

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

Francesco Bianchi[†] Roberto Gómez-Cram[‡] Thilo Kind[§] Howard Kung[¶]

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A high-frequency approach is used 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 stock prices and to a decrease in long-term U.S. Treasury yields. VAR evidence shows that the tweets had an important impact on actual monetary policy, the stock market, bond premia, and the macroeconomy.

Keywords: High-Frequency Identification, Social Media, Asset Prices, Fed Funds Rate, Central Bank Independence.

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[†]Johns Hopkins University, NBER, & CEPR. francesco.bianchi@jhu.edu

[‡]London Business School. rgomezcram@london.edu

[§]SAFE. kind@safe-frankfurt.de

[¶]London Business School & CEPR. hkung@london.edu

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

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

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

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

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

respect to maturity, indicating that market participants expect the President to persistently impact monetary policy.

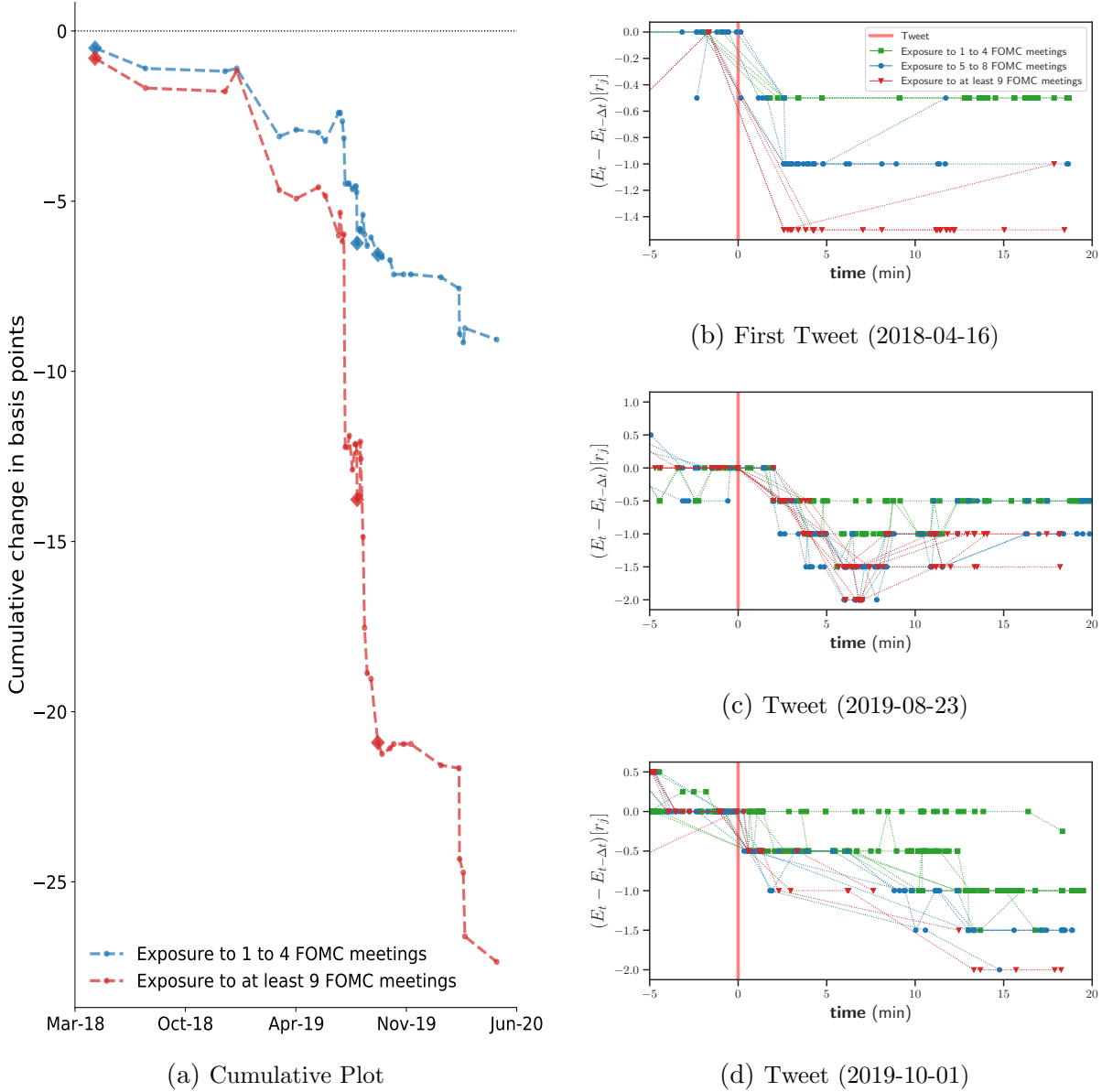
The left column of Figure 1 shows all of the jumps in the expected FFR over narrow event windows associated with President Trump tweets criticizing the Federal Reserve. The jumps are reported as a cumulative sum to convey both their average effect and relative sizes. It is immediate to see that the tweets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

The average effect of the tweets across all contracts is around -0.26 bps per tweet. This

Figure 1: Tweets and Market Expectations



Notes: 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 short horizon FFF contract exposed to 1 to 4 FOMC meetings. The red line corresponds to long horizon FFF contract exposed to at least 9 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)

effect grows with the time horizon, with a peak of -0.64 bps at the longest horizon.⁵ Similar results are obtained when inferring short rate expectations using Eurodollar futures (EDF), including at longer horizons. To interpret the economic magnitude of the estimated effects, note that the typical change in the target rate at each FOMC meeting is ± 25 bps. Consider a scenario in which agents are considering the possibility of either a 25 bps interest rate cut or no change. A -0.26 bps revision in expectations implies that each tweet, on average, leads to a 1% per tweet increase in the probability of an interest rate cut over the next year.⁶ As shown in Figure 1, if we add the estimated effect across all Trump tweets in our sample, the total effect is equal to -10 bps and -27 bps for short and long maturity FFF contracts, respectively.

While the high-frequency approach followed in our benchmark analysis allows for a clean identification, the estimates may not quantify the total magnitude of the effect since market participants may require some time to price in fully the tweet’s new information. Extending the event window to a day increases the magnitude of the estimates up to a factor of eight, suggesting that the revision in expectations is significantly larger. The average effect on FFR expectations pooled across horizons increases in magnitude from -0.26 bps to -2.15 bps, implying an 8.6% per tweet increase in the probability of a 25 bps rate cut. Adding up the daily effects across all of Trump tweets equals -64 and -115 bps for short and long maturity FFF contracts, respectively (see Figure D.3 in the Online Appendix).

To further establish how important the Trump tweets are, we compute the effects of macroeconomic announcements on interest rate expectations and compare them with our benchmark estimates. For example, we find that the average impact of a unit surprise in initial jobless claims on interest rate expectations is -0.04 bps which is about six times smaller than the average effect of the Trump tweets. More generally, we find that only five of the 50 most relevant macroeconomic indicators had a larger effect on interest rate expectations than the Trump tweets over this period. Overall, our evidence with the FFF and EDF contracts

⁵As the target rate is only changed during the FOMC meetings, outstanding short maturity futures 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.

⁶The 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 1% increase in the probability of no change.

illustrates how markets believe that the President can influence the conduct of monetary policy in a sizeable and persistent way.

We next estimate the response of different asset prices using high-frequency regressions. Using U.S. Treasury futures for medium- to long-term maturities, we show that treasury yields fall within minutes around Trump tweets at each maturity up to 30 years, with the peak effect around ten years. The evidence that the tweets had an impact on long-term bonds supports the notion that President Trump's attacks on the Fed not only generate persistent downward revisions in short rate expectations but also influence term premia, in line with the estimates of the impact of quantitative easing (QE) policies on the term structure (Swanson, 2021). The political pressure exerted on the Fed can be expected to impact both interest rate and QE policies when central bank independence is limited. Consistent with this view, the effects on long-term bond prices increase in magnitude around those tweets by President Trump that explicitly criticizes the large-scale asset purchase policy of the Fed. Finally, we find that the stock market level increases significantly within minutes of Trump tweets. This result is consistent with the evidence from Bernanke and Kuttner (2005) which documents how stock market valuation increases in response to an interest rate cut.

Recently released Fed transcripts reveal that FOMC members were acutely aware of the risks for central bank independence implied by the vocal approach of President Trump. During the December 2016 FOMC meeting, Vice Chairman Stanley Fischer noted that “[t]here will likely also be challenges to the current operating procedures of the Federal Reserve and to its independence.” In the same FOMC meeting, Governor Tarullo noted that “Vice Chairman Dudley was right yesterday to point out that our risks are likely to involve compromises to our credibility, and that we’re not really modeling those in a coherent way. Those are outside our usual modeling practice. An Administration that’s willing to discard the 25-year-old precedent of White House respect for the Federal Reserve’s monetary policy independence strikes me as capable of contributing to a loss of credibility.” In the same remarks, he also explicitly referred to the precedent of political interference under the Johnson administration (Transcript (2016)). More recent transcripts will become available over the next few years, with the usual five-year delay. It will certainly be interesting to read how FOMC members reacted to the more explicit attacks of President Trump.

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 for a clean identification of the events of interest under the assumption that no other relevant news arrives over such a short period. Next, we test whether the tweets had an actual effect on the path of the FFR. This 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 show that the *ex-post* fed funds future pricing error (i.e., the difference between the futures implied FFR and the arithmetic average of the daily effective FFR during the contract month) is significantly smaller immediately after Trump tweets. Notably, the reductions in pricing errors are about ten times larger when we extend the post-event window to a day.

Two important related questions are whether the effects of these tweets persist over several months and if the tweets affect the path of macro and financial variables. We follow the recent literature that combines high-frequency identification strategies with VAR analysis to address these questions. These papers use the 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 an instrument for a “tweet shock.”

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 \(2020\)](#).

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 stock prices. The effect on the shadow FFR is an order of magnitude larger than the initial high-frequency (5-minute or 1-day) 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 implies that it is unlikely 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 tweets reveal bad news about the future that in turn lead to a downward revision in expectations about the future FFR). If that were the case, we should observe a subsequent decline in asset prices and real activity.

Finally, in the Online Appendix, 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.

Our findings that market participants do not perceive the Federal Reserve as fully independent from the executive branch have 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 \(2019\)](#)). Like these papers, we measure expectations of the FFR 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.

We connect to the literature that uses textual analysis to extract news affecting asset prices (e.g., [Cohen, Diether, and Malloy \(2013\)](#), [Boudoukh, Feldman, Kogan, and Richardson \(2013\)](#), [Buehlmaier and Whited \(2018\)](#), [Chen, De, Hu, and Hwang \(2014\)](#), [Hoberg and Moon \(2019\)](#), [Kelly, Manela, and Moreira \(2019\)](#), [Gentzkow, Kelly, and Taddy \(2019\)](#), [Cookson, Engelberg, and Mullins \(2021\)](#), and [Arteaga-Garavito, Croce, Farroni, and Wolfskeil \(2021\)](#)). Our results emphasize how President Trump tweets about the Fed can influence market expectations about the future path of monetary policy.

2 Data Description

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). At the beginning of our sample period (December 2015), the Fed lifted the target rate from the lower bound and started a tightening cycle in which it raised rates gradually until December 2018. The Fed maintained its target rate between 2.25 and 2.5 percent until July 2019 and started discussions about tapering its large-scale asset purchases. Then in July 2019, the Fed cut interest rates for the first time in 11 years, followed by two additional rate cuts during that year, reversing nearly all of 2018’s rate increases. Finally, in March 2020, the Fed implemented two consecutive rate cuts that brought back the target rate to the lower bound.

The 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, 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 additional results, 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).

We use U.S. Treasury futures to measure market expectations on long-term interest rates. We use tick-by-tick trade data for each of the Treasury benchmark tenors offered by the Chicago Mercantile Exchange (CME) Group: 2-year (TU), 5-year (FV), 10-year (TYF), and 30-year (US). Treasury futures contracts are standardized instruments and highly liquid. For instance, over 4.2 million contracts were traded daily, on average, in 2018. The data are cleaned following the same procedure as the federal funds futures and eurodollar futures data. We provide details of these contracts in the Online Appendix.

Intraday series for the stock market index is inferred from the SPDR S&P 500 ETF (ticker: SPY). The 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). Similar to the futures contract, we also drop observations with zero volume.

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), while the eurodollar futures (EDF)

are used to back out market expectations of the U.S. three-month LIBOR interest rate. 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:

$$FFF_{t,i} = E_t \overline{FFR}_i + \alpha_{t,i}, \quad (1)$$

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:

$$FFF_{t,i} = E_t [\overline{FFT}_i] + E_t [\overline{FFR}_i - \overline{FFT}_i] + \alpha_{t,i}. \quad (2)$$

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:

$$(E_t - E_{t-\Delta t}) [\overline{FFT}_i] = FFF_{t,i} - FFF_{t-\Delta t,i}, \quad (3)$$

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 U.S. 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 as described in equation (3). In the benchmark estimation, we allow for a [-0.1 min, +5 min] window around the tweet to give time for markets to react. That is, we take the difference between the rate associated with the first trade 5 minutes after the tweet and the rate associated with the last transaction 0.1 minutes before the tweet. If there are no trades 120 minutes before or after the tweet, we conclude that the tweet did not impact rates.⁷ [Figure D.1](#) of the Online Appendix provides a depiction of how the two trade observations are selected.

In [Section 3.2](#), we choose a relatively short time window for our benchmark analysis to isolate the effects of the tweets we are interested in. President Trump can sometimes

⁷The pre-event window ends 0.1 min before the tweet to ensure 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 5 min after the tweet to give investors time to react and trade on the news. The cutoffs at 120 min before and after the tweet ensure that only contracts with recent trades are considered.

engage in a long series of tweets related to different topics. A short window minimizes the possibility of other tweets falling inside the window. Furthermore, for each tweet, we confirm that no further 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 as having at least an asterisk to highlight the event. Section 3.3 considers longer alternative event windows and documents stronger results.

3.2 Benchmark Estimates

We estimate revisions in expectations of the FFR across different horizons caused by the selected tweets. 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.⁸ 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.

We run a pooled ordinary least squares (OLS) regression, where we group all contracts into different buckets based on the number of FOMC meetings j a certain contract is exposed to. For each bucket j , we then regress 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:

$$(E_t - E_{t-\Delta t})[r_j] = \alpha_j + \varepsilon_j, \quad (4)$$

⁸The 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.

Table 1: **FFF and EDF Contracts by Horizon**

| Panel A: FFF | | | | | | |
|--|---------------------------|---------|---------|---------|---------|----------|
| | Exposure to FOMC Meetings | | | | | |
| | All | 0 | 1–4 | 5–8 | 9–10 | 11–12 |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| <i>Regression Const. α</i> | -0.26 | 0.02 | -0.16 | -0.27 | -0.31 | -0.64 |
| <i>t – stat</i> | [-7.88] | [0.91] | [-5.99] | [-5.56] | [-4.33] | [-3.07] |
| Observations | 647 | 31 | 235 | 238 | 97 | 46 |
| Panel B: EDF | | | | | | |
| | Exposure to FOMC Meetings | | | | | |
| | All | 1–8 | 9–12 | 13–16 | 17–20 | 21–24 |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| <i>Regression Const. α</i> | -0.23 | -0.11 | -0.32 | -0.22 | -0.21 | -0.89 |
| <i>t – stat</i> | [-9.95] | [-3.39] | [-2.99] | [-2.58] | [-3.76] | [-15.94] |
| Observations | 1047 | 249 | 69 | 168 | 491 | 70 |

This table estimates the impact of President Trump 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 12 meetings. Panel B infers market expectations of the three-month interest rate using eurodollar futures (EDF) contracts where horizon j is defined as the number of FOMC meetings a selected EDF contract (and underlying) is exposed to ranging from 1 to 24 meetings. The event study regresses the revision in expectations of 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 $(E_t - E_{t-\Delta t})[r_j]$ 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 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 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).

where $(E_t - E_{t-\Delta t})[r_j]$ 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 tweets on the expected fed funds rate of meeting exposure j , and ε_j is the error term. The regression results are reported in Panel A of Table 1.⁹

Column (1) of Table 1 measures the average effect across all horizons by pooling all contracts with a nonzero meeting exposure. The average effect implied by the pooling regression is around -0.26 bps (t -statistic = -7.88). Columns (2) through (6) show the

⁹Table D.3 of the Online Appendix shows regression results for the FFF sorted by contract exposure to the number of FOMC meetings j , rather than grouping them into buckets.

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 a short maturity contract exposed to one to four FOMC meetings imply that the expected interest rate declines by 0.16 bps following a tweet. The change in the expected interest rate for a contract exposed to 11 to 12 FOMC meetings (a contract that expires more than one year later), declines by 0.64 bps. Excluding the zero maturity contract, the coefficients are statistically different from zero at the 1% level for all contract horizons. 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. Column (2) shows that 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.

Panel B of Table 1 runs the same event study regression specified in equation (4) but focusing on the EDF contracts that give us expectations of three-month nominal interest rates across different horizons. An advantage of EDF contracts is that they have maturities that extend out for several years. Therefore, we can measure the effect of Trump tweets on short-term interest rates exposed to a more significant number of FOMC meetings. As before, the EDF contracts are organized based on the contract exposure to the number of FOMC meetings.

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 number of FOMC meetings a certain contract is exposed to. The magnitudes of the coefficients are also similar between the two contracts, with an average effect of around -0.23 bps (see Column (1)). The peak effect with the EDF contract occurs at the longest maturity included in our estimation with an estimated coefficient of -0.89 bps that is statistically significant.¹⁰ Overall, we conclude that the evidence based on EDF

¹⁰All EDF contracts are exposed to at least one FOMC meeting. The reason is that the EDF contracts

contracts reinforces the conclusion that the tweets criticizing the Federal Reserve induce a downward revision in expected interest rates.

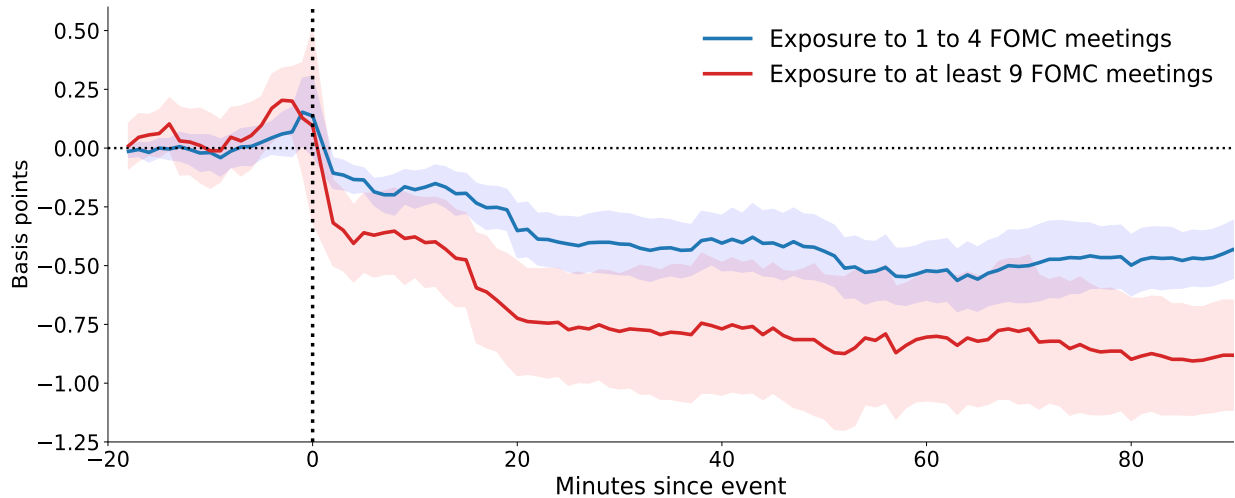
To interpret the economic magnitude of the estimated effects note that the typical change in the fed funds target is ± 25 bps. Consider an example with two possible scenarios: The rates will remain unchanged or the Fed will cut rates by 25 bps. Then, using our benchmark estimates, a decline of 0.26 bps corresponds to a 1% per tweet increase in the probability of a 25 bps target cut. This estimate corresponds to the average effect of each tweet. If we add the impact across all of Trump tweets in our sample, the total cumulative effect of Trump tweets is equal to -10 bps and -27.3 bps for short and long maturity FFF contracts, respectively (depicted in Figure 1). Our cumulative effects are modest compared to the monetary policy tightening cycle from December 2015 to December 2018 when the Fed raised rates by 225 bps (this is 8 to 22 times larger). However, it is worth emphasizing that our estimates here are for a five-minute event window. We find that the effects grow significantly in magnitude when expanding the event window. We examine the persistence of the effects next.

3.3 Persistence of the Effects

The previous subsection showed that Trump tweets statistically affect market expectations about monetary policy in a short window around the tweet. In this subsection, we consider longer event windows to ask whether this effect persists over time and whether it grows in magnitude. Expanding the event window allows us to better measure the economic significance of the effect, as market participants might need some time to fully price in the new information contained in the tweet.

Figure 2 shows the effect of the tweets on changes in the expected federal funds rate for different event windows. We plot the cumulative rate change in the 20 minutes preceding the Trump tweets and the 100 minutes following. The blue line corresponds to revisions in FFR expectations inferred from contracts exposed to one to four FOMC meetings and the red line corresponds to the change in FFR expectation computed from contracts exposed to at least nine FOMC meetings. The plot highlights that there are (i) no pre-trends in the fed funds futures prices before the selected tweets; (ii) the tweets generate an immediate sharp settle based on the three-month London interbank offered rate at expiration. It thus clearly includes the next FOMC meeting.

Figure 2: **Event Study Plot**



Notes: This figure plots the average effect of the tweets on changes in the expected federal funds rate across contracts that are exposed to one to four FOMC meetings (blue line) and at least 9 FOMC meetings (red line). 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 100 min after. The blue and red shades represent the 99% error bands.

drop in the expected fed funds rate, especially at longer horizons; and (iii) the effect grows three times larger compared to our benchmark high-frequency evidence as the post-event window is extended up until 100 minutes.

We next extend the event window from our benchmark analysis to a day. Table 2 presents the regression results. We find that President Trump tweets generate a negative revision in the expected future FFR and short rates with an effect that intensifies with horizon, mirroring our benchmark estimates. However, the main takeaway of Table 2 is that the effects are about eight times larger when we use a one-day post-event window. For example, the average estimated effect on FFF contracts with a nonzero meeting exposure is about -2.15 bps when we use a daily event window compared to -0.26 bps using a five-minute event window from our benchmark analysis. Table D.4 in the Online Appendix shows that this result is robust to excluding tweets where a FOMC meeting occurs on the same day as the tweet or on the next day.

Consider again a scenario in which agents are considering the possibility of a 25 bps

Table 2: **FFF and EDF Contracts by Horizon: Daily event window**

| Panel A: FFF | | | | | | |
|--|---------------------------|---------|---------|---------|---------|---------|
| | Exposure to FOMC Meetings | | | | | |
| | All | 0 | 1–4 | 5–8 | 9–10 | 11–12 |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| <i>Regression Const. α</i> | -2.15 | -0.01 | -1.88 | -2.12 | -2.65 | -2.86 |
| <i>t – stat</i> | [-2.72] | [-0.13] | [-2.29] | [-2.61] | [-3.67] | [-2.59] |
| Observations | 637 | 20 | 179 | 181 | 71 | 51 |

| Panel B: EDF | | | | | | |
|--|---------------------------|---------|---------|---------|---------|---------|
| | Exposure to FOMC Meetings | | | | | |
| | All | 1–8 | 9–12 | 13–16 | 17–20 | 21–24 |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| <i>Regression Const. α</i> | -2.10 | -1.70 | -1.83 | -2.89 | -1.74 | -2.18 |
| <i>t – stat</i> | [-13.42] | [-5.19] | [-2.67] | [-6.61] | [-7.78] | [-3.75] |
| Observations | 839 | 201 | 50 | 134 | 397 | 57 |

This table estimates the impact of President Trump 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 12 meetings. Panel B infers market expectations of the three-month interest rate using eurodollar futures (EDF) contracts where horizon j is defined as the number of FOMC meetings a selected EDF contract (and underlying) is exposed to ranging from 1 to 24 meetings. The event study regresses the revision in expectations of 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 $(E_t - E_{t-\Delta t})[r_j]$ 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 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 24 hours after. The outer event window is four hours before and 36 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).

interest rate cut. The daily average effect on interest rate expectations across all tweets is equal to -2.15 bps, implying an 8.6% per tweet increase in the probability of a 25 bps rate cut. In turn, adding up the daily effects across all of Trump tweets in our sample equals -64 bps and -115 bps for short and long maturity FFF contracts, respectively (see Figure D.3 in the Online Appendix). The last monetary policy tightening cycle of 225 bps was about 2 to 4 times larger than the daily effects of all Trump tweets put together.

3.4 Comparing Trump tweets with Macroeconomic News

To further establish how important Trump tweets are, we now compute the effects of macroeconomic announcements on interest rate expectations from January 2015 to January 2020. We then compare the impact of macro announcements to the Trump tweets.

We use the Bloomberg Professional Service real-time data on expected and realized macroeconomic indicators to measure the effects of macroeconomic news on interest rate expectations. We define macroeconomic news, for indicator k at time t , as the difference between realizations (announcements), A_{kt} , and expectations, E_{kt} :

$$S_{kt} = \frac{A_{kt} - E_{kt}}{\hat{\sigma}_k}, \quad (5)$$

where $\hat{\sigma}_k$ is the sample standard deviation of $(A_{kt} - E_{kt})$. As in [Balduzzi, Elton, and Green \(2001\)](#) and [Andersen, Bollerslev, Diebold, and Vega \(2003\)](#), we standardize the macro news to facilitate comparisons across announcements, since the units of measurement differ across economic indicators. However, the standardization does not affect the statistical significance of the estimated coefficients since $\hat{\sigma}_k$ is constant for any indicator k . We use the median analysts' forecasts from the last preceding weekly survey reported by Bloomberg as a measure of E_{kt} .¹¹

We then run the following regression:

$$(E_t - E_{t-\Delta t})[r_j] = a_{jk} + b_{jk}S_{kt} + \varepsilon_j, \quad (6)$$

where $(E_t - E_{t-\Delta t})[r_j]$ denotes the change in the market expectation of the FFR in the event window Δt , a_j is a constant capturing the average effect of a macroeconomic announcement with a zero surprise, and b_j captures the average effect on FFR for a unit surprise in the macroeconomic announcement k . Because the macroeconomic announcements are pre-scheduled and released at a specific time, we follow the same high-frequency identification strategy as in [Section 3.2](#) and compute interest rate changes in a tight window around each specific announcements.

Table 3 presents the effect of an unexpected rise in initial jobless claims on interest

¹¹For each macroeconomic indicator, Bloomberg collects forecasts of economists from major consulting firms and investment banks and releases the median forecasts from the survey shortly before each announcement.

Table 3: **The Effect of Initial Jobless Claims News on Interest Rate Expectations**

| | Exposure to FOMC Meetings | | | | | |
|---------------------|---------------------------|------------------|------------------|------------------|------------------|------------------|
| | All (1) | 0 (2) | 1-4 (3) | 5-8 (4) | 9-10 (5) | 11-12 (6) |
| \hat{a} | 0.04 [1.32] | -0.01 [-0.86] | 0.03 [1.71] | 0.05 [1.44] | 0.11 [1.75] | 0.02 [0.17] |
| \hat{b} | -0.08 [-2.58] | 0.00 [0.28] | -0.03 [-2.25] | -0.09 [-2.55] | -0.16 [-2.37] | -0.16 [-2.13] |
| $\hat{a} + \hat{b}$ | -0.04 | -0.01 | -0.01 | -0.04 | -0.05 | -0.14 |
| Observations | 4035 | 151 | 1190 | 1176 | 431 | 279 |

This table estimates the impact of macroeconomic announcements on changes in expectations of short rates. We 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 12 meetings. The event study regresses the revision in expectations of the short rate r_j of horizon j on a constant and the macro surprise S_{kt} around each macroeconomic announcement according to:

$$(E_t - E_{t-\Delta t})[r_j] = a_j + b_j S_{kt} + \varepsilon_j,$$

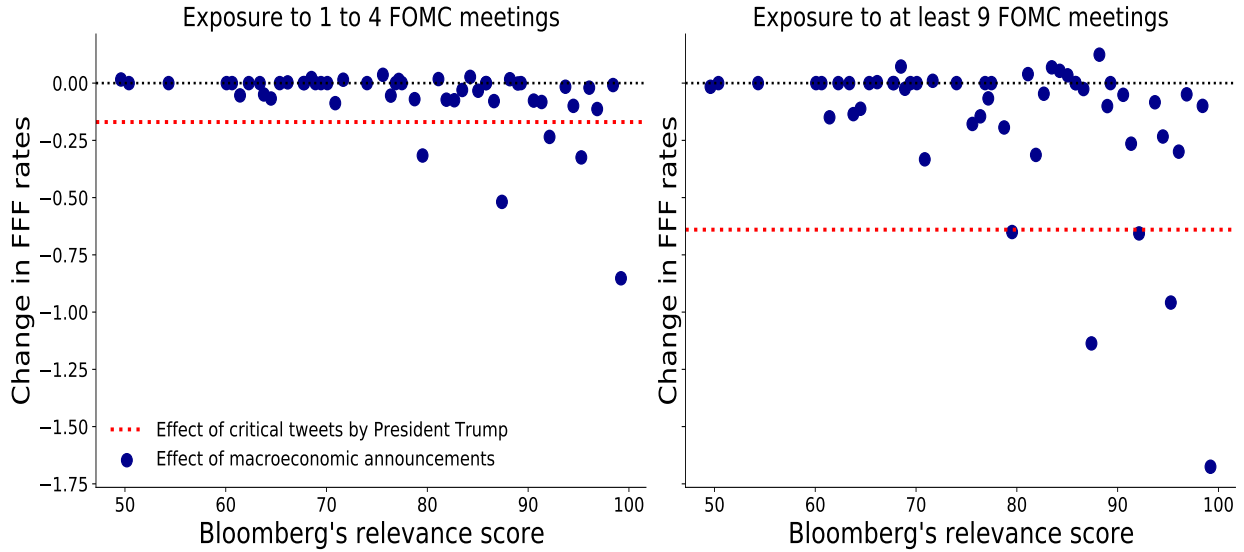
where $(E_t - E_{t-\Delta t})[r_j]$ denotes the change in the market expectation of the short rate in the event window, a_j is a constant capturing the average effect of a macroeconomic announcement with a zero surprise, and b_j captures the average effect on FFR for a unit surprise in the macroeconomic announcement. S_{kt} is the standardized news associated with indicator k at time t . 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. 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).

rate expectations. The slope coefficients, \hat{b}_j , are negative and statistically significant for all FFF contracts with a nonzero meeting exposure and the effect increases with horizon. To facilitate comparisons with the documented effects of Trump tweets, Table 3 also shows the average impact per announcement of a unit surprise in initial claims (i.e., $\hat{a} + \hat{b}$). Column (1) shows the average effect pooled across all maturities. Compared to the regressions reported in Panel A of Table 3, the estimated effect is about six times smaller in magnitude. The average effect of initial claims news is -0.04 bps compared to -0.26 bps for the Trump tweets.

Figure 3 extends this analysis by showing the average effect of the 50 most relevant macroeconomic indicators on interest rate expectations. We select the top macroeconomic indicators using Bloomberg’s relevance score, which measures the popularity of an economic release and takes on values from 1 to 100.¹² The figure plots on the y-axis the average effect

¹²On the Bloomberg terminal, users can select to be alerted of the announcement dates of various economic events. Bloomberg’s relevance score represents the number of “alerts” set by all users for each specific event relative to all alerts set for all other U.S. economic events.

Figure 3: **Effect of Macro Announcements on Interest Rate Expectations**



Notes: This figure shows the average effect of macroeconomic news releases on interest rate expectations. For each macroeconomic indicator k , we run the following regression:

$$(E_t - E_{t-\Delta t})[r_j] = a_{kj} + b_{kj}S_{kt} + \varepsilon_j,$$

where $(E_t - E_{t-\Delta t})[r_j]$ denotes the change in the market expectation of the short rate in the event window and S_{kt} is the standardized macroeconomic surprise (higher values mean worse economic performance). We 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 12 meetings. The left panel shows results for FFF contracts exposed to one to four FOMC meetings. The right panel shows results for FFF contracts exposed to at least 9 FOMC meetings. The y-axis plots $\hat{a}_k + \hat{b}_k$ in basis points, whereas the x-axis is the Bloomberg's relevance score.

of a unit macroeconomic surprise on interest rate expectations (i.e., $\hat{a}_k + \hat{b}_k$), while the x-axis represents the Bloomberg's relevance score.¹³ To facilitate the comparison, we normalize the macroeconomic surprise, S_k , such that an increase is bad macroeconomic news. The main takeaway is that only five macroeconomic indicators (Change in Nonfarm Payrolls, ADP Employment Change, ISM Manufacturing, Retail Sales Advance MoM, ISM Services Index) had a larger effect on interest rate expectations than the effect of Trump tweets in this period as shown by the horizontal red dotted line.

¹³Table D.5 in the Online Appendix lists the 50 macroeconomic indicators, Bloomberg's relevance score, the number of macro announcements considered, and the average effect of a unit macro surprise on interest rate expectations.

3.5 Effect on Bonds and Stocks

Table 4 reports the impact of President Trump’s tweets using high-frequency data from bonds and stocks. Panels A and B consider the effect on U.S. Treasury futures for medium- to long-term maturities and Panel C examines stock market evidence.

To measure the effect of Trump tweets on long-term interest rate expectations, we use 2-, 5-, 10-, and 30-year U.S. Treasury futures contracts offered by the CME Group. Panel A of Table 4 reports the regression estimate of the inverse price change in the U.S. Treasury futures contract on a constant term, similar to our specification in equation (4) and we use the same event window as in the benchmark estimation in Section 3.2. Bond yields cannot be directly obtained from these contracts.¹⁴ We however consider inverse price change in our analysis here with these contracts to facilitate comparison with bond yield movements. The central finding of Panel A is that Trump tweets also induced a downward revision in long-term interest rates. The effects on 2-year Treasury futures are negative but small and statistically insignificant, whereas the effects on longer-term Treasury futures are negative, large, and statistically significant, with t-statistics above 1.89. The magnitude of the effects is monotonically increasing from two to ten years before declining slightly at 30 years.

The evidence that the tweets had a large impact on long-term U.S. Treasuries and that the effects increase with maturity (i.e., the tweets changed the slope of the yield curve) suggests that the tweets not only influenced the expected path of the federal funds rates but also potentially influenced the term premia component, in line with an impact on the quantitative easing policy (Swanson, 2021). Indeed, the tweet: “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!” (March 29, 2019) suggests that President Trump criticized both the interest rate policy as well as the large-scale asset purchase (QE) policy of the Federal Reserve. Consequently, in case of limited central bank independence, the pressure can be expected to have an impact on both interest rate and QE policies.

¹⁴The reason why we cannot compute the yields is that each futures contract has an associated delivery bond basket that determines the bond maturity range that can be delivered at maturity but not the precise maturity date nor the coupon rate.

Table 4: **Estimated effects of Trump tweets on Bonds and Stocks**

| Panel A: Effects of Trump tweets on U.S. Treasury Futures | | | | |
|---|------------|-------------|---------|---------|
| | (1) | (2) | (3) | (4) |
| | 2-Year | 5-Year | 10-Year | 30-Year |
| α | -0.34 | -0.38 | -2.11 | -1.21 |
| | [-1.42] | [-2.67] | [-1.89] | [-4.34] |
| Panel B: Effects of Trump tweets Criticizing QE Policies on U.S. Treasury Futures | | | | |
| | 2-Year | 5-Year | 10-Year | 30-Year |
| α | -0.20 | -0.35 | -1.39 | -0.95 |
| | [-1.36] | [-2.91] | [-1.84] | [-4.28] |
| β_{QE} | 0.74 | -0.15 | -4.60 | -3.23 |
| | [-1.07] | [-0.34] | [-1.82] | [-2.89] |
| Panel C: Effects of Trump tweets on Stocks | | | | |
| | High freq. | Daily freq. | | |
| | (1) | (2) | | |
| α | 0.28 | 1.71 | | |
| | [1.40] | [1.92] | | |

This table considers the impact of the Trump’s attacks using intraday data from other asset classes. Panel A and B uses futures on U.S. Treasury prices. Panel C considers data from equity markets using ETFs that track the level of the S&P500 index (ticker: SPY). Panel A regresses the inverse changes in log prices of U.S. Treasury futures on a constant around the tweets:

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

where Δp_j is the change in the log of U.S. Treasury future prices around each tweet in the event window and α_j measures it’s average effect. Panel B regresses $(-\Delta p_j)$ onto a constant and a dummy variable, $I_{QE,t}$ that takes the value of one if Trump explicitly criticized the large-scale asset purchase (QE) policy of the Federal Reserve:

$$(E_t - E_{t-\Delta t})[-\Delta p_j] = \alpha_j + \beta_{QE}I_{QE,t} + \varepsilon_j.$$

In Panel A and B, 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. Panel C regresses changes in the log price of the ETF on a constant around the tweets in the event window. We consider two different frequencies. The high frequency takes a 5 minute window around the tweet, while the daily frequency considers a 24 hour window. All estimates 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).

Next, we analyze the impact of the subset of our benchmark tweets that explicitly criticize the tapering of QE policy. These tweets are indicated by an asterisk in Table D.1 in the Online Appendix. We then compare the effect of these QE-related tweets with the other tweets criticizing the Fed from our benchmark analysis on long-term U.S. treasury futures. Panel B of Table 4 reports estimates from regressing the inverse price change of U.S. Treasury futures contracts on a constant term and an indicator variable that takes the value of one if

the tweet criticizes QE policies and zero otherwise. Panel B shows that Trump tweets that explicitly criticize QE tapering decrease long-term yields significantly more than the other tweets used in our benchmark analysis. This evidence highlights how President Trump’s attacks on the Fed for expansionary monetary policy were directed at both short rate and QE policies.¹⁵

The first column of Panel C of Table 4 contains the estimates of the impact of the tweets on the level of the stock market index (SPY) using high-frequency data. We run the event study using the log change in the prices in a narrow window around the selected tweets. We find that the average immediate impact on the level of the stock market index is 0.28 bps (t -statistic = 1.40). The second column shows the average effect at the daily frequency. Consistent with our results in Section 3.3, the estimated effect of 1.71 bps is larger in magnitude with increased statistical significance (t -statistic = 1.92) when focusing on longer time windows. The positive response of the stock market to an interest rate cut is consistent with the evidence from [Bernanke and Kuttner \(2005\)](#) who find that surprise interest rate cuts increase stock market valuations. In terms of economic magnitudes, the estimated effects are about four times smaller than the estimates in [Bernanke and Kuttner \(2005\)](#) and [Swanson \(2021\)](#).¹⁶

Overall, a positive 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. Our VAR analysis below confirms this interpretation of the results.

¹⁵We thank the referee for this suggestion.

¹⁶For instance, [Bernanke and Kuttner \(2005\)](#) find that a 25 bps unanticipated cut in the federal funds rate target leads to a 100 bps increase in the aggregate stock indices, while [Swanson \(2021\)](#) documents that a 8.4 bps decrease in the federal funds rate causes stock prices to increase by about 40 bps. We document that President Trump’s pressure for more expansionary monetary policy decreases on average the market expectation of the FFR by 0.26 bps and increases stock market valuations by 0.28 bps.

3.6 Additional Robustness Results

The Online Appendix presents a series of robustness results. We have selected tweets by President Trump criticizing the Fed thus far. However, some relevant public attacks on the Fed might have occurred outside the Twitter platform. We explore this possibility in Section B.1 of the Online Appendix. We consider instances in which President Trump criticized the Federal Reserve through other media outlets. We find 26 additional events related to the confrontation between the President and the Fed Chairman that do not overlap with our set of tweets. We then determine the accurate to the second timestamps for when each article was posted online in order to compute changes in expected interest rates in a narrow window around each article (as we did in Section 3.2). Similar to our benchmark estimates, we find that President Trump’s public attacks outside the Twitter platform cause a downward revision in interest rate expectations with an effect that intensifies with the horizon.

Sections 3.2 and 3.5 provide direct evidence that President Trump tweets negatively affected short and long term interest rate expectations. In Appendix B.2, we provide additional support for this result using Forex data to measure intraday interest rate differentials between the U.S. and four other regions using covered interest rate parity (CIP). We document negative effects on the average interest rate differentials at various maturities implied by CIP.

Finally, Section B.3 presents results for 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.

3.7 Economic Interpretation

Our main results presented in Table 1 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 only at short horizons. Panel A of Figure D.2 in the Online 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 D.2 in the Online 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 completely 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 2019 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.

Next, we show that the tweets attacking the Federal Reserve were followed by an actual change in the conduct of monetary policy.

4 Tweets and the Monetary Policy Reversal

We have shown above that President Trump 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 no other relevant news will arrive over such a short period. Two important related considerations are if the tweets affect the actual path of the FFR and if they affect the path of macro and financial variables. We find evidence that the Trump threats contributed to the monetary policy reversal in 2019.

4.1 Do the tweets affect the actual path of the FFR?

President Trump’s tweets led to a change in interest rate expectations. Next, we investigate whether the changes in market expectations were eventually realized after the tweets. This analysis has important additional ramifications, as we are checking if the actual Fed policy was influenced by the tweets and not only market expectations about Fed independence.

Panel A of Table 5 reports estimates from a pooled OLS regression of the form

$$(E_t - E_{t-\Delta t}) |FE_{jt}| = a_j + \epsilon_{jt}, \quad (7)$$

where $(E_t - E_{t-\Delta t}) |FE_{jt}|$ denotes the change in the absolute value of the *ex-post* fed funds future pricing error in a narrow window around the tweet as in Section 3.2. Pricing errors are smaller after the tweet when $a_j < 0$, suggesting that Trump tweets lead to a change in interest rate expectations and some of this change is eventually realized. To compute the pricing error FE_{jt} , we take the difference between the federal funds futures rate at time t (and time $t - \Delta t$) and the fed funds futures payoff (i.e., the arithmetic average of daily effective federal funds rates during the contract month rounded to the nearest one-tenth of one basis point). The pricing error is zero when the FFF contract expires. We further scale this variable by the average daily effective federal funds rate for the delivery month, so that the pricing error is expressed in percentage terms.

Panel A of Table 5 shows that Trump tweets immediately reduce pricing errors. Col-

Table 5: **Change in FFF Pricing Errors around Trump tweets**

| | Exposure to FOMC Meetings | | | | | |
|--|---------------------------|----------|------------|------------|-------------|--------------|
| | All (1) | 0 (2) | 1-4 (3) | 5-8 (4) | 9-10 (5) | 11-12 (6) |
| Panel A: High frequency | | | | | | |
| <i>Regression Const. α</i> | -1.75 | 0.02 | -0.46 | -1.85 | -2.26 | -6.22 |
| <i>t - stat</i> | [-2.53] | [1.14] | [-0.98] | [-2.05] | [-2.22] | [-2.64] |
| Observations | 636 | 30 | 230 | 234 | 96 | 46 |
| Panel B: Daily frequency | | | | | | |
| <i>Regression Const. α</i> | -18.00 | 0.00 | -17.53 | -17.22 | -26.61 | -22.75 |
| <i>t - stat</i> | [-5.47] | [0.21] | [-2.10] | [-4.72] | [-4.01] | [-2.69] |
| Observations | 459 | 17 | 164 | 165 | 66 | 47 |

This table estimates the change in pricing errors around President Trump tweets criticizing the Fed. We report the regression estimates for the following Equation:

$$(E_t - E_{t-\Delta t}) |FE_{jt}| = a_j + \epsilon_{jt},$$

where $FE(ff)_{jt}$ denotes the the *ex-post* pricing error, where horizon j is defined as the number of FOMC meetings a selected FFF contract is exposed to ranging from 0 to 12 meetings. In panel A, we use the benchmark estimation over the event window (inner (outer) window of 0.1 minutes (four hours) before and five minutes (two hours) after). In panel B, we use the daily estimation window that goes from 0.1 minute before the tweet to 24 hours after the tweet. We exclude tweets where a FOMC meeting occurs on the same day as the tweet or on the next day. To compute the pricing error, we calculate for each contract the difference between the fed funds futures closing rate and the arithmetic average of daily effective federal funds rates during contract month rounded to the nearest one-tenth of one basis point. We scale this difference in rates by the average daily effective federal funds rate for the delivery month so that the forecast error is expressed in percentage terms. Coefficient estimates are in percentage points.

umn (1) shows that the average reduction implied by the pooling regression is around -1.75 percent (*t*-statistic = -2.53). Columns (2) through (6) show that the declines are both larger in magnitude and more significant as the horizon increases. The reduction in pricing errors for contracts with a zero FOMC meeting exposure is positive but small and statistically insignificant. In contrast, the reductions for contracts exposed to several meetings are negative, large, and statistically significant. Panel B of Table 5 shows that the reductions in pricing errors are about ten times larger if the post-event window is extended to a day. Overall, the significant reduction in the pricing errors provides direct evidence that some of the changes in interest rate expectations were eventually realized.

4.2 Do the tweets affect the path of macro and financial variables?

To address this question, 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 an instrument for a “tweet shock.” The approach in [Jarociński and Karadi \(2020\)](#) builds on [Stock and Watson \(2018\)](#), while the precise implementation of using a Cholesky ordering with the instrument first builds on [Plagborg-Møller and Wolf \(2021\)](#).

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 m_t is a vector of surprises in the FFF rate observed in month t and y_t is a vector of N_y macroeconomic and financial variables observed in month t . To construct m_t , we add up the intraday surprises occurring in month t in response to the set of tweets by President Trump criticizing the Fed. 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 zero. 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.

The vector y_t includes five variables: the shadow FFR constructed by [Wu and Xia \(2016\)](#),¹⁷ the log of the S&P500, the log real GDP,¹⁸ the log of the GDP deflator, and

¹⁷The shadow FFR constructed by [Wu and Xia \(2016\)](#) 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.

¹⁸To 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.

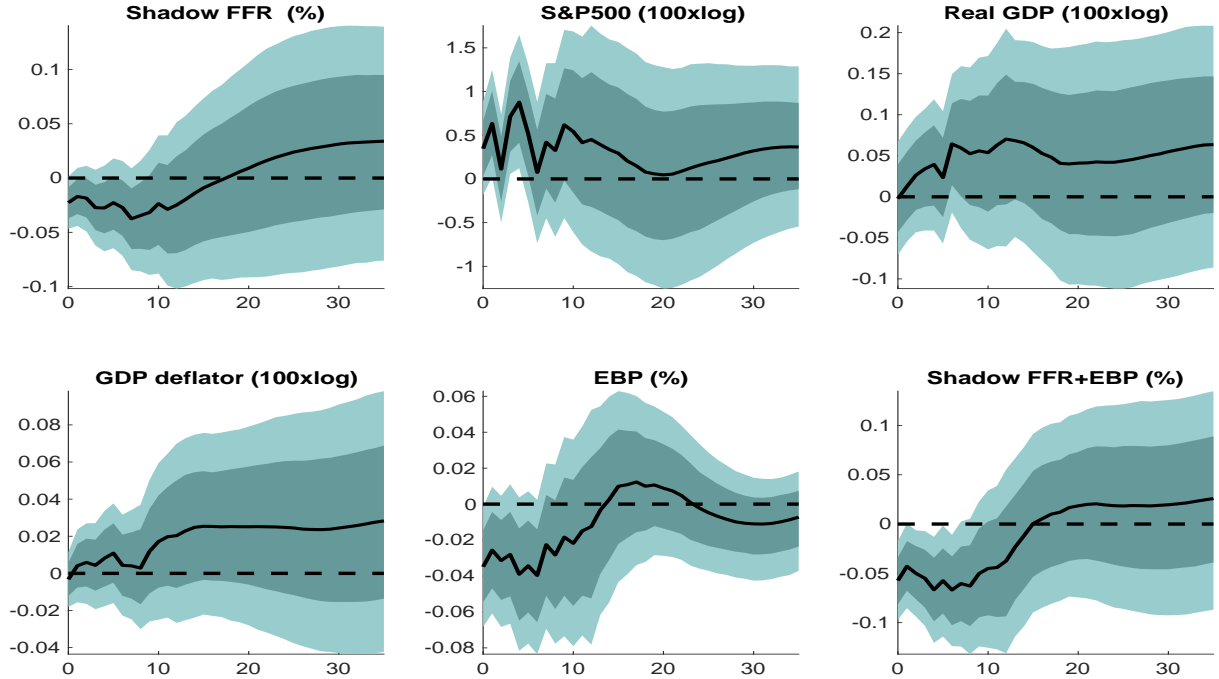
the excess bond premium (EBP) as an indicator of financial conditions (Gilchrist and Zakrajšek (2012)). The shadow FFR is included as the monetary policy rate because it allows us to capture the effects of unconventional monetary policy at the zero lower bound. When the zero lower bound is binding, the 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. When the zero lower bound is not binding the rate tracks the actual FFR very closely.¹⁹ We plot these five series along with the FFF surprises in Figure D.5 of the Online Appendix.

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 Melosi (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.

Figure 4 presents the impulse responses 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. We report the median together with 68% and 90% credible sets. We find that a tweet shock is followed by a relatively persistent drop in the shadow FFR lasting for about 15 months. The peak effect is around -4 bps, which is about 15 (2) times larger than the initial high-frequency (daily-frequency) shocks. To put these numbers into perspective, Aruoba and Drechsel (2022) use state-of-the-art machine learning techniques and textual analysis tools to identify monetary policy shocks from FOMC documents. Aruoba and Drechsel (2022) find that a monetary policy shock has a persistent effects on yields that last for about 20

¹⁹We 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. Results based on using 1-year constant Treasury yields are qualitatively similar, but tend to be noisier.

Figure 4: VAR analysis: Impulse responses to a tweet shock



Notes: 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 October 2001 to February 2020.

months with a peak effect of about 8 bps.

Figure 4 also shows that EBP (corporate spread) decreases significantly after a tweet shock, a finding in line with [Gertler and Karadi \(2015\)](#) who show that spreads tend to decline after a monetary policy easing.²⁰ Notably, 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. Furthermore, the tweet shock results in an increase in stock prices consistent with our high-frequency results and further suggesting that the identified shocks seem quite similar to monetary policy easing.²¹ We also report the response of the sum of the shadow rate and the EBP. Note that this

²⁰The excess bond premium is related to the health of financial intermediaries ([Gilchrist and Zakrajšek, 2012](#)). Similar to the impulse response of the excess bond premium, a tweet shock also decreases the LIBOR-OIS and TED spreads, as these spreads are also related to the health of financial intermediaries.

²¹The large fluctuations in the S&P500 in the first eight months are driven partly by noise, given the short sample we are working on. Figure D.6 in the Online Appendix shows that the IRFs can be smoothed by imposing tighter priors in our Bayesian estimation to further reduce overfitting of a model with many free parameters and a short estimation sample. The magnitude of the overall response does not change.

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. Finally, 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.²² 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 tweets reveal bad news about the future that in turn lead to a downward revision in expectations about the future FFR).²³

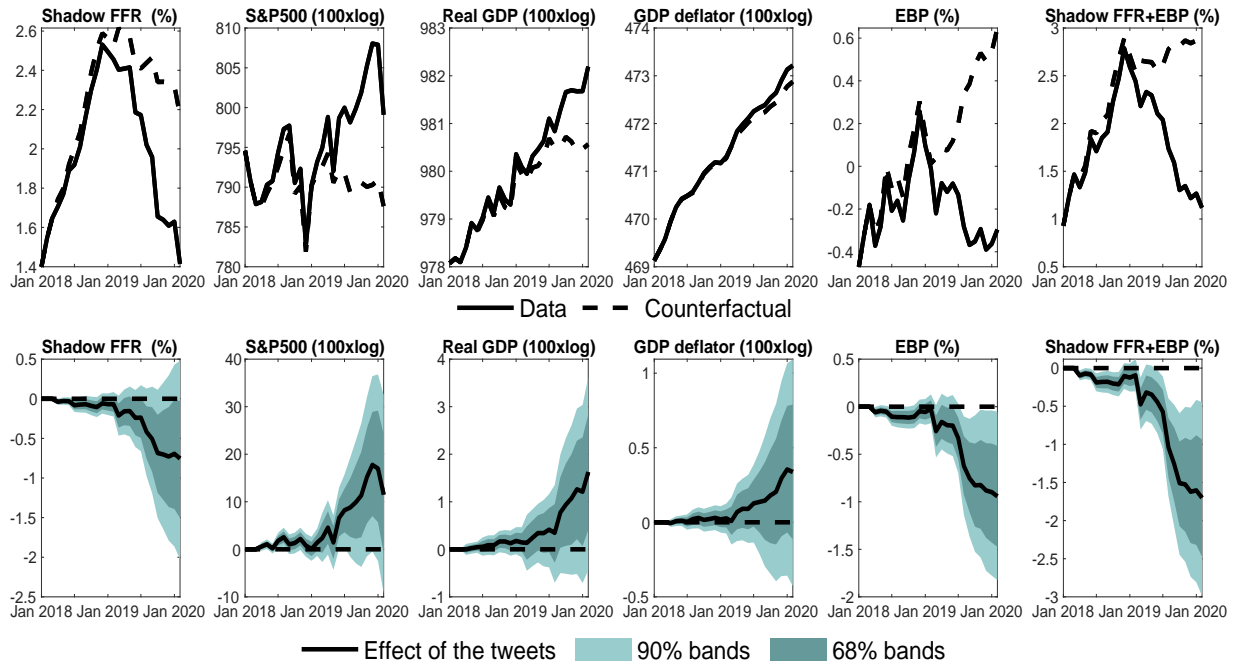
In light of these impulse responses, it is interesting to isolate the effects of the tweets on the actual path of the FFR and the other variables. To do so, we construct a counterfactual simulation that removes the tweets and computes the corresponding path of the macro variables. The first row of Figure 5 shows the actual path and the counterfactual path, while the second row of Figure 5 shows the difference between the actual and counterfactual series. Such difference represents the overall effect of President Trump tweets, as identified with the high-frequency approach.

The shadow FFR and the EBP rate are around 0.7% and 0.9% lower than 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 significant decline in the sum of these two variables suggests that the tweets might have contributed to a reversal of the monetary policy stance. The effect on the stock market is also estimated to be large, with a peak of close to 18%. Such a finding suggests that a significant fraction of the run-up in the stock market at the end of the sample can be attributed to a regime change in

²²The 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).

²³The impulse responses are not driven by the behavior of the S&P500 during our estimation period, as dropping the series from the VAR produces very similar results.

Figure 5: VAR analysis: Cumulative effect of the tweets on realized variables



Notes: The first row reports the realized data (black line) and a counterfactual simulation that removes all tweet shocks (black dashed line). The second row reports the differences between the realized data and a counterfactual simulation. 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.

the conduct of monetary policy.²⁴ The effects on the real economy are also estimated to be important. Real GDP at the end of the period is 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.

5 Conclusions

In this paper, we use a high-frequency analysis to show that President Trump tweets criticizing the Fed affected market expectations about future monetary policy. Our high-frequency

²⁴Consistent with the stock price responses documented in Figure 5, [Bianchi, Lettau, and Ludvigson \(2022\)](#) propose a macro-finance model of monetary transmission to show that asset valuations can increase and remain high for several years in response to a regime shift to dovish policy. In contrast, an expansionary monetary policy shock (and no regime change in the conduct of monetary policy) has negligible effects on valuations.

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 with horizon. The criticism by President Trump also leads to an increase in the stock market index, in line with economic theory about the effects of more dovish monetary policy. We also document that the tweets had a large impact on U.S. Treasury futures for medium- to long-term maturities and the effects increased with the horizon of the interest rate. Overall, our findings suggest that financial markets do not perceive the Federal Reserve as being fully independent of the executive branch.

After establishing that Trump tweets led to a change in interest rate expectations, we show that market participants' expectations moved in the right direction after the tweet, suggesting that the tweets affected the Fed's policy decisions. 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.
- 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.
- Andersen, T. G., T. Bollerslev, F. X. Diebold, C. Vega, 2003. Micro effects of macro announcements: Real-time price discovery in foreign exchange. *American economic review* 93(1), 38–62.
- Arteaga-Garavito, M. J., M. Croce, P. Farroni, I. Wolfskeil, 2021. When the Markets Get CO.V.I.D: COntagion, Viruses, and Information Diffusion.. Working paper Bocconi University.
- Aruoba, S. B., T. Drechsel, 2022. Identifying Monetary Policy Shocks: A Natural Language Approach. .
- Balduzzi, P., E. J. Elton, T. C. Green, 2001. Economic news and bond prices: Evidence from the US Treasury market. *Journal of financial and Quantitative analysis* 36(4), 523–543.
- 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., M. Lettau, S. C. Ludvigson, 2016. Monetary policy and asset valuation. Unpublished working paper. National Bureau of Economic Research.
- Bianchi, F., M. Lettau, S. C. Ludvigson, 2022. Monetary policy and asset valuation. *The Journal of Finance* 77(2), 967–1017.
- Bianchi, F., L. Melosi, 2017. Escaping the great recession. *American Economic Review* 107(4), 1030–58.

- 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.
- Boudoukh, J., R. Feldman, S. Kogan, M. Richardson, 2013. Which news moves stock prices? A textual analysis. Unpublished working paper. National Bureau of Economic Research.
- Buehlmaier, M. M., T. M. Whited, 2018. Are financial constraints priced? Evidence from textual analysis. *The Review of Financial Studies* 31(7), 2693–2728.
- Chen, H., P. De, Y. J. Hu, B.-H. Hwang, 2014. Wisdom of crowds: The value of stock opinions transmitted through social media. *The Review of Financial Studies* 27(5), 1367–1403.
- 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.
- Cohen, L., K. Diether, C. Malloy, 2013. Legislating stock prices. *Journal of Financial Economics* 110(3), 574–595.
- 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.
- Cookson, J. A., J. Engelberg, W. Mullins, 2021. Echo chambers. Available at SSRN 3603107.
- 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.

- Gentzkow, M., B. Kelly, M. Taddy, 2019. Text as data. *Journal of Economic Literature* 57(3), 535–74.
- 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.
- Hoberg, G., S. K. Moon, 2019. The offshoring return premium. *Management Science* 65(6), 2876–2899.
- 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.
- Kelly, B. T., A. Manela, A. Moreira, 2019. Text selection. Unpublished working paper. National Bureau of Economic Research.
- 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.
- Plagborg-Møller, M., C. K. Wolf, 2021. Local projections and VARs estimate the same impulse responses. *Econometrica* 89(2), 955–980.
- 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.
- Stock, J. H., M. W. Watson, 2018. Identification and estimation of dynamic causal effects in macroeconomics using external instruments. *The Economic Journal* 128(610), 917–948.
- 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.
- Swanson, E. T., 2021. Measuring the effects of federal reserve forward guidance and asset purchases on financial markets. *Journal of Monetary Economics* 118, 32–53.
- Timiraos, N., 2019. Fed Readies First Interest-Rate Cut Since 2008. www.wsj.com/articles/fed-readies-first-interest-rate-cut-since-2008-11564563601.
- Transcript, F., 2016. Meeting of the Federal Open Market Committee. <https://www.federalreserve.gov/monetarypolicy/files/FOMC20161214meeting.pdf>.
- 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.

For Online Publication

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

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|--------------------------|------------------------|------------|------------------------|
| Francesco Bianchi | Roberto Gómez-Cram | Thilo Kind | Howard Kung |
| Johns Hopkins University | London Business School | SAFE | London Business School |
| NBER, CEPR | | | CEPR |

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A Data

A.1 Event Selection

Tweets

The entire 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, 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 **Federal** 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 D.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 D.6 are based on the same set of tweets which include the same keywords. Tweets are dropped according to the technical criteria 1-2, i.e. tweets which are off-topic, or doubles. 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.

U.S. Treasury Futures

We use U.S. Treasury futures to measure market expectations on long-term interest rates. We use tick-by-tick trade data for each of the Treasury benchmark tenors offered by the Chicago Mercantile Exchange (CME) Group: 2-year (Symbol: TU), 5-year (FV), 10-year (TYF), and 30-year (US). Each futures contract has an associated delivery bond basket that determines the bond maturity range that can be delivered at maturity. For instance, the 2-year note contract delivers into any U.S. government fixed coupon bond with a remaining maturity between 1 3/4 to 2 years. For the 5-year and 10-year notes, the bond maturity range is 4 1/6 to 5 1/4 years and 6 1/2 to 10 years, respectively. The range goes from 15 to 25 years for the 30-year bond futures. This delivery mechanism ensures that the futures prices are closely linked to U.S. government notes' and bonds' prices. However, in practice, most market participants trade U.S. Treasury futures contracts to either close the position before maturity or roll it over into longer expiry futures contracts. For instance, since 2007, less than 10% U.S. Treasury futures positions resulted in physical delivery at maturity. The data is cleaned following the same procedure as the federal funds futures and eurodollar futures data.

U.S. Treasury futures contracts are settled through physical-delivery on the last business day of 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. 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

Intraday series for the stock market index is inferred from the SPDR S&P 500 ETF (ticker: SPY). The trade 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 median 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 and additional analysis

This appendix presents a series of robustness checks. Each section is self-contained so readers can skip each section without loss.

B.1 News outside the Twitter platform

In this appendix, we present a series of robustness checks. The benchmark estimates illustrated how President Trump 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 of President Trump tweets that criticize the Federal Reserve but are not likely to contain other information about the state of the economy. However, some relevant public attacks on the Fed might have occurred outside the Twitter platform. We explore this possibility next. To do so, we identify other instances in which President Trump openly criticized the Fed using other news that did not coincide with our selected tweets.

We 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 [Table D.2](#).

A relevant example of these distinct Bloomberg news events occurred 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 D.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.

We next revisit the high-frequency evidence from [Section 3.2](#) using these 26 additional events. [Panel A](#) in [Table D.7](#) presents the regression results for the fed funds futures contracts. Similar to the regression results reported in [Panel A](#) of [Table 1](#), the estimated effects

are negative and decrease as we increase the contract horizon. Panel B shows that these 26 additional events also decrease expected short term rates as measured by the EDF contracts. Overall, these estimates illustrate how President Trump’s public attacks outside the Twitter platform on the Fed led to a change in interest rate expectations.

B.2 Effects using foreign exchange rate data

Foreign exchange (forex) rate 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:

$$i_{t,n} - i_{t,n}^* = (1/n) * (f_{t,n} - s_t), \quad (8)$$

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 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 (8) between the US and the foreign currency. Panel A of Table D.8 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:

$$\frac{1}{m} \sum_{c=1}^m \Delta(i_{j,t,n} - i_{j,t,n,c}^*) = \alpha_j + \varepsilon_j, \quad (9)$$

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.

Overall, these results with forex data support the notion that President Trump had a material impact on expected monetary policy, manifested in lower interest rates across various

maturities implied by CIP. However, these results should only be seen as providing corroborating evidence to our main results that use direct measures of interest rate expectations (e.g., FF, EDF, and U.S. Treasury futures contracts) as deviations from the CIP condition can be considerable, especially after 2008 as shown in [Du, Tepper, and Verdelhan \(2018\)](#). In principle, it is possible that President Trump’s attacks on the Fed also induced systematic changes in arbitrage opportunities. Nevertheless, decomposing such an effect is outside the scope of this paper.

B.3 Placebo tests

Table [D.9](#) 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 [4](#). 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.

B.4 High-Frequency Identification and Event Window Selection

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 D.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.

B.5 Economic Interpretation

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 D.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 D.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 D.2 in the Appendix provides a depiction of this alternative example.

C Historical antecedents and corroborating evidence

In this 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.

C.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 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 D.8 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 D.8, 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.²⁵

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 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 tweets came to perturb an equilibrium that

²⁵The following day the employment report showed an increase in unemployment and Chairman Greenspan decided for a 50 bps cut.

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.

C.2 Corroborating Evidence

In this 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 D.7 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. 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.²⁶ 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

²⁶The series of tweets includes two tweets that are particularly 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.

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.

D Additional tables and figures

Table D.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 D.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 D.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 D.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 B.1. The list of related events in which President Trump criticized 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 not 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 from 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 tough 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 D.3: FFF Contracts by Horizon

This table estimates the impact of President Trump tweets criticizing the Fed on changes in expectations of short rates. We 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 of 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 $(E_t - E_{t-\Delta t})[r_j]$ 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 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).

| Exposure 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 |

Table D.4: **Excluding Tweets around FOMC days: Daily Event Window**

| Panel A: FFF | | | | | | |
|--|---------------------------|---------|---------|---------|---------|---------|
| | Exposure to FOMC Meetings | | | | | |
| | All | 0 | 1–4 | 5–8 | 9–10 | 11–12 |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| <i>Regression Const. α</i> | -2.19 | -0.01 | -2.01 | -2.15 | -2.65 | -2.76 |
| <i>t – stat</i> | [-2.55] | [-0.13] | [-2.24] | [-2.43] | [-3.36] | [-2.12] |
| Observations | 583 | 20 | 166 | 166 | 65 | 43 |

| Panel B: EDF | | | | | | |
|--|---------------------------|---------|---------|---------|---------|---------|
| | Exposure to FOMC Meetings | | | | | |
| | All | 1–8 | 9–12 | 13–16 | 17–20 | 21–24 |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| <i>Regression Const. α</i> | -2.08 | -1.76 | -1.75 | -2.93 | -1.73 | -1.74 |
| <i>t – stat</i> | [-12.22] | [-4.94] | [-2.26] | [-5.62] | [-7.66] | [-2.53] |
| Observations | 825 | 183 | 44 | 112 | 393 | 29 |

This table estimates the impact of President Trump 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. 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 12 meetings. Panel B infers market expectations of the three-month interest rate using eurodollar futures (EDF) contracts where horizon j is defined as the number of FOMC meetings a selected EDF contract (and underlying) is exposed to ranging from 1 to 24 meetings. The event study regresses the revision in expectations of 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 $(E_t - E_{t-\Delta t})[r_j]$ 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 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 24 hours after. The outer event window is four hours before and 36 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).

Table D.5: **Effect of Macro announcements on FFF Contracts**

| Macroeconomic indicator | Bloomberg's | Estimated effect (i.e., $\hat{a} + \hat{b}$) | | Number of Events |
|-----------------------------------|-----------------|---|--------------------------------------|------------------|
| | Relevance Score | Exposure to 1-4 FOMC meetings | Exposure to at least 9 FOMC meetings | |
| Change in Nonfarm Payrolls | 99.21 | -0.85 | -1.68 | 54 |
| ADP Employment Change | 87.40 | -0.52 | -1.14 | 54 |
| ISM Manufacturing | 95.28 | -0.32 | -0.96 | 108 |
| Retail Sales Advance MoM | 92.13 | -0.23 | -0.66 | 54 |
| ISM Services Index | 79.53 | -0.32 | -0.65 | 108 |
| Richmond Fed Manufact. Index | 70.87 | -0.09 | -0.33 | 55 |
| MNI Chicago PMI | 81.89 | -0.07 | -0.31 | 110 |
| CPI MoM | 96.06 | -0.02 | -0.30 | 55 |
| New Home Sales | 91.34 | -0.08 | -0.26 | 55 |
| U. of Mich. Sentiment | 94.49 | -0.10 | -0.23 | 109 |
| Philadelphia Fed Business Outlook | 78.74 | -0.07 | -0.19 | 55 |
| Monthly Budget Statement | 75.59 | 0.04 | -0.18 | 54 |
| NFIB Small Business Optimism | 61.42 | -0.05 | -0.15 | 54 |
| Pending Home Sales MoM | 76.38 | -0.05 | -0.15 | 55 |
| Dallas Fed Manf. Activity | 63.78 | -0.05 | -0.14 | 55 |
| Retail Sales Ex Auto MoM | 64.49 | -0.07 | -0.11 | 54 |
| Housing Starts | 88.98 | -0.00 | -0.10 | 55 |
| Initial Jobless Claims | 98.43 | -0.01 | -0.10 | 237 |
| Conf. Board Consumer Confidence | 93.70 | -0.02 | -0.08 | 55 |
| Import Price Index MoM | 77.17 | 0.01 | -0.07 | 54 |
| Industrial Production MoM | 90.55 | -0.08 | -0.05 | 54 |
| GDP Annualized QoQ | 96.85 | -0.11 | -0.05 | 54 |
| Empire Manufacturing | 82.68 | -0.07 | -0.05 | 54 |
| PPI Final Demand MoM | 86.61 | -0.08 | -0.03 | 54 |
| Continuing Claims | 68.90 | 0.00 | -0.02 | 237 |
| Existing Home Sales MoM | 49.61 | 0.02 | -0.02 | 55 |
| PCE Core Deflator MoM | 60.08 | 0.00 | 0.00 | 110 |
| CPI Ex Food and Energy YoY | 54.33 | -0.00 | -0.00 | 55 |
| Capacity Utilization | 63.39 | 0.00 | 0.00 | 54 |
| CPI YoY | 70.08 | 0.00 | 0.00 | 55 |
| CPI Ex Food and Energy MoM | 76.85 | -0.00 | -0.00 | 55 |
| PPI Final Demand YoY | 67.72 | 0.00 | 0.00 | 54 |
| Personal Consumption | 67.80 | 0.00 | 0.00 | 54 |
| GDP Price Index | 77.48 | 0.00 | 0.00 | 54 |
| PCE Core Deflator YoY | 50.39 | -0.00 | -0.00 | 108 |

Table D.5: Effect of Macro announcements on FFF Contracts (continued)

| Macroeconomic indicator | Bloomberg's | Estimated effect (i.e., $\hat{a} + \hat{b}$) | | |
|------------------------------|-----------------|---|--------------------------------------|------------------|
| | Relevance Score | Exposure to 1-4 FOMC meetings | Exposure to at least 9 FOMC meetings | Number of Events |
| CPI Ex Food and Energy YoY | 54.33 | -0.00 | -0.00 | 55 |
| Capacity Utilization | 63.39 | 0.00 | 0.00 | 54 |
| CPI YoY | 70.08 | 0.00 | 0.00 | 55 |
| CPI Ex Food and Energy MoM | 76.85 | -0.00 | -0.00 | 55 |
| PPI Final Demand YoY | 67.72 | 0.00 | 0.00 | 54 |
| Personal Consumption | 67.80 | 0.00 | 0.00 | 54 |
| GDP Price Index | 77.48 | 0.00 | 0.00 | 54 |
| PCE Core Deflator YoY | 50.39 | -0.00 | -0.00 | 108 |
| Change in Manufact. Payrolls | 69.45 | -0.00 | -0.00 | 54 |
| ISM Prices Paid | 74.02 | -0.00 | -0.00 | 162 |
| Personal Income | 85.83 | -0.00 | -0.00 | 55 |
| Personal Spending | 85.83 | 0.00 | 0.00 | 55 |
| Building Permits | 62.28 | 0.00 | 0.00 | 55 |
| Retail Sales Ex Auto and Gas | 60.63 | -0.00 | -0.00 | 54 |
| Unemployment Rate | 89.29 | 0.00 | 0.00 | 54 |
| PPI Ex Food and Energy YoY | 65.35 | 0.00 | 0.00 | 54 |
| PPI Ex Food and Energy MoM | 66.14 | 0.00 | 0.00 | 54 |
| Current Account Balance | 71.65 | 0.01 | 0.01 | 19 |
| Factory Orders | 85.04 | -0.03 | 0.03 | 54 |
| Wholesale Inventories MoM | 81.10 | 0.02 | 0.04 | 92 |
| Trade Balance | 84.25 | 0.03 | 0.05 | 54 |
| Leading Index | 83.46 | -0.03 | 0.07 | 55 |
| FHFA House Price Index MoM | 68.50 | 0.02 | 0.07 | 55 |
| Existing Home Sales | 88.19 | 0.02 | 0.12 | 55 |

This table estimates the impact of macroeconomic announcements on changes in expectations of short rates. We infer market expectations of the FFR using fed funds futures (FFF) contracts. The event study regresses the revision in expectations of the short rate r_j of horizon j on a constant and the macro surprise S_{kt} around each macroeconomic announcement according to:

$$(E_t - E_{t-\Delta t})[r_j] = a_j + b_j S_{kt} + \varepsilon_j,$$

where $(E_t - E_{t-\Delta t})[r_j]$ denotes the change in the market expectation of the short rate in the event window. S_{kt} is the standardized news associated with indicator k at time t . To facilitate the comparison, we normalize the macroeconomic surprise, S_k , such that an increase is bad news about the economy. We select the 50 most relevant macroeconomic indicators using Bloomberg's relevance score, which measures the popularity of an economic release and ranges from 1 to 100. To compute the interest rate changes we use an inner event window of 0.1 minutes before the tweet and five minutes after. Our sample period starts goes from January 2015 to January 2020.

Table D.6: Alternative Tweet Selection Criteria

This table estimates the impact of President Trump 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. The table 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. The event study regresses the revision in expectations of 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 $(E_t - E_{t-\Delta t})[r_j]$ 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 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 |

Table D.7: **FFF and EDF Contracts by Horizon: Bloomberg News**

| Panel A: FFF | | | | | | |
|--|---------------------------|--------|---------|---------|---------|---------|
| | Exposure to FOMC Meetings | | | | | |
| | All | 0 | 1–4 | 5–8 | 9–10 | 11–12 |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| <i>Regression Const. α</i> | -0.38 | 0.08 | -0.13 | -0.49 | -0.51 | -0.93 |
| <i>t – stat</i> | [-2.90] | [1.51] | [-1.78] | [-3.65] | [-3.09] | [-2.64] |
| Observations | 321 | 12 | 94 | 97 | 35 | 22 |

| Panel B: EDF | | | | | | |
|--|---------------------------|---------|---------|----------|----------|----------|
| | Exposure to FOMC Meetings | | | | | |
| | All | (1, 8) | (9, 12) | (13, 16) | (17, 20) | (21, 24) |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| <i>Regression Const. α</i> | -0.22 | -0.06 | -0.29 | -0.16 | -0.24 | -0.35 |
| <i>t – stat</i> | [-6.72] | [-1.88] | [-4.16] | [-2.14] | [-2.87] | [-6.99] |
| Observations | 430 | 123 | 46 | 46 | 87 | 128 |

This table estimates the impact of President Trump criticizing the Federal Reserve through other media outlets on changes in expectations of short rates. We use a Bloomberg article (Condon (2019)) for such a list of related events. 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 12 meetings. Panel B infers market expectations of the three-month interest rate using eurodollar futures (EDF) contracts where horizon j is defined as the number of FOMC meetings a selected EDF contract (and underlying) is exposed to ranging from 1 to 24 meetings. The event study regresses the revision in expectations the short rate r_j of horizon j on a constant around each selected Bloomberg events in the event window according to:

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

where $(E_t - E_{t-\Delta t})[r_j]$ 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 Bloomberg events 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).

Table D.8: Effects on Interest Rate Differentials using Forex Data

This table considers the impact of the Trump’s attacks using intraday data from other asset classes. The table 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 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 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. 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 |

Table D.9: 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. The table 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. The event study regresses the revision in expectations of 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 $(E_t - E_{t-\Delta t})[r_j]$ 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 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 | | | | | | | | | | | |
|---------------------------------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| Exposure 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 |

Figure D.1: Event Window

This figure illustrates the selection of trades to study the impact of an event which occurs at 0. The symbols \times , \circ , \square 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, \circ . Within each subset, $[T_0, T_1]$ and $[T_2, T_3]$, the two trades closest to the inner window are selected, \times .

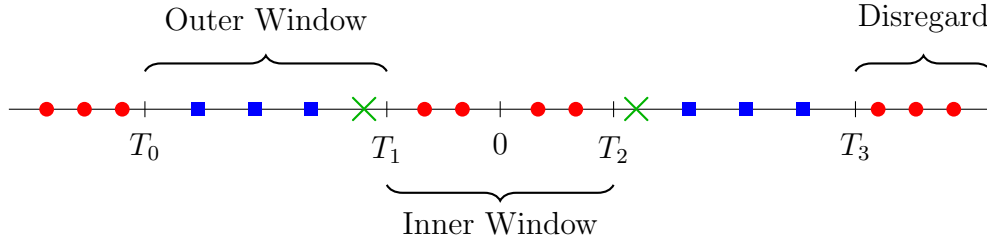


Figure D.2: Interest Rate Cut Timing

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.

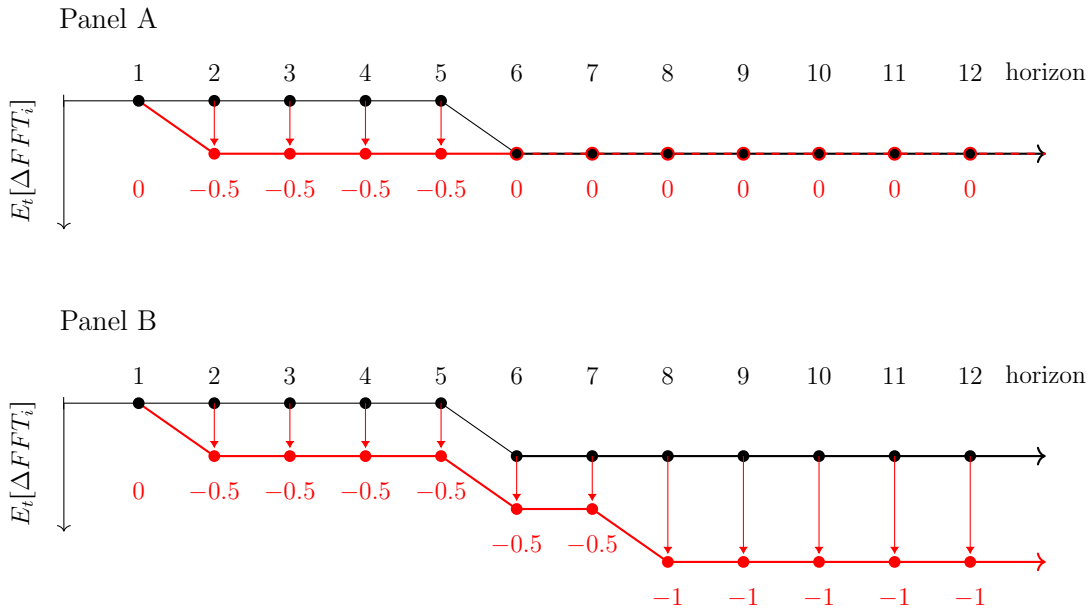
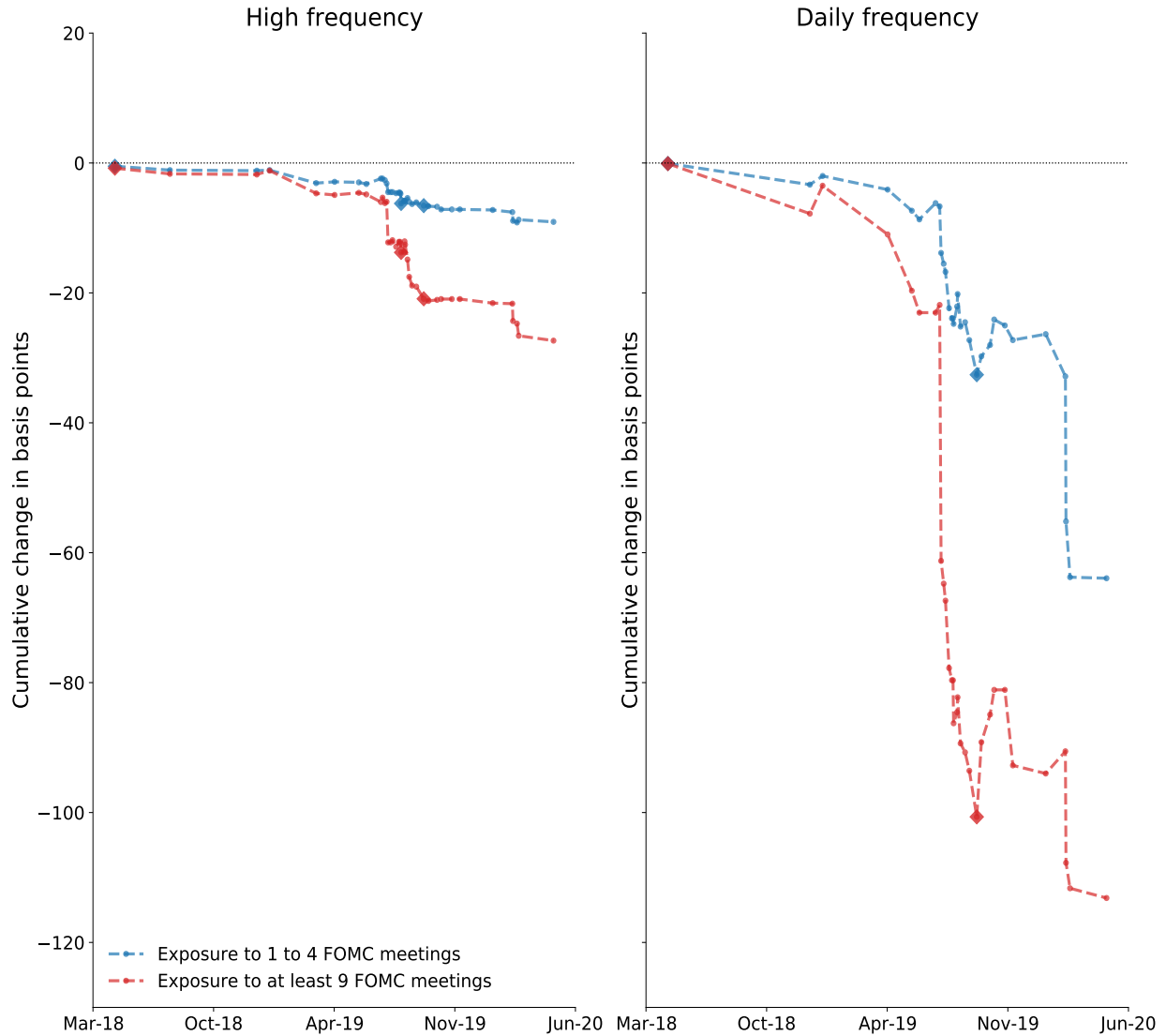


Figure D.3: Cumulative effects plot



Notes: 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 short horizon FFF contract exposed to 1 to 4 FOMC meetings. The red line corresponds to long horizon FFF contract exposed to at least 9 FOMC meetings. Figure (b) 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 24 hours (48 hours) after) with the units in bps. The blue line corresponds to short horizon FFF contract exposed to 1 to 4 FOMC meetings. The red line corresponds to long horizon FFF contract exposed to at least 9 FOMC meetings.

Figure D.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.

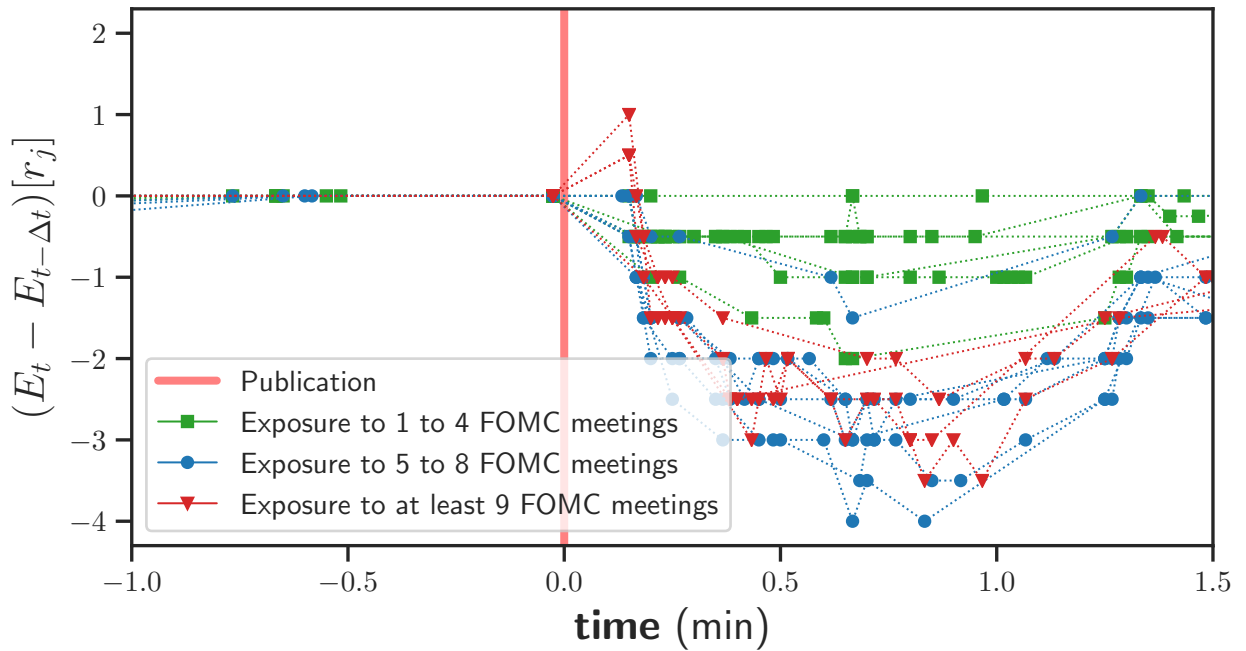


Figure D.5: VAR analysis: Time Series

This figure reports the data used in the VAR exercise: the "Twitter shocks," the shadow FFR, the log of the S&P500, the log of real GDP, the log of the GDP deflator, and the excess bond premium (EBP). The Twitter shocks at monthly frequency are obtained by summing together the surprises in the FFF over the corresponding month. We use contracts exposed to at least four FOMC meetings. The sample is 2001:10-2020:2.

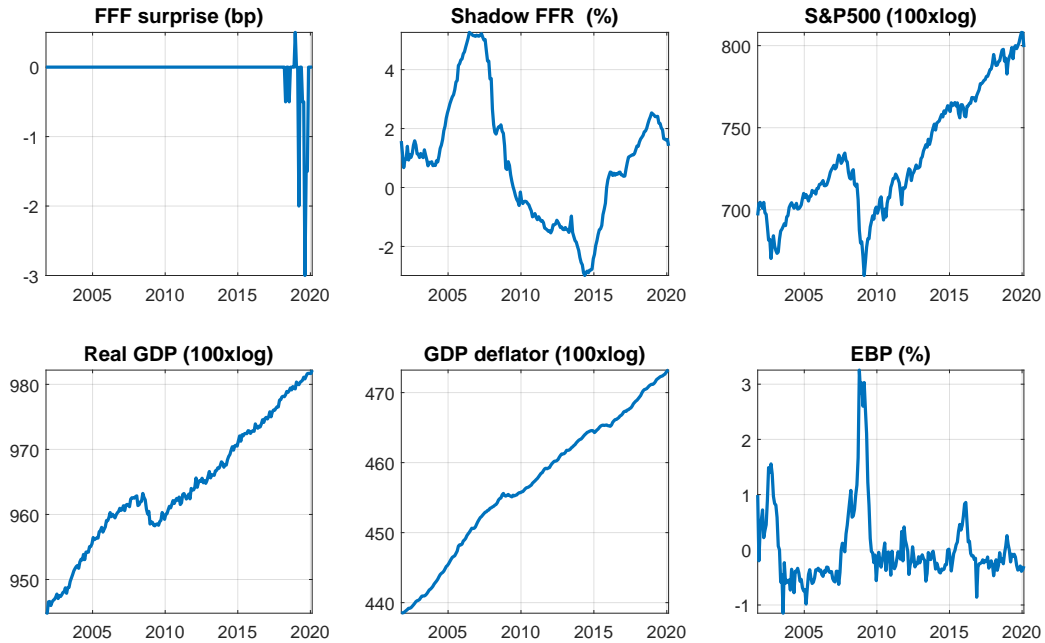
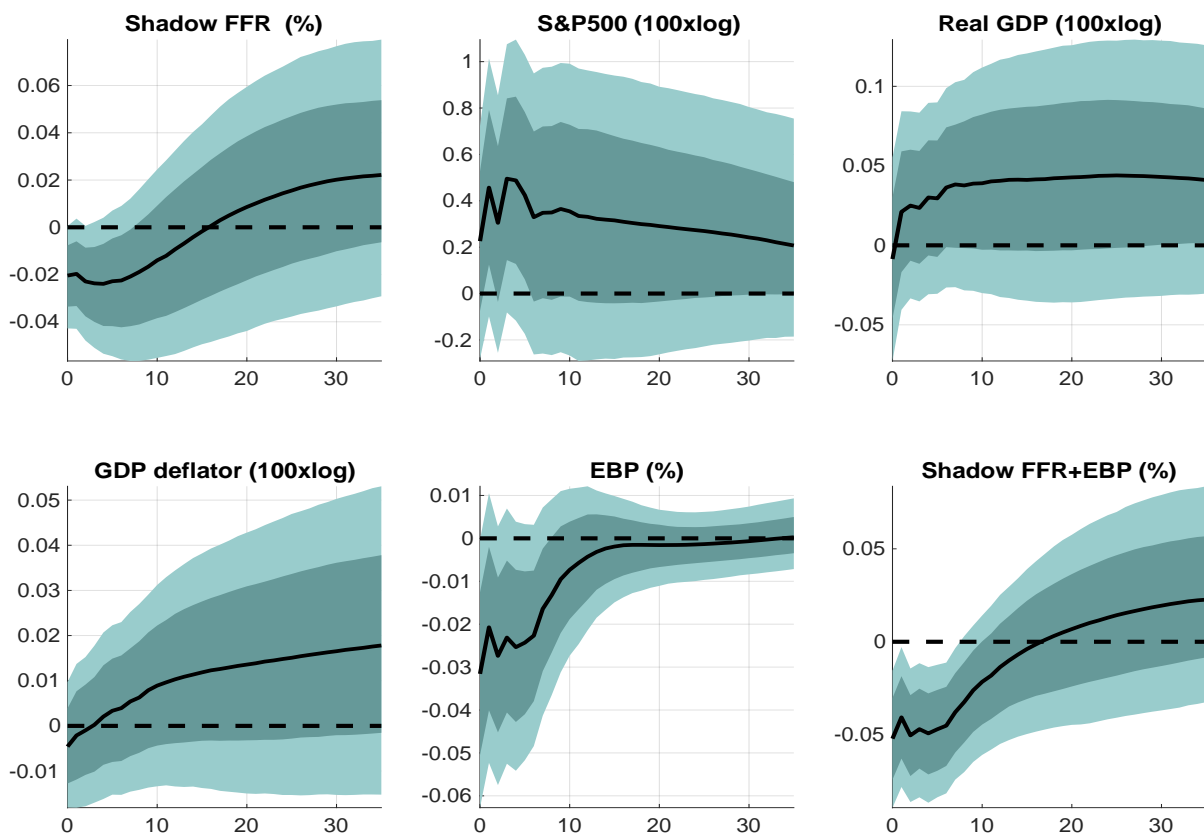


Figure D.6: Impulse responses to a tweet shock (tighter priors)



Notes: 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 October 2001 to February 2020.

Figure D.7: 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.

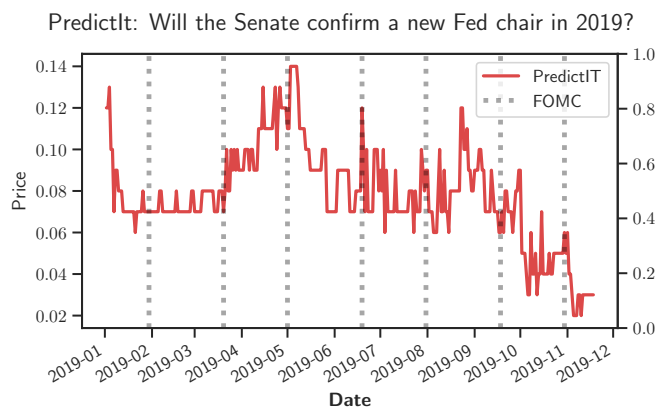


Figure D.8: Historical Antecedents

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.”

