings	0	1	2	3	4	5	6	7	8	9	10
Regression Const. α	−0.036	−0.143***	−0.133**	−0.143*	−0.235***	−0.204***	−0.26***	−0.25***	−0.356***	−0.351***	−0.549**
std. err.	0.031	0.06	0.066	0.077	0.081	0.08	0.099	0.089	0.119	0.147	0.246
t-stat.	−1.15	−2.38	−2.0	−1.85	−2.89	−2.56	−2.64	−2.8	−3.0	−2.38	−2.23
N	49	49	49	49	49	49	48	48	45	47	41
Panel B: EDF											
Time to Expiration	1Q	2Q	3Q	4Q	5Q	6Q	7Q	2Y	3Y	4Y	5Y
Regression Const. α	−0.076	−0.167**	−0.24**	−0.245**	−0.214	−0.266**	−0.202	−0.306***	−0.235*	−0.323***	−0.558**
std. err.	0.071	0.083	0.118	0.124	0.133	0.126	0.126	0.128	0.123	0.13	0.27
t-stat.	−1.07	−2.0	−2.03	−1.98	−1.61	−2.11	−1.6	−2.4	−1.91	−2.48	−2.06
N	46	48	48	49	49	47	47	49	49	48	43

Table 2: Average and Horizon Effects Across FFF and EDF Contracts

This table examines the average effect of the tweets on changes in short rate expectations across all contract horizons (Panel A) and horizon effect of changes in interest rate expectations across all contracts (Panel B) inferred using intraday fed funds futures (FFF) and eurodollar futures (EDF) prices. The same contract horizons are used in these pooled regressions as in Table 1. Panel A regresses the revision in expectations the short rate r pooling across the contract horizons on a constant around each selected tweet in the event window according to:

$$(E_t - E_{t-\Delta t})[r] = \alpha + \varepsilon,$$

where $(E_t - E_{t-\Delta t})$ denotes the change in the market expectation of the short rate in the event window, α captures the average effect across all contract horizons, ε is the error term. Panel B runs the regression pooling across contracts of all horizons:

$$(E_t - E_{t-\Delta t})[r] = \alpha + \beta \cdot \texttt{horizon} + \varepsilon$$

where $(E_t - E_{t-\Delta t})$ denotes the revision in expectations in around each tweet in the event window specified, α is the intercept relating to the average effect across horizons, `horizon` is the demeaned contract horizon, β is the coefficient measuring the horizon effects of the selected tweets on expectation revisions, and ε is the error term. For all of the regressions in this table, the inner event window is 0.1 minutes before the tweet and five minutes after, while the outer event window is four hours before and two hours after. All estimates of are quoted in bps. The sample period starts on the announcement day of the presidential campaign of Donald Trump (June 16, 2015) and ends on the inauguration day of Biden (January 20, 2021).

Panel A: Pooling Regression					
	Const. α	t-stat			N
FFF	−0.256***	−7.21			474
EDF	−0.255***	−6.25			523
FFF and EDF	−0.256***	−9.38			997
Panel B: Horizon Regression					
	Const. α	t-stat(α)	Coef. β	t-stat(β)	N
FFF	−0.256***	−7.27	−0.038***	−2.46	474
EDF	−0.255***	−6.28	−0.017*	−1.69	523

Table 3: Other Asset Classes

This table considers the impact of the Trump attacks using intraday data from other asset classes. Panels A and B uses forex spot rates and futures rates for the currency pairs GBP/USD, YEN/USD, EUR/USD, CHF/USD. We use the forex data to infer interest rate differentials at different maturities using covered interest rate parity (CIP). Panel C considers data from equity markets using ETFs that track the level of the S&P500 index (ticker: SPY) and the volatility (ticker: VXX). Panel A regresses the changes in the equal-weighted portfolio of the interest rate differentials on a constant around the tweets in the event window for maturities j of one quarter to seven quarters:

$$\frac{1}{m}\sum_{c=1}^{m}\Delta(i_{j,t,n}-i^{*}_{j,t,n,c})=\alpha_j+\varepsilon_j,$$

where $\Delta(i_{j,t,n}-i^{*}_{j,t,n,c})\equiv(i_{j,t,n}-i^{*}_{j,t,n,c})-(i_{j,t-\Delta t,n}-i^{*}_{j,t-\Delta t,n,c})$ is the change in the interest rate differential of maturity j with foreign country c implied by CIP around each tweet in the event window, α_j measures the average effect on the changes in the interest rate differential across the foreign countries, and ε_j is the error term. Panel B runs regresses changes in interest rate differentials for a given currency pair on a constant pooling across maturities around the tweets in the event window:

$$\Delta(i_{t,n}-i^{*}_{t,n,c})=\alpha_c+\varepsilon_c$$

where α captures the average effect across maturities on the changes in the interest rate differential between USD and the currency of foreign country c, and ε is the error term. The estimates in Panels A and B are quoted in bps. Panel C regresses changes in the log price of the ETF on a constant around the tweets in the event window. The estimates in Panel C are quoted in percentages. For all of the regressions in this table, the inner event window is 0.1 minutes before the tweet and five minutes after, while the outer event window is four hours before and two hours after. All estimates of are quoted in bps. The sample period starts on the announcement day of the presidential campaign of Donald Trump (June 16, 2015) and ends on the inauguration day of Biden (January 20, 2021).

Panel A: Equal-Weighted Currency by Maturity							
	1Q	2Q	3Q	4Q	5Q	6Q	7Q
Const. α	−3.401	−0.879***	−0.792**	−2.382	−0.858***	−0.388**	−0.946***
t-stat	−0.86	−2.39	−2.24	−1.48	−2.92	−2.27	−2.88
Panel B: Pooling Across Maturity by Currency							
	EUR	GBP	JPY	CHF	All		
Const. α	−0.44***	−1.106**	−0.459***	−3.936	−1.221***		
t-stat	−3.1	−2.03	−2.37	−1.31	−2.51		
Panel C: ETF Evidence							
	SPY	VXX					
Const. α	2.508	−8.425					
t-stat	0.94	−0.79					
N	25	25					

Table 4: Big News

This table reports the average effect of big news (i.e., newsworthy tweets and Bloomberg events) on price changes across different asset classes. Panel A uses high-frequency data to regress intraday price changes on a constant around the big news using the benchmark event window (inner (outer) window of 0.1 minutes (four hours) before and five minutes (two hours) after). The first two columns infer changes in average short rate expectations across contract horizons using the fed funds futures (FFF) and eurodollar futures (EDF) contracts with the same regression specification as in Panel A of Table 2, with the estimates reported in bps. The last three columns consider log price changes in ETFs that track the stock market index (ticker: SPY), implied stock market volatility (ticker: VXX), and breakeven inflation (ticker: RINF). The SPY and VXX estimates are quoted in percentages while the RINF estimates are in bps. Panel B regresses daily changes in nominal treasury yields and forward rates around the big news on a constant for various maturities with the estimates reported in bps. Panel C regresses daily changes in the TED spread and LIBOR-OIS spread on a constant around the big news with the estimates reported in bps. The sample period starts on the announcement day of the presidential campaign of Donald Trump (June 16, 2015) and ends on the inauguration day of Biden (January 20, 2021).

Panel A: High Frequency Results

	FFF	EDF	SPY	VXX	RINF
Const. α	−0.333***	−0.285***	4.767**	−16.85*	10.59*
t-stat	−11.12	−7.961	1.96	−1.719	1.665

Panel B: Nominal Treasury Yields and Forward Rates

	3M	6M	1Y	2Y	3Y	5Y
Treasury Yields	−1.480	−0.942	−1.401	−1.897*	−2.013*	−1.941*
t-stat	−1.358	−1.043	−1.546	−1.843	−1.826	−1.757
Forward Rates			−2.305*	−2.368*	−2.106*	−1.589
t-stat			−1.900	−1.749	−1.684	−1.447

Panel C: Financial Stability

	TED	LIBOR-OIS
Const. α	0.932*	3.259*
t-stat	1.658	1.671

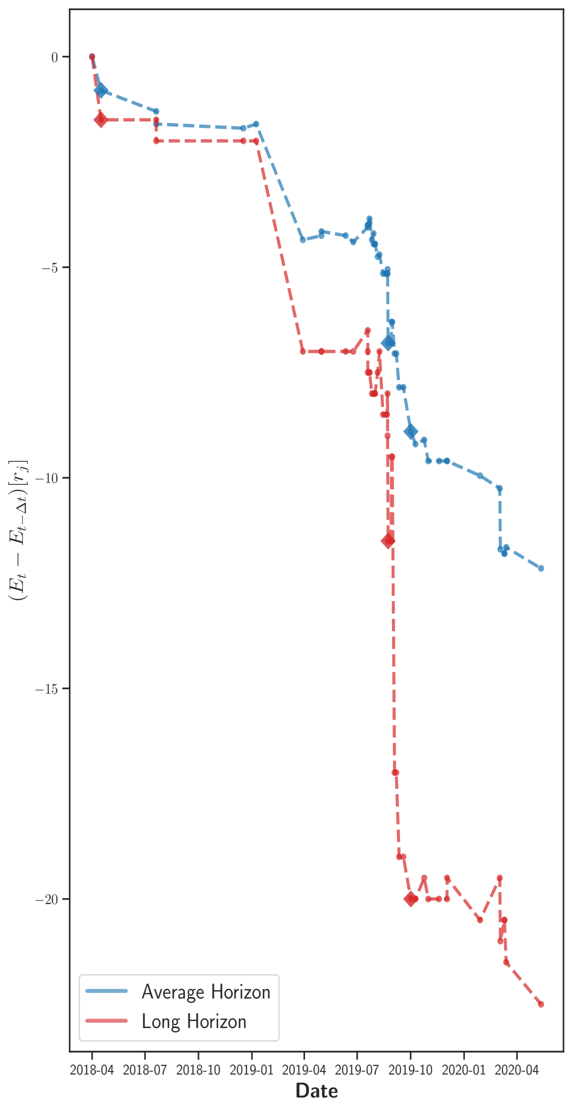
Table 5: Posterior Odds Ratios

This table reports the peak of the effect of the tweets measured with respect to the posterior median in the VAR counterfactual analysis, the value of the posterior odds ratios in favor of a change of the same sign at this peak, and the maximum value of the posterior odds ratios.

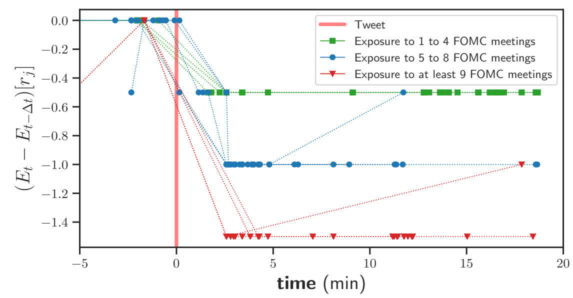
	Shadow FFR	S&P500	Real GDP	GDP deflator	EBP	FFR+EBP
Peak effect	−0.73	17.73	1.61	0.33	−0.94	−1.66
Odd ratio at peak	5.37	16.86	9.38	3.65	22.53	73.07
Max odd ratio	20.74	60.54	9.38	3.65	44.20	346.83

Figure 1: Tweets and Market Expectations

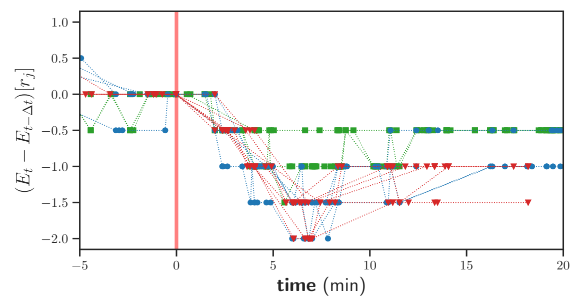
Figure (a) plots the cumulative changes in the expected FFR around each tweet used in the benchmark estimation over the event window (inner (outer) window of 0.1 minutes (four hours) before and five minutes (two hours) after) with the units in bps. The blue line corresponds to the average across all FFF contract horizons. The red line corresponds to long horizon FFF contract exposed to 10 FOMC meetings. Figure (b) to (d) plot the expected FFR responses at different horizons around three examples of newsworthy tweets with the units in bps. Figure (b) corresponds to the tweet, "Russia and China are playing the Currency Devaluation game as the U.S. keeps raising interest rates. Not acceptable!" (2018-04-16). Figure (c) corresponds to the tweet, "Now the Fed can show their stuff!" (2019-08-23). Figure (d) corresponds to the tweet, "As I predicted, Jay Powell and the Federal Reserve have allowed the Dollar to get so strong, especially relative to ALL other currencies, that our manufacturers are being negatively affected. Fed Rate too high. They are their own worst enemies, they don't have a clue. Pathetic!" (2019-10-01)



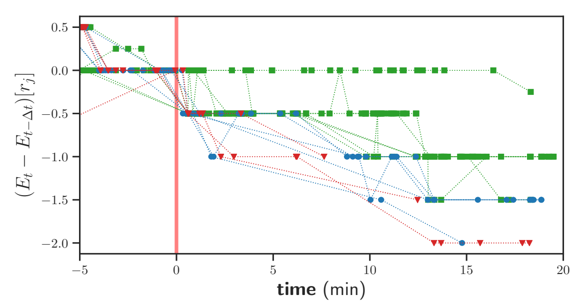
(a) Cumulative Plot



(b) First Tweet (2018-04-16)



(c) Tweet (2019-08-23)



(d) Tweet (2019-10-01)

Figure 2: VAR analysis: Impulse responses to a tweet shock

This figure reports impulse responses to a one standard deviation tweet shock obtained using VAR analysis. The impulse responses are obtained using a Bayesian VAR estimated over the period 2001:10-2020:2.

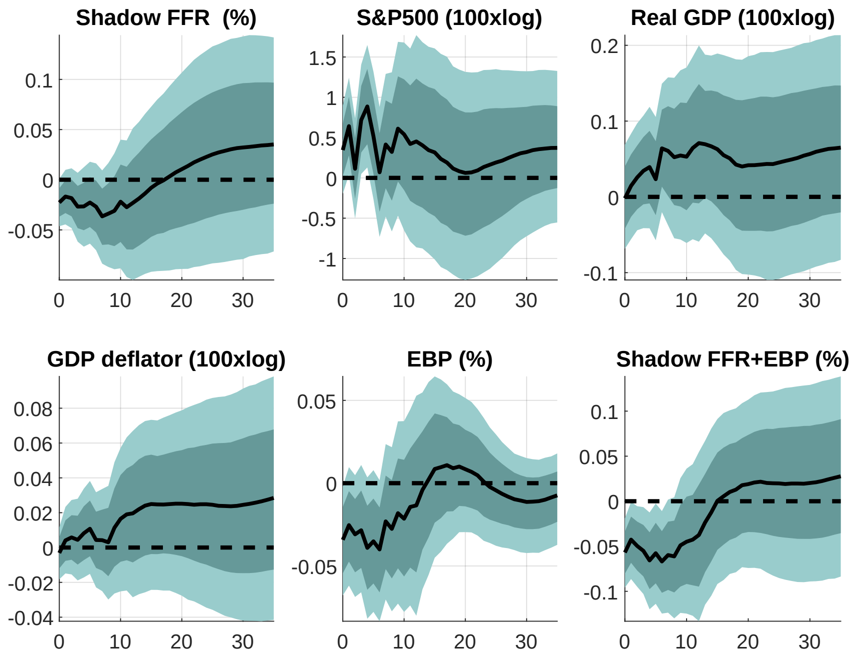


Figure 3: VAR analysis: Cumulative effect of the tweets on realized variables

This figure reports the differences between the realized data and a counterfactual simulation that removes all tweet shocks. The difference can be interpreted as the estimated cumulative effect of the tweets on the variables based on the VAR analysis. The counterfactual simulations are obtained using a Bayesian VAR estimated over the period 2001:10-2020:2.

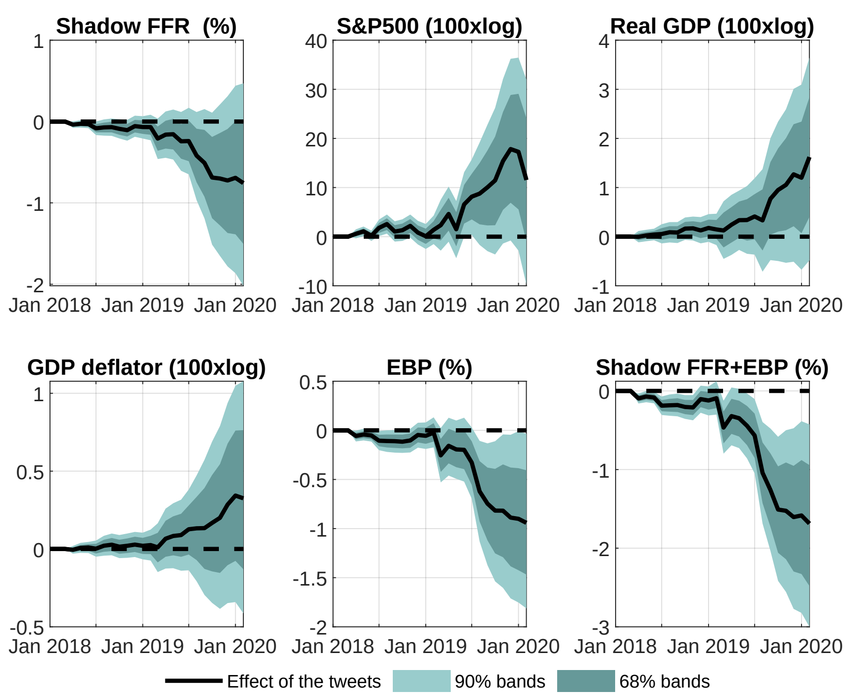


Figure 4: News Threatening the Removal of Powell

This plot shows the changes in expected federal funds rates at different horizons with respect to the Bloomberg story that Trump allegedly asked White House lawyers for options on removing Powell. The contracts are color-coded by their exposure to prior FOMC meetings before expiration. Group A is exposed up to 4 FOMC meetings, Group B up to 8, and Group C to at least 9 meetings. Changes are reported as a percentage of the average absolute change in federal fund futures following FOMC meetings announcement since June 2015.

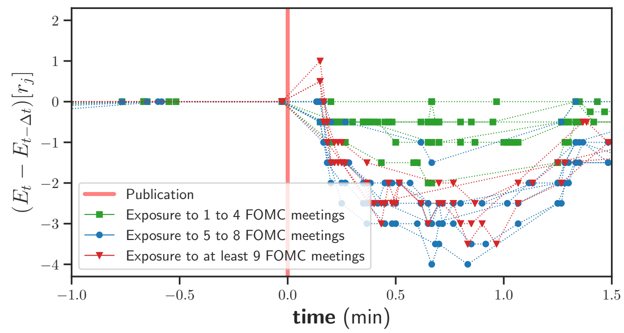


Figure 5: Bets on the Removal of Powell

This figure shows the daily price of a contract that pays 1$ if the Senate confirms a new Fed chair in 2019 on PredictIt together with the scheduled FOMC meetings during 2019.

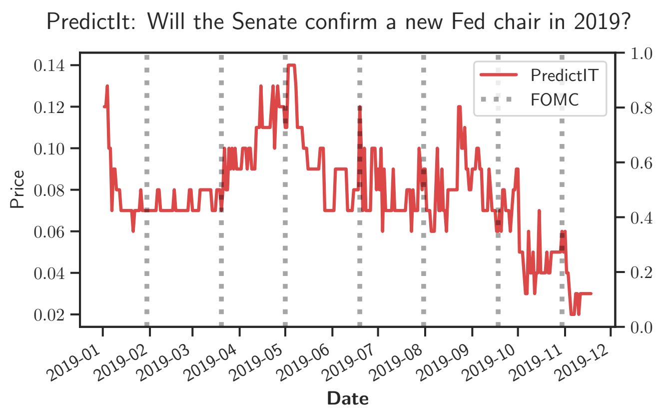
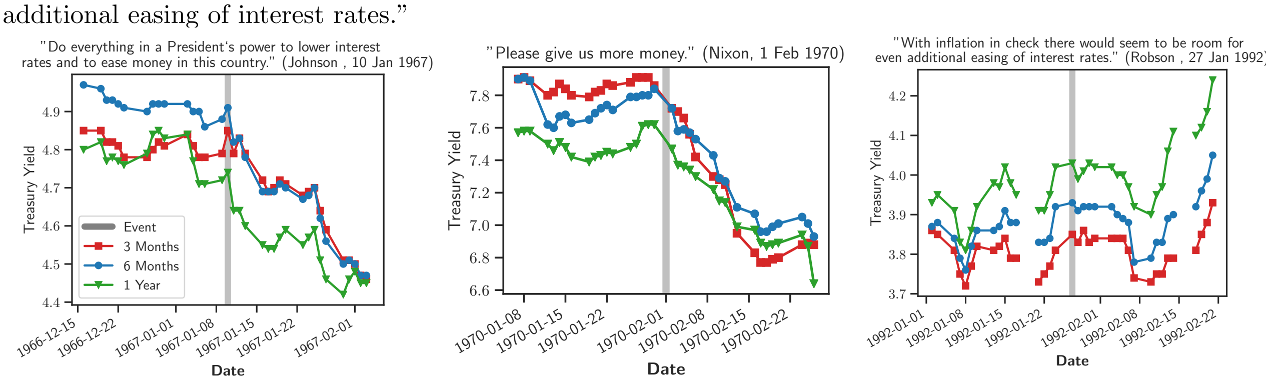


Figure 6: Historical Antecedents

This figure plots the response of nominal treasury yields of maturities of three months to one year around notable historical events challenging Fed independence publicly. The left figure corresponds to President Johnson's State of the Union speech in January 10, 1967 where he pledged to "do everything in a President's power to lower interest rates and to ease money in this country." The middle figure corresponds to the welcoming ceremony to the White House on February 1, 1970 for the newly appointed Chairman Burns in which Nixon remarks "Please give us more money!" The right figure corresponds to when President H.W. Bush expressed his discontent about monetary policy via John Robson (Deputy Secretary of the Treasury) on January 27, 1992 by saying that "with inflation in check there would seem to be room for even additional easing of interest rates."



For Online Publication

Threats to Central Bank Independence: High-Frequency Identification with Twitter

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A Data

A.1 Event Selection

Tweets
The entire set of tweets are collected from the Twitter account of President Trump from his personal account (`@realDonaldTrump`). Each observation includes the text, the accurate to the second timestamp, a classification of the tweet into either a reply or a retweet, and the number of likes and replies. All tweets issued after the announcement of his presidential campaign in June 2015 till the end of his presidency January 2021 are considered. The benchmark criteria for selecting tweets which pose a threat to central bank independence are as following. Select any tweet by @realDonaldTrump which includes one of the following words: *fed, reserve, interest, rate, jerome, jay, powell*. This includes tweets which contain word extensions such as the word 'federal' is captured by 'fed'. Next, the obtained set of tweets is cleaned according to

1. Off-topic tweets
   Drop tweets that do not refer to the topic of interest. For example, 'fed' appears in a tweet that refers to the law enforcement agency
   Example: *Terrible shootings in ElPaso, Texas. Reports are very bad, many killed. Working with State and Local authorities, and Law Enforcement. Spoke to Governor to pledge total support of* ***Fed****eral Government. God be with you all!*

2. Double tweets
   Drop subsequent tweets that occur after an initial tweet within a small time frame (i.e. threads) are dropped. This eliminates the possibility of double counting a particular event.
   Example:
   2019-10-31 09:37:39 *People are VERY disappointed in Jay Powell and the Federal Reserve. The Fed has called it wrong from the beginning, too fast, too slow. They even tightened in the beginning. Others are running circles around them and laughing all the way to the bank. Dollar & Rates are hurting...*
   2019-10-31 09:37:45 *....our manufacturers. We should have lower interest rates than Germany, Japan and all others. We are now, by far, the biggest and strongest Country, but the Fed puts us at a competitive disadvantage. China is not our problem, the Federal Reserve is! We will win anyway.*

3. Announcements
   Drop tweets that announce a new appointment to the Federal Reserve or a withdrawal of a candidate.
   Example: *It is my pleasure to announce that @StephenMoore , a very respected Economist, will be nominated to serve on the Fed Board. I have known Steve for a long time – and have no doubt he will be an outstanding choice!*

4. Retweets
   Drop tweets which do not contain new information other than the reiteration of the President of a tweet by someone else and are indicated by quotation marks.

Example: *"If the Fed backs off and starts talking a little more Dovish, I think we're going to be right back to our 2800 to 2900 target range that we've had for the S&P 500." Scott Wren, Wells Fargo.*

5. Irrelevance
   Drop tweets which are not a direct criticism of the Federal Reserve. While they are not off-topic and mention the Federal Reserve, these tweets don't advocate a clear pressure on the Fed to lower interest rates.
   Example: *It is so important to audit The Federal Reserve, and yet Ted Cruz missed the vote on the bill that would allow this to be done.*

6. Trade, Tariffs and Exports
   Drop tweets which include other information about the economy, in particular, comments on trade, tariffs or exports with respect to a specific country.
   Example: *Despite the unnecessary and destructive actions taken by the Fed, the Economy is looking very strong, the China and USMCA deals are moving along nicely, there is little or no Inflation, and USA optimism is very high!*

Table C.1 reports the date and text for all tweets used in our benchmark analysis. In the robustness Appendix B, an alternative selection criteria is considered. The results in table C.7 are based on the same set of tweets which include the same keywords. Tweets are dropped according to the technical criteria 1-3, i.e. tweets which are off-topic, doubles or announcements. In contrast to the benchmark specification we include tweets which were classified as irrelevant, announcements or which did contain information on trade, tariffs, or exports.

Other News

The set of instances in which President Trump criticized the Federal Reserve in public statements outside Twitter is based on a Bloomberg article (Condon (2019)) which lists several related events. The associated second accurate timestamp is obtained by identifying the first appearance of each event on the Bloomberg terminal.

FOMC Announcements

All past and future FOMC meeting days are collected from the website of the Federal Reserve Bank. For precise timestamps of past FOMC announcements we select the timestamp of the first report on the federal funds rate decision. The first report is the earliest report on the Terminal News Ticker from Bloomberg.

A.2 Asset Prices

Federal Funds Futures

Market expectations of the future fed funds rate are inferred from tick-by-tick trade data of 30-day federal funds futures on the Chicago Board of Trade Exchange (XCBT) obtained from the CBE. CME Globex is open from Sunday to Friday from 5pm to 4pm. This dataset covers the period of January 1995 to January 2021. Price, volume, contract expiration, entry date, second precision timestamps of trades, and the trading sequence are observed. Observations with zero volume, indicating that the trade was cancelled, are dropped from the sample. If there are multiple trades of the same contract within the same second, the trade with the lowest sequence number is used (i.e., the earliest trade within that particular second).

Federal funds future contracts are financially settled on the first business day following the last trading day. For an expiring contract, the last trading day corresponds to the last business day in the delivery month of the futures contract. The price quotation for this type of contract is 100 minus the arithmetic average of the daily effective federal funds rate during the contract month (expiration month). The corresponding daily federal funds overnight rate is provided by the Federal Reserve Bank of New York. On weekends or holidays, this rate is equal to the previous reported rate on a business day.

Eurodollar Futures

Eurodollar futures traded on the Chicago Board of Trade Exchange (XCBT) are obtained from the CBE. The dataset covers the period of January 1982 to January 2021. Price, volume, contract expiration, entry date, second precision timestamps of trades, and the trading sequence are observed. Observations with zero volume, indicating that the trade was cancelled, are dropped from the sample. If there are multiple trades of the same contract within the same second, the trade with the lowest sequence number is used (i.e., the earliest trade within that particular second).

Eurodollar future contracts are financially settled on the second London business day prior to the third Wednesday of the contract month. The price quotation for this type of contract is 100 minus the three-month London interbank offered rate for spot settlement on the third Wednesday of the contract month.

Exchange Rates

The second-by-second bid and ask spot rates for the four currency pairs GBP/USD, YEN/USD, CHF/USD, and EUR/USD are obtained from Dukascopy (https://www.dukascopy.com). We take the average of the bid and ask spot rate. The tick-by-tick bid and ask data for the corresponding FX futures are obtained from Refinitiv. After the raw data is cleaned following Barndorff-Nielsen, Hansen, Lunde, and Shephard (2008) and Bollerslev, Li, and Xue (2018), the timestamps are aggregated on three minutes which is the smallest time interval in which a sufficient number of bids and asks occur to compute the midpoint. The dataset covers the period from January 2015 to January 2021. FX future contracts are settled via physical delivery on the third Wednesday of the contract month. The price quotation for this type of contract is U.S. dollars and cents per foreign currency increment.

ETFs: SPY, VXX, RINF

Intraday series for the stock market index is inferred from the SPDR S&P 500 ETF (ticker: SPY), breakeven inflation is from the ProShares Inflation Expectations ETF (ticker: RINF), and the VIX index is from the iPath Series B S&P500 VIX Short Term Futures ETN (ticker: VXX). All series are obtained from the Trade and Quote (TAQ) database. The raw data is cleaned following Barndorff-Nielsen, Hansen, Lunde, and Shephard (2008) and Bollerslev, Li, and Xue (2018). Market microstructure noise is further reduced by resampling the data and taking the first price within each second. Our sample period starts on the announcement day of the presidential campaign of Donald Trump (June 16, 2015) and ends on the inauguration day of Biden (January 20, 2021).

B Robustness

In this appendix, we present a series of robustness checks. Tables C.3 and C.4 use longer event windows than our benchmark estimation from Table 1 for robustness. Both of these tables consider an inner window of ten seconds before and one day after the tweet and an outer window with cutoffs of one week before and one week after the tweet. Table C.3 uses all selected tweets from the benchmark estimation while Table C.4 excludes tweets where a FOMC meeting occurs on the same day as the tweet or on the next day. In both specifications we find that President Trump's tweets generate a negative revision in the expected future FFR and short rates with an effect that intensifies with horizon, mirroring our benchmark estimates. We use a tighter event window in our benchmark estimation (inner window of ten seconds before and five minutes after and an outer window with cutoffs of four hours before and two hours after) as extending the event window increases the chances that confounding factors can affect the results. For sharper identification, we therefore choose a narrow time window even at the cost of underestimating the size of the effects of President Trump's tweets. Furthermore, for the results presented in the paper we use Bloomberg to verify that no other economic news is released within the event window for each tweet in our benchmark specification.

Table C.5 considers a placebo test where 100 randomly selected tweets in the same sample period but excluding tweets that are selected under the benchmark and alternative criteria are used to estimate Equation 3. We repeat the random selection 100 times and report the average of the 100 estimation results. We find that the slope coefficients across horizons are all close to zero and not statistically significant, confirming that tweets not related to monetary policy do not have any effect on market expectations about future monetary policy.

Table C.6 estimates the impact of President Trump's tweets criticizing the Fed on changes in expectations of short rates for five different inner event window specifications. The outer event window is identical to the benchmark case (two hours before and four hours after). The shortest value for T_1 is 0.1 min and the largest value is 10 min. T_2 ranges from 5 min to 60 min. Out of 50 coefficients, only four are not significant.

Table C.7 runs the benchmark estimation from Table 1 using a less stringent selection criteria. For example, under the alternative selection criteria, tweets that do not directly criticize the conduct of monetary policy, but are indirectly related are included. Consistent with the benchmark estimation, the average effects are negative and statistically significant across horizon with an increasing magnitude.

C Additional figures

The identifying assumption of our high-frequency approach is that no other systematic shocks to market expectations about the future federal funds rates occur within a particular time window around the tweet. Figure C.1 highlights how two trades are selected for measuring changes in the expected federal funds rate target. The symbols $\times$, $\circ$, $\square$ represent an observed price due to a trade. All trades that fall outside the outer windows, $t < T_0$, $t > T_3$, or within the inner window, $T_1 < t < T_2$, are disregarded. Of the remaining trades inside the two intervals $[T_0, T_1]$ and $[T_2, T_3]$, the trades closest to the inner window are selected.

The results presented in the paper demonstrate that political pressure from tweets advocating lower rates significantly affect expectations about the fed funds rate. The revision in expectations caused by the tweets is present across all contract horizons with an effect that increases over time. Thus, the tweets do not simply affect expectations about the timing of changes that markets were already anticipating, but instead move market expectations about the stance of monetary policy. Figure C.2 illustrates this point following the example presented in the paper.

Suppose that right before the tweet markets expect that the Fed will cut rates in six months, but not in the near future. If a tweet only induces a change in expectations about the timing of the already anticipated interest rate cut, a revision in expectations would be observed at only short horizons. Panel A of Figure C.2 in the Appendix illustrates this example. Our estimates documenting that the revision in expectations increases with the time horizon indicates that the revision in expectations is more pervasive. Markets are not sure if the Fed will succumb to the political pressure in the immediate future (e.g., during the next FOMC meeting), but they assign an increasing probability to this outcome occurring at some point in the future. Suppose that, as in the previous case, before the tweet, markets expect that the Fed will cut interest rates in six months. If now the tweet generates a decline in expectations both at short and long horizons, we can infer that the tweet does not merely change the timing of an already anticipated decline. Panel B of Figure C.2 in the Appendix provides a depiction of this alternative example.

Figure C.3 plots the average effect of the tweets on changes in the expected federal funds rate across all contract horizons of the federal funds futures considered in the benchmark estimation for different event windows. For the pre-event window, we obtain the average change by fixing the outer event window, T_0 and T_3, to 240 min and 0.1 min, respectively, before the tweet. T_1 is set to 20 min before each tweet. We then vary T_2 from 19 min until 1 min before the event to obtain the average effect for different horizons prior the event. For the post-event window, we use the benchmark time window for $T_0 = -240$ min, $T_1 = -0.1$ min, and $T_3 = 120$ min and vary T_2 from 1 min after the tweet until 80 min after. The plot highlights that there are (i) no pre-trends in the fed funds futures prices before the selected tweets and (ii) the effect grows larger as the post-event window is extended up until 60 minutes and then flattens out.

Table C.1: Tweets

This table reports the text and date of all tweets used in our empirical benchmark analysis. The tweets are collected from President Trump's personal Twitter account (`@realDonaldTrump`). Our sample period starts on the announcement day of the presidential campaign of Donald Trump (June 16, 2015) and ends on the inauguration day of Biden (January 20, 2021). The first tweet criticizing the Federal Reserve is on April 16, 2018 and the last tweet on May 12, 2020. Tweets which are above the median with respect to the number of replies and referred to as "newsworthy tweets" are highlighted by an asterisk at the end.

Date	Text
2018-04-16	Russia and China are playing the Currency Devaluation game as the U.S. keeps raising interest rates. Not acceptable! [*]
2018-07-20	China, the European Union and others have been manipulating their currencies and interest rates lower, while the U.S. is raising rates while the dollars gets stronger and stronger with each passing day - taking away our big competitive edge. As usual, not a level playing field...
2018-07-20	....The United States should not be penalized because we are doing so well. Tightening now hurts all that we have done. The U.S. should be allowed to recapture what was lost due to illegal currency manipulation and BAD Trade Deals. Debt coming due & we are raising rates - Really? [*]
2018-12-17	It is incredible that with a very strong dollar and virtually no inflation, the outside world blowing up around us, Paris is burning and China way down, the Fed is even considering yet another interest rate hike. Take the Victory! [*]
2019-01-08	Economic numbers looking REALLY good. Can you imagine if I had long term ZERO interest rates to play with like the past administration, rather than the rapidly raised normalized rates we have today. That would have been SO EASY! Still, markets up BIG since 2016 Election! [*]
2019-03-29	Had the Fed not mistakenly raised interest rates, especially since there is very little inflation, and had they not done the ridiculously timed quantitative tightening, the 3.0% GDP, & Stock Market, would have both been much higher & World Markets would be in a better place! [*]
2019-04-30	China is adding great stimulus to its economy while at the same time keeping interest rates low. Our Federal Reserve has incessantly lifted interest rates, even though inflation is very low, and instituted a very big dose of quantitative tightening. We have the potential to go...
2019-04-30	....up like a rocket if we did some lowering of rates, like one point, and some quantitative easing. Yes, we are doing very well at 3.2% GDP, but with our wonderfully low inflation, we could be setting major records &, at the same time, make our National Debt start to look small!
2019-06-11	This is because the Euro and other currencies are devalued against the dollar, putting the U.S. at a big disadvantage. The Fed Interest rate way too high, added to ridiculous quantitative tightening! They don't have a clue!
2019-06-24	Despite a Federal Reserve that doesn't know what it is doing - raised rates far too fast (very low inflation, other parts of world slowing, lowering & easing) & did large scale tightening, $50 Billion/month, we are on course to have one of the best Months of June in US history... [*]
2019-07-19	Because of the faulty thought process we have going for us at the Federal Reserve, we pay much higher interest rates than countries that are no match for us economically. In other words, our interest costs are much higher than other countries, when they should be lower. Correct!
2019-07-19	I like New York Fed President John Williams first statement much better than his second. His first statement is 100% correct in that the Fed "raised" far too fast & too early. Also must stop with the crazy quantitative tightening. We are in a World competition, & winning big,...
2019-07-19	....Fed: There is almost no inflation!
2019-07-22	With almost no inflation, our Country is needlessly being forced to pay a MUCH higher interest rate than other countries only because of a very misguided Federal Reserve. In addition, Quantitative Tightening is continuing, making it harder for our Country to compete. As good..... [*]
2019-07-22	It is far more costly for the Federal Reserve to cut deeper if the economy actually does, in the future, turn down! Very inexpensive, in fact productive, to move now. The Fed raised & tightened far too much & too fast. In other words, they missed it (Big!). Don't miss it again!
2019-07-26	Q2 GDP Up 2.1% Not bad considering we have the very heavy weight of the Federal Reserve anchor wrapped around our neck. Almost no inflation. USA is set to Zoom!
2019-07-29	The E.U. and China will further lower interest rates and pump money into their systems, making it much easier for their manufacturers to sell product. In the meantime, and with very low inflation, our Fed does nothing - and probably will do very little by comparison. Too bad!
2019-07-29	The Fed "raised" way too early and way too much. Their quantitative tightening was another big mistake. While our Country is doing very well, the potential wealth creation that was missed, especially when measured against our debt, is staggering. We are competing with other..... [*]
2019-07-31	What the Market wanted to hear from Jay Powell and the Federal Reserve was that this was the beginning of a lengthy and aggressive rate-cutting cycle which would keep pace with China, The European Union and other countries around the world.... [*]

Table C.1: Tweets (continued)

Date	Text
2019-08-01	Experts stated that the Fed should not have tightened, and then waited too long to undo their mistake. James Bullard of St. Louis Fed said they waited too long to correct the mistake that they made last December. “Mistake, Powell cut rate and then he started talking.” @LouDobbs
2019-08-05	China dropped the price of their currency to an almost a historic low. It’s called “currency manipulation.” Are you listening Federal Reserve? This is a major violation which will greatly weaken China over time! [*]
2019-08-08	As your President, one would think that I would be thrilled with our very strong dollar. I am not! The Fed’s high interest rate level, in comparison to other countries, is keeping the dollar high, making it more difficult for our great manufacturers like Caterpillar, Boeing,..... [*]
2019-08-14	We are winning, big time, against China. Companies & jobs are fleeing. Prices to us have not gone up, and in some cases, have come down. China is not our problem, though Hong Kong is not helping. Our problem is with the Fed. Raised too much & too fast. Now too slow to cut.... [*]
2019-08-19	Our Economy is very strong, despite the horrendous lack of vision by Jay Powell and the Fed, but the Democrats are trying to “will” the Economy to be bad for purposes of the 2020 Election. Very Selfish! Our dollar is so strong that it is sadly hurting other parts of the world... [*]
2019-08-21	So Germany is paying Zero interest and is actually being paid to borrow money, while the U.S., a far stronger and more important credit, is paying interest and just stopped (I hope!) Quantitative Tightening. Strongest Dollar in History, very tough on exports. No Inflation!..... [*]
2019-08-22	Germany sells 30 year bonds offering negative yields. Germany competes with the USA. Our Federal Reserve does not allow us to do what we must do. They put us at a disadvantage against our competition. Strong Dollar, No Inflation! They move like quicksand. Fight or go home! [*]
2019-08-22	The Economy is doing really well. The Federal Reserve can easily make it Record Setting! The question is being asked, why are we paying much more in interest than Germany and certain other countries? Be early (for a change), not late. Let America win big, rather than just win!
2019-08-23	Now the Fed can show their stuff! [*]
2019-08-28	Our Federal Reserve cannot “mentally” keep up with the competition - other countries. At the G-7 in France, all of the other Leaders were giddy about how low their Interest Costs have gone. Germany is actually “getting paid” to borrow money - ZERO INTEREST PLUS! No Clue Fed!
2019-08-29	The Economy is doing GREAT, with tremendous upside potential! If the Fed would do what they should, we are a Rocket upward!
2019-08-30	If the Fed would cut, we would have one of the biggest Stock Market increases in a long time. Badly run and weak companies are smartly blaming these small Tariffs instead of themselves for bad management...and who can really blame them for doing that? Excuses!
2019-09-03	Germany, and so many other countries, have negative interest rates, “they get paid for loaning money,” and our Federal Reserve fails to act! Remember, these are also our weak currency competitors!
2019-09-06	I agree with @jimcramer, the Fed should lower rates. They were WAY too early to raise, and Way too late to cut - and big dose quantitative tightening didn’t exactly help either. Where did I find this guy Jerome? Oh well, you can’t win them all!
2019-09-11	The Federal Reserve should get our interest rates down to ZERO, or less, and we should then start to refinance our debt. INTEREST COST COULD BE BROUGHT WAY DOWN, while at the same time substantially lengthening the term. We have the great currency, power, and balance sheet.....
2019-09-18	Jay Powell and the Federal Reserve Fail Again. No “guts,” no sense, no vision! A terrible communicator!
2019-10-01	As I predicted, Jay Powell and the Federal Reserve have allowed the Dollar to get so strong, especially relative to ALL other currencies, that our manufacturers are being negatively affected. Fed Rate too high. They are their own worst enemies, they don’t have a clue. Pathetic! [*]
2019-10-09	They don’t have a clue, but I do. The USA is doing great despite the Fed!
2019-10-24	The Federal Reserve is derelict in its duties if it doesn’t lower the Rate and even, ideally, stimulate. Take a look around the World at our competitors. Germany and others are actually GETTING PAID to borrow money. Fed was way too fast to raise, and way too slow to cut! [*]
2019-10-31	People are VERY disappointed in Jay Powell and the Federal Reserve. The Fed has called it wrong from the beginning, too fast, too slow. They even tightened in the beginning. Others are running circles around them and laughing all the way to the bank. Dollar & Rates are hurting...
2019-11-19	At my meeting with Jay Powell this morning, I protested fact that our Fed Rate is set too high relative to the interest rates of other competitor countries. In fact, our rates should be lower than all others (we are the U.S.). Too strong a Dollar hurting manufacturers & growth! [*]

Table C.1: Tweets (continued)

Date	Text
2019-12-02	Manufacturers are being held back by the strong Dollar, which is being propped up by the ridiculous policies of the Federal Reserve - Which has called interest rates and quantitative tightening wrong from the first days of Jay Powell!
2019-12-02	The Fed should lower rates (there is almost no inflation) and loosen, making us competitive with other nations, and manufacturing will SOAR! Dollar is very strong relative to others.
2020-01-28	The Fed should get smart & lower the Rate to make our interest competitive with other Countries which pay much lower even though we are, by far, the high standard. We would then focus on paying off & refinancing debt! There is almost no inflation-this is the time (2 years late)! [*]
2020-03-02	As usual, Jay Powell and the Federal Reserve are slow to act. Germany and others are pumping money into their economies. Other Central Banks are much more aggressive. The U.S. should have, for all of the right reasons, the lowest Rate. We don't, putting us at a.....
2020-03-03	The Federal Reserve is cutting but must further ease and, most importantly, come into line with other countries/competitors. We are not playing on a level field. Not fair to USA. It is finally time for the Federal Reserve to LEAD. More easing and cutting! [*]
2020-03-10	Our pathetic, slow moving Federal Reserve, headed by Jay Powell, who raised rates too fast and lowered too late, should get our Fed Rate down to the levels of our competitor nations. They now have as much as a two point advantage, with even bigger currency help. Also, stimulate! [*]
2020-03-10	The Federal Reserve must be a leader, not a very late follower, which it has been! [*]
2020-03-13	The Federal Reserve must FINALLY lower the Fed Rate to something comparable to their competitor Central Banks. Jay Powell and group are putting us at a decided economic & physiological disadvantage. Should never have been this way. Also, STIMULATE! [*]
2020-05-12	As long as other countries are receiving the benefits of Negative Rates, the USA should also accept the GIFT. Big numbers! [*]

Table C.2: Other News

This table reports the text and date of all the additional news events outside Twitter used in our empirical analysis in section 4. The list of related events in which President Trump critisized the Fed is based on a Bloomberg article (Condon (2019)).

Date	Text
2018-07-19	I am not thrilled the central bank is raising borrowing costs and potentially slowing the economy.
2018-07-19	I don't like all of this work that we're putting into the economy and then I see rates going up.
2018-08-20	I expected Powell to be a cheap-money Fed Chairman but Powell instead had raised interest rates
2018-10-16	The Fed is my biggest threat for endangering economic growth through interest-rate hikes. The central bank is independent so I don't speak to them, but I'm not happy with what he's doing because it's going too fast.
2018-10-24	I maybe regret appointing Powell to head the Fed but I'm not going to fire him.
2018-11-20	The central bank is a problem and I would like to see the Fed with a lower interest rate.
2018-11-26	I think the Fed right now is a much bigger problem than China. I think its – I think it's incorrect what they're doing. I don't like what they're doing. I don't like the $50 billion. I don't like what they're doing in terms of interest rates.
2018-11-27	I am not even a little bit happy with my selection of Jay. I think the Fed is a much bigger problem than China.
2018-11-27	I'm doing deals and I'm note being accommodated by the Fed. They're making a mistake because I have a gut and my gut tells me more sometimes than anybody else's brain can ever tell me.
2018-12-12	I think it would be foolish for the Fed to raise interest rates. But what can I say? You have to understand, we're fighting some trade battles and we're winning. But I need accommodation too.
2018-12-22	Bloomberg: Trump discussed firing Powell following the most recent interest-rate hike.
2018-12-25	Well, we'll see. They're raising interest rates too fast. That's my opinion. But I certainly have confidence. But I think it will straighten. They're raising interest rates too fast because they think the economy is so good. But I think that they will get it pretty soon.
2019-02-05	The Fed on a dinner between Trump and Powell: They did not discuss his expectations for monetary policy
2019-03-02	A gentleman that likes raising interest rates in the Fed, we have a gentleman that loves quantitative tightening in the Fed, we have a gentleman that likes a very strong dollar in the Fed. Can you imagine if we left interest rates where they were, if we didn't do quantitative tightening? Taking money out of the market if we didn't do quantitative talk, and this would lead to a little bit lower dollar.
2019-03-22	The U.S. economy would have grown faster if the Fed hadn't raised interest rates. Hopefully now we won't do the tightening
2019-04-05	The Fed should cut interest rates. I think they really slowed us down. There's no inflation.
2019-04-11	Powell reassures Democratic lawmakers he would not give in to political pressure. In addition he received an unscheduled phone call form the president.
2019-04-26	The figure (GDP growth) would have been higher if not for the Fed. If we kept the same interest rates and the same quantitative easing that the previous administration had, that 3.2 would have been much higher.
2019-06-10	The Fed doesn't listen to me in comparison to the control of China's leader has over the country's central bank. They devalue their currency. They have for years. It's put them at a tremendous advantage. We don't have that advantage because we have a Fed that doesn't lower interest rates.
2019-06-18	Bloomberg: The White House explored the legality of stripping Powell of his chairmanship and demoting him to a Fed governor.
2019-06-23	I did not threat to demote Powell but raising rates as much as the Fed did in 2018 was wrong
2019-06-24	I'm not happy with his actions. No, I don't think he's done a good job.
2019-06-26	Nobody ever heard of him before, and now I made him and he wants to show how touch he is. Ok, let him show how tough he is. He's not doing a good job. The U.S. would be better off if Mario Draghi were in charge of U.S. monetary policy.
2019-07-05	If we had a Fed that would lower interest rates, we would be like a rocket ship. We don't have a Fed that know what they're doing.

Table C.3: Longer Event Windows

This table estimates the impact of President Trump's tweets criticizing the Fed on changes in expectations of short rates over a longer horizon. The inner event window is 0.1 minutes before the tweet and 24 hours after. The outer event window is seven days before and seven days after. Panel A infers market expectations of the FFR using fed funds futures (FFF) contracts where horizon j is defined as the number of FOMC meetings a selected FFF contract is exposed to ranging from 0 to 10 meetings. Panel B infers market expectations of the three-month interest rate using eurodollar futures (EDF) contracts where horizon j corresponds to the maturity of the EDF contract ranging from 1 quarter to 5 years. The event study regresses the revision in expectations the short rate r_j of horizon j on a constant around each selected tweet in the event window according to:

$$(E_t - E_{t-\Delta t})[r_j] = \alpha_j + \varepsilon_j,$$

where $(E_t - E_{t-\Delta t})$ denotes the change in the market expectation of the short rate in bps in the event window, α_j is a constant capturing the average effect of President Trump's tweets on the expected fed funds rate of meeting exposure j, and ε_j is the error term.

Panel A: FFF											
Expsure to FOMC Meetings	0	1	2	3	4	5	6	7	8	9	10
Regression Coef. α	−1.005**	−1.347**	−1.469**	−1.378*	−1.459*	−1.51**	−1.602**	−1.745**	−2.071***	−2.561***	−3.051***
std. err.	0.468	0.679	0.676	0.738	0.757	0.759	0.768	0.771	0.762	0.834	0.938
t-stat.	−2.15	−1.98	−2.17	−1.87	−1.93	−1.99	−2.09	−2.26	−2.72	−3.07	−3.25
N	49	49	49	49	49	49	49	49	49	49	49
Panel B: EDF											
Time to Expiration	1Q	2Q	3Q	4Q	5Q	6Q	7Q	2Y	3Y	4Y	5Y
Regression Coef. α	−0.936	−1.854***	−2.177***	−2.296***	−2.255***	−2.457***	−2.415***	−2.612***	−2.429***	−2.306***	−1.786***
std. err.	0.974	0.772	0.808	0.799	0.789	0.819	0.81	0.773	0.748	0.792	0.746
t-stat.	−0.96	−2.4	−2.69	−2.87	−2.86	−3.0	−2.98	−3.38	−3.25	−2.91	−2.39
N	47	48	48	49	49	47	47	49	49	49	49

Table C.4: Longer Event Windows and Excluding Tweets around FOMC Announcements

This table estimates the impact of President Trump's tweets criticizing the Fed on changes in expectations of short rates over a longer horizon and excludes tweets where a FOMC meeting occurs on the same day as the tweet or on the next day. The inner event window is 0.1 minutes before the tweet and 24 hours after. The outer event window is seven days before and seven days after. Panel A infers market expectations of the FFR using fed funds futures (FFF) contracts where horizon j is defined as the number of FOMC meetings a selected FFF contract is exposed to ranging from 0 to 10 meetings. Panel B infers market expectations of the three-month interest rate using eurodollar futures (EDF) contracts where horizon j corresponds to the maturity of the EDF contract ranging from 1 quarter to 5 years. The event study regresses the revision in expectations the short rate r_j of horizon j on a constant around each selected tweet in the event window according to:

$$(E_t - E_{t-\Delta t})[r_j] = \alpha_j + \varepsilon_j,$$

where $(E_t - E_{t-\Delta t})$ denotes the change in the market expectation of the short rate in bps in the event window, α_j is a constant capturing the average effect of President Trump's tweets on the expected fed funds rate of meeting exposure j, and ε_j is the error term.

Panel A: FFF											
Expsure to FOMC Meetings	0	1	2	3	4	5	6	7	8	9	10
Regression Const. α	−1.186**	−1.407*	−1.442**	−1.326*	−1.372*	−1.419*	−1.477*	−1.616**	−1.826**	−1.814**	−2.198***
std. err.	0.516	0.746	0.722	0.756	0.765	0.771	0.766	0.773	0.788	0.8	0.853
t-stat.	−2.3	−1.89	−2.0	−1.75	−1.79	−1.84	−1.93	−2.09	−2.32	−2.27	−2.58
N	43	43	43	43	43	43	43	43	43	43	43
Panel B: EDF											
Time to Expiration	1Q	2Q	3Q	4Q	5Q	6Q	7Q	2Y	3Y	4Y	5Y
Regression Const. α	−0.936	−1.854***	−2.177***	−2.296***	−2.255***	−2.457***	−2.415***	−2.612***	−2.429***	−2.306***	−1.786***
std. err.	0.974	0.772	0.808	0.799	0.789	0.819	0.81	0.773	0.748	0.792	0.746
t-stat.	−0.96	−2.4	−2.69	−2.87	−2.86	−3.0	−2.98	−3.38	−3.25	−2.91	−2.39
N	47	48	48	49	49	47	47	49	49	49	49

Table C.5: FFF and EDF Contracts by Horizon: Placebo

This table reports the results for an event study that includes 100 randomly selected tweets by President Trump since June 2015 from his Twitter account @realDonaldTrump. Tweets on the Federal Reserve are excluded. The event study is conducted 100 times (100 times 100 tweets) and the table reports the average of the 100 estimation results. Panel A infers market expectations of the FFR using fed funds futures (FFF) contracts where horizon j is defined as the number of FOMC meetings a selected FFF contract is exposed to ranging from 0 to 10 meetings. Panel B infers market expectations of the three-month interest rate using eurodollar futures (EDF) contracts where horizon j corresponds to the maturity of the EDF contract ranging from 1 quarter to 5 years. The event study regresses the revision in expectations the short rate r_j of horizon j on a constant around each selected tweet in the event window according to:

$$(E_t - E_{t-\Delta t})[r_j] = \alpha_j + \varepsilon_j,$$

where $(E_t - E_{t-\Delta t})$ denotes the change in the market expectation of the short rate in bps in the event window, α_j is a constant capturing the average effect of President Trump's tweets on the expected fed funds rate of meeting exposure j, and ε_j is the error term. The inner event window is 0.1 minutes before the tweet and 5 minutes after. The outer event window is two hours before and four hours after.

Panel A: FFF											
Expsure to FOMC Meetings	0	1	2	3	4	5	6	7	8	9	10
Regression Const. α	0.005	0.014	0.019	0.03	0.013	0.03	0.009	0.025	0.009	0.014	0.042
std. err.	0.042	0.068	0.076	0.098	0.117	0.124	0.15	0.158	0.187	0.194	0.209
t-stat.	0.04	0.14	0.12	0.17	0.01	0.11	−0.03	0.09	−0.02	0.02	0.13
Panel B: EDF											
Time to Expiration	1Q	2Q	3Q	4Q	5Q	6Q	7Q	2Y	3Y	4Y	5Y
Regression Const. α	0.026	0.003	0.036	0.019	0.019	0.037	0.033	0.039	0.045	0.04	0.016
std. err.	0.158	0.144	0.16	0.168	0.17	0.172	0.176	0.186	0.197	0.211	0.316
t-stat.	0.08	−0.05	0.23	0.1	0.11	0.21	0.17	0.14	0.18	0.18	0.11

Table C.6: Alternative Inside Event Windows

This table estimates the impact of President Trump's tweets criticizing the Fed on changes in expectations of short rates for five different inner event window specifications. The outer event window is identical to the benchmark case (two hours before and four hours after). The regression results infer market expectations of the FFR using fed funds futures (FFF) contracts where horizon j is defined as the number of FOMC meetings a selected FFF contract is exposed to ranging from 0 to 10 meetings. The event study regresses the revision in expectations the short rate r_j of horizon j on a constant around each selected tweet in the event window according to:

$$(E_t - E_{t-\Delta t})[r_j] = \alpha_j + \varepsilon_j,$$

where $(E_t - E_{t-\Delta t})$ denotes the change in the market expectation of the short rate in bps in the event window, α_j is a constant capturing the average effect of President Trump's tweets on the expected fed funds rate of meeting exposure j, and ε_j is the error term.

	Exposure to FOMC Meetings										
Variable	0	1	2	3	4	5	6	7	8	9	10
Panel A: [1 min, 5 min]											
Regression Const. α	−0.051*	−0.173***	−0.102	−0.153*	−0.255***	−0.235***	−0.271***	−0.271***	−0.322**	−0.351**	−0.585***
t-stat.	−1.75	−2.69	−1.43	−1.85	−2.91	−2.84	−2.71	−2.68	−2.32	−2.23	−2.37
Panel B: [0.1 min, 15 min]											
Regression Const. α	−0.066	−0.148*	−0.184**	−0.204**	−0.245*	−0.306***	−0.323**	−0.469***	−0.556***	−0.587***	−0.524*
t-stat.	−1.32	−1.66	−2.31	−2.02	−1.93	−2.38	−2.26	−2.76	−2.91	−2.86	−1.93
Panel C: [5 min, 5 min]											
Regression Const. α	−0.051*	−0.194***	−0.173***	−0.163*	−0.265***	−0.224***	−0.229**	−0.245**	−0.322***	−0.287*	−0.463*
t-stat.	−1.75	−2.85	−2.45	−1.76	−2.99	−2.5	−2.27	−2.21	−2.34	−1.83	−1.82
Panel D: [10 min, 30 min]											
Regression Const. α	−0.112	−0.194	−0.265*	−0.378**	−0.429**	−0.51***	−0.521**	−0.552**	−0.533**	−0.511*	−0.547
t-stat.	−1.04	−1.15	−1.9	−2.29	−2.22	−2.47	−2.17	−2.14	−2.03	−1.84	−1.62
Panel E: [10 min, 60 min]											
Regression Const. α	−0.24**	−0.347	−0.429***	−0.592***	−0.612***	−0.663***	−0.781***	−0.802***	−0.744***	−0.717***	−0.614**
t-stat.	−2.16	−1.63	−2.38	−2.87	−2.76	−2.86	−3.08	−3.11	−2.69	−2.39	−2.01

Table C.7: Alternative Tweet Selection Criteria

This table estimates the impact of President Trump's tweets criticizing the Fed on changes in expectations of short rates for an alternative tweet selection criteria. In addition to all previous tweets by President Trump which criticize the Federal Reserve, the event study includes tweets which do not criticize the federal reserve directly. Furthermore, the study includes tweets that criticize the Federal Reserve but also contain other news on trade, tariffs, or exports. Panel A infers market expectations of the FFR using fed funds futures (FFF) contracts where horizon j is defined as the number of FOMC meetings a selected FFF contract is exposed to ranging from 0 to 10 meetings. Panel B infers market expectations of the three-month interest rate using eurodollar futures (EDF) contracts where horizon j corresponds to the maturity of the EDF contract ranging from 1 quarter to 5 years. The event study regresses the revision in expectations the short rate r_j of horizon j on a constant around each selected tweet in the event window according to:

$$(E_t - E_{t-\Delta t})[r_j] = \alpha_j + \varepsilon_j,$$

where $(E_t - E_{t-\Delta t})$ denotes the change in the market expectation of the short rate in bps in the event window, α_j is a constant capturing the average effect of President Trump's tweets on the expected fed funds rate of meeting exposure j, and ε_j is the error term. The inner event window is 0.1 minutes before the tweet and 5 minutes after. The outer event window is two hours before and four hours after.

Panel A: Federal Funds Futures											
Expsure to FOMC Meetings	0	1	2	3	4	5	6	7	8	9	10
Regression Coef. α	−0.036	−0.143***	−0.133**	−0.143*	−0.235***	−0.204***	−0.26***	−0.25***	−0.356***	−0.351***	−0.549**
std. err.	0.031	0.06	0.066	0.077	0.081	0.08	0.099	0.089	0.119	0.147	0.246
t-stat.	−1.15	−2.38	−2.0	−1.85	−2.89	−2.56	−2.64	−2.8	−3.0	−2.38	−2.23
N	49	49	49	49	49	49	48	48	45	47	41
Panel B: Eurodollar Futures											
Time to Expiration	1Q	2Q	3Q	4Q	5Q	6Q	7Q	2Y	3Y	4Y	5Y
Regression Coef. α	−0.076	−0.167**	−0.24**	−0.245**	−0.214	−0.266**	−0.202	−0.306***	−0.235*	−0.323***	−0.558**
std. err.	0.071	0.083	0.118	0.124	0.133	0.126	0.126	0.128	0.123	0.13	0.27
t-stat.	−1.07	−2.0	−2.03	−1.98	−1.61	−2.11	−1.6	−2.4	−1.91	−2.48	−2.06
N	46	48	48	49	49	47	47	49	49	48	43

Figure C.1: Event Window

This figure illustrates the selection of trades to study the impact of an event which occurs at 0. The symbols ×, ○, □ represent trades. Trades that fall outside the outer windows, $t < T_0$, $t > T_3$, or within the inner window, $T_1 < t < T_2$, are disregarded, ○. Within each subset, $[T_0, T_1]$ and $[T_2, T_3]$, the two trades closest to the inner window are selected, ×.

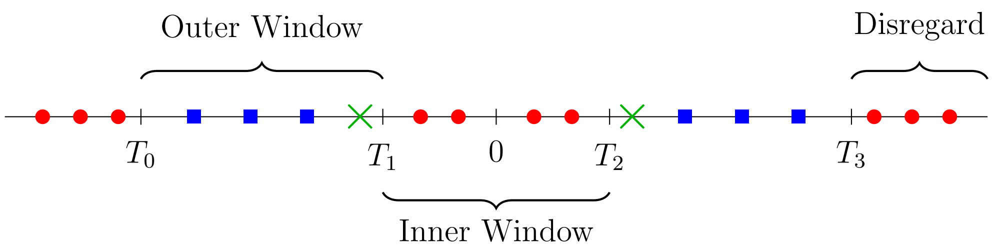

Figure C.2: Interest Rate Cut Timing

This figure provides two illustrative examples highlighting the importance of the timing of the interest rate cuts in relation to our benchmark estimates. In both panels, the black and red lines represent the expected path of the average FFR before and after the tweet, respectively. The numbers on top of the lines represent the time horizon, while the numbers below the lines represent the change in expectations at that horizon. Panel A presents an example of a revision in expectations that only affects short horizons. Panel B presents an example in which the size of the revision of expectations grows over time.

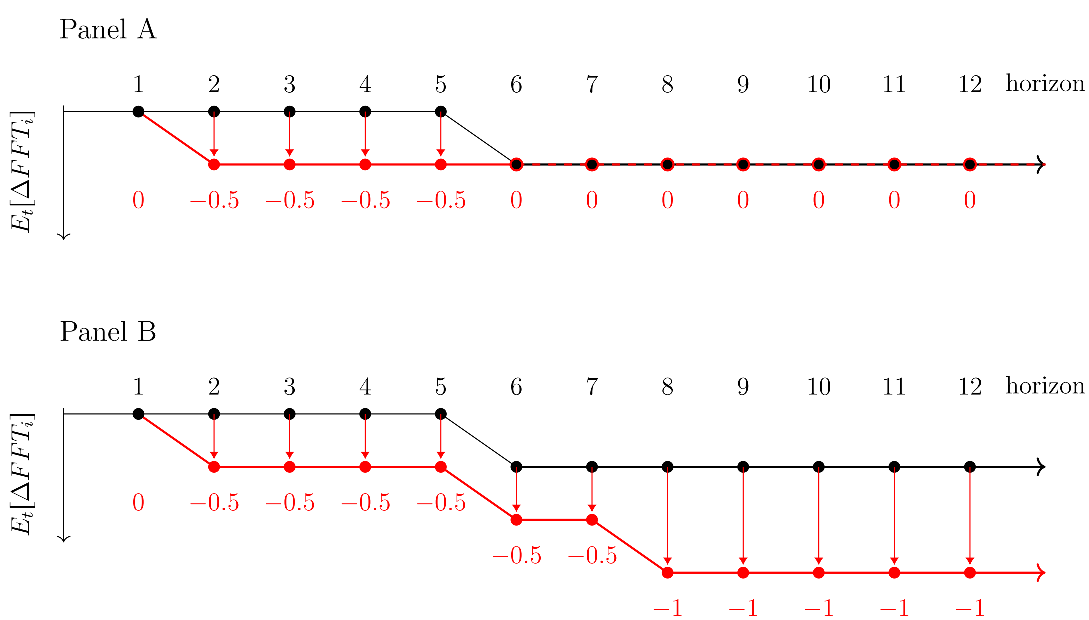

Figure C.3: Event-Study Plot

This figure plots the average effect of the tweets on changes in the expected federal funds rate across all contract horizons of the federal funds futures considered in the benchmark estimation. For the pre-event window, we obtain the average change by fixing the outer event window, T_0 and T_3, to 240 min and 0.1 min, respectively, before the tweet. T_1 is set to 20 min before each tweet. We then vary T_2 from 19 min until 1 min before the event to obtain the average effect for different horizons prior the event. For the post-event window, we use the benchmark time window for $T_0 = -240$ min, $T_1 = -0.1$ min, and $T_3 = 120$ min and vary T_2 from 1 min after the tweet until 80 min after. The blue shade represents the 99% error bands.