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Threats to central bank independence: High-frequency identification with twitter[☆]

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ABSTRACT

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.

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

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[1] Crowe and Meade (2007) provide a survey of the evolution of central bank independence across countries.
[2] Some examples include Alesina and Summers (1993) and Grilli et al. (1991).
[3] Fessenden (1965) details instances of Fed interference by Presidents Johnson and Nixon.

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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 (Kohn, 2013). The unconventional policies implemented in the aftermath of the financial crisis further increased scrutiny on central banks. The widespread public criticism of central banks 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!" Following this tweet, market expectations of the Federal Funds Rate (FFR) as measured by Federal Funds Futures (FFF) decline, with an increasing magnitude with respect to maturity.

In this paper, 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 FFR 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 FFR.

The average effect of the tweets across all contracts is around -0.26 bps per tweet. This effect grows with the time horizon, with a peak of -0.64 bps at the longest horizon. 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.

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.

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. This result is robust to using a daily window around the tweets and the announcements. Overall, the results illustrate 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 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 yields decrease 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." 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).

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.

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. The VAR 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-min 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." If President Trump tweets were simply revealing bad news about the future that in turn lead to a downward revision in expectations about the future FFR, we should observe a subsequent decline in asset prices and real activity.

The methodological approach of our paper relates to the literature identifying monetary policy shocks using high-frequency data (e.g., Cochrane and Piazzesi, 2002; Faust et al., 2004; Gürkaynak et al., 2007; Kuttner, 2001; Nakamura and Steinsson, 2018) and papers studying the effect of these shocks on interest rates using a high-frequency approach (e.g., Beechey and Wright, 2009; Gertler and Karadi, 2015; Gilchrist et al., 2019; Gürkaynak et al., 2005a; Gürkaynak et al., 2005b; Hanson and Stein, 2015; Krishnamurthy and Vissing-Jorgensen, 2011; Swanson, 2011; Swanson, 2017). 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.

Acemoglu et al. (2008); Alesina (1988); Alesina and Summers (1993); Cukierman et al. (1992); Grilli et al. (1991), and Binder (2021) construct indices of central bank independence across countries and examine the impact of the degree of independence on macroeconomic outcomes. We identify threats to central bank independence using high-frequency financial data and messages from the social media account of the President. Evidence that the Fed closely monitors and is affected by market expectations of its own actions (e.g., Faust, 2016; 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.

Our findings complement the literature examining the effect of informal communication of policymakers between FOMC meetings on equity markets (e.g., Cieslak et al., 2018; Lucca and Moench, 2015). 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. In doing so, we connect to the literature that uses textual analysis to extract news affecting asset prices (Arteaga-Garavito et al., 2021; Bianchi et al., 2021; Boudoukh et al., 2013; Buehlmaier and Whited, 2018; Chen et al., 2014; Cohen et al., 2013; Cookson et al., 2021; Gentzkow et al., 2019; Hoberg and Moon, 2019; Kelly et al., 2019).

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, but initiated quantitative tightening (QT) in October 2017. 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 zero 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 et al. (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 et al. (2008) and Bollerslev et al. (2018). Similar to the futures contract, we also drop observations with zero volume.

3. Threats to central bank independence

This section formally assesses how critical tweets by President Trump directed at the Fed advocating lower interest rates affect *market expectations* of the future path of monetary policy. Before we present the systematic analysis of the effects of the Trump tweets, we provide a graphical representation that encapsulates our main findings in Fig. 1. The panel in the upper-right corner of the figure illustrates the impact of the first tweet on the expected FFR implied by FFF prices in a 30-min window. The FFF contracts are stratified based on the number of FOMC announcements occurring before the corresponding expiration month. The changes in expected rates are measured in basis points. The second and third panels in the left column of the figure 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. The left column of the figure shows all of the jumps in the expected FFR as measured by FFF contracts over narrow event windows associated with President Trump’s tweets criticizing the Federal Reserve. The jumps are reported as a cumulative sum to convey 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 producing large revisions in expectations.

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:

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

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.

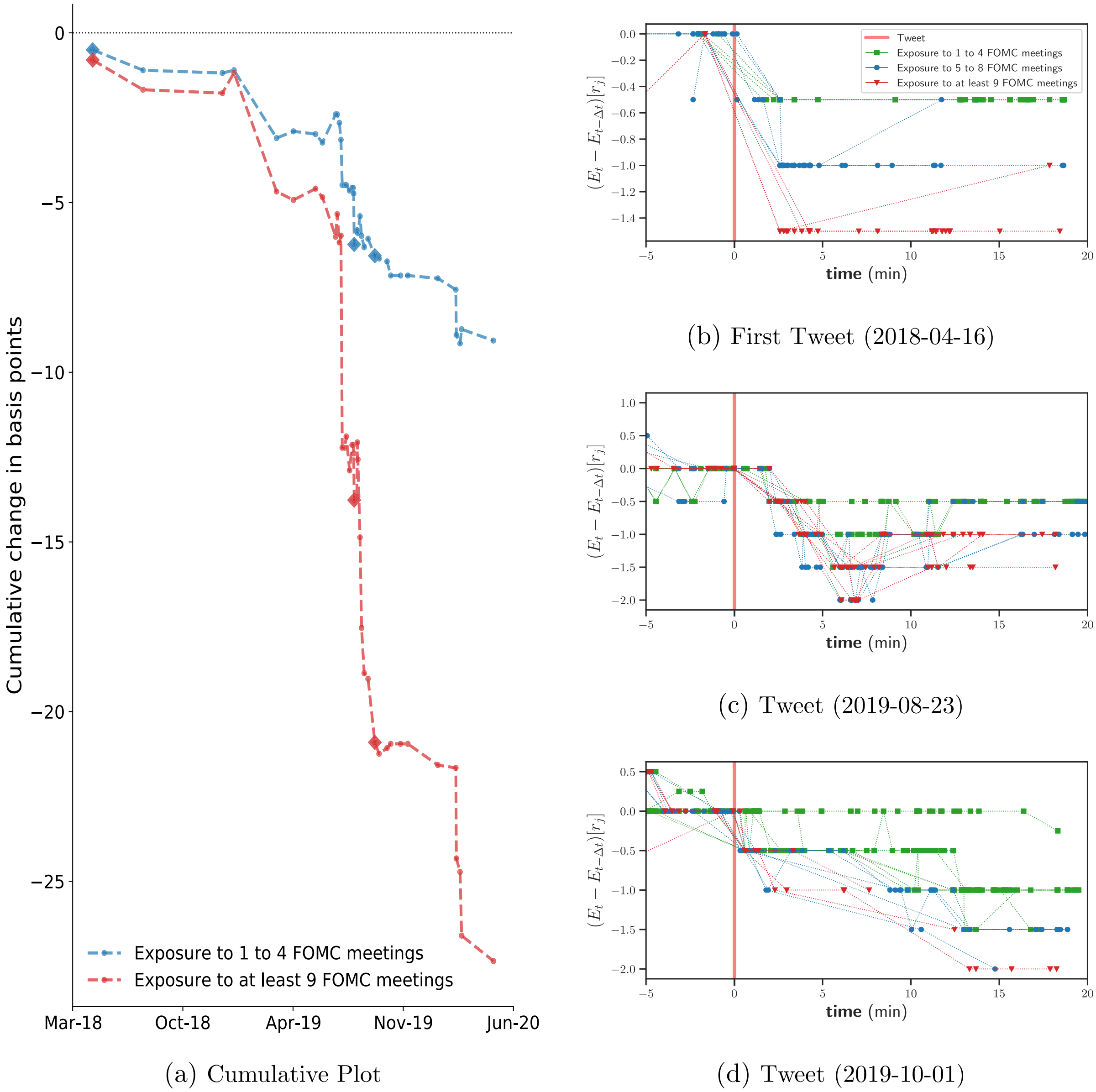

Fig. 1. Tweets and market expectations. *Notes*: Figure (a) plots the cumulative changes in the expected FFR around each tweet used in the benchmark estimation over the event window (inner (outer) window of 0.1 min (four hours) before and five minutes (two hours) after) with the units in bps. The blue 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). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

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

$$FFF_{t,i} = E_t\left[\overline{FFT}_i\right] + E_t\left[\overline{FFR}_i - \overline{FFT}_i\right] + \alpha_{t,i}. \tag{2}$$

Following the methodology of Gürkaynak et al. (2005b) and Nakamura and Steinsson (2018), the baseline results assume that the tweets do not systematically affect covariances between the pricing kernel and the fed funds rates at short horizons and the discrepancy between the effective and target rates. Under these two assumptions, the revision in expectations following a tweet can be obtained from the change in futures interest rates:

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

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 Eq. (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 min after the tweet and the rate associated with the last transaction 0.1 min before the tweet. If there are no trades 120 min before or after the tweet, we conclude that the tweet did not impact rates.[4] 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 short time window for our benchmark analysis to isolate the effects of the tweets we are interested in. President Trump can sometimes 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.[5] 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:

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

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.[6]

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 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

[4] The 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.

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

[6] Table 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.

Table 1
FFF and EDF contracts by horizon .

Panel A: FFF

		Exposure to FOMC Meetings				
	All (1)	0 (2)	1–4 (3)	5–8 (4)	9–10 (5)	11–12 (6)
Regression Const. α	−0.26	0.02	−0.16	−0.27	−0.31	−0.64
$t-stat$	[−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)	1–8 (2)	9–12 (3)	13–16 (4)	17–20 (5)	21–24 (6)
Regression Const. α	−0.23	−0.11	−0.32	−0.22	−0.21	−0.89
$t-stat$	[−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:
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 min 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).

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 Eq. (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.[7] Overall, we conclude that the evidence based on EDF 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 Fig. 1). Our cumulative effects are modest compared to the monetary

[7] All EDF contracts are exposed to at least one FOMC meeting. The reason is that the EDF contracts settle based on the three-month London interbank offered rate at expiration. It thus clearly includes the next FOMC meeting.

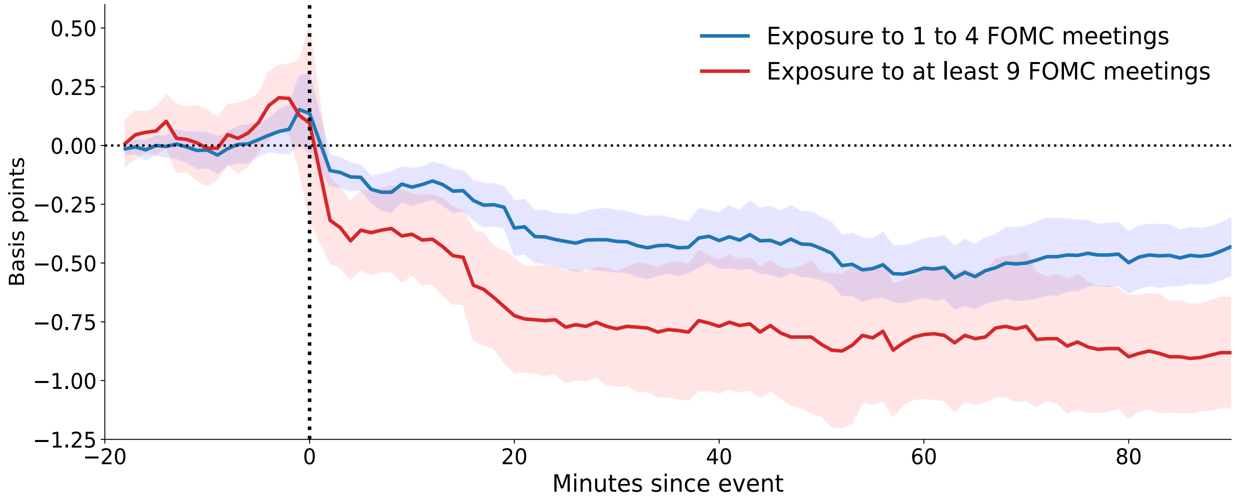

Fig. 2. Event study plot. *Notes*: This figure plots the average effect of the tweets on changes in the expected federal funds rate across contracts that are exposed to one to four FOMC meetings (blue line) and at least 9 FOMC meetings (red line). For the pre-event window, we obtain the average change 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. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

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 min preceding the Trump tweets and the 100 min 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 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 min.

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 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.[8]

[8] Figure D.3 in the Online Appendix adds up the daily effects across all of Trump tweets in our sample, which equal −64 bps and −115 bps for short and long maturity FFF contracts, respectively.

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)
Regression Const. α	−2.15	−0.01	−1.88	−2.12	−2.65	−2.86
$t-stat$	[−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)
Regression Const. α	−2.10	−1.70	−1.83	−2.89	−1.74	−2.18
$t-stat$	[−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:
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 min before the tweet and 24 h after. The outer event window is four hours before and 36 h 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).

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}:

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

where $\hat{\sigma}_k$ is the sample standard deviation of $(A_{kt} - E_{kt})$. As in Balduzzi et al. (2001) and Andersen et al. (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}.[9]

We then run the following regression:

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

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 prescheduled 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 rate expectations using our benchmark event window (Panel A) and daily event window (Panel B). The slope coefficients, $\hat{b}_j$, are negative and statistically

[9] For 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 .

Panel A: 5-min event window

		Exposure to FOMC Meetings				
	All	0	1–4	5–8	9–10	11–12
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{a}$	0.04	−0.01	0.03	0.05	0.11	0.02
	[1.32]	[−0.86]	[1.71]	[1.44]	[1.75]	[0.17]
$\hat{b}$	−0.08	0.00	−0.03	−0.09	−0.16	−0.16
	[−2.58]	[0.28]	[−2.25]	[−2.55]	[−2.37]	[−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

Panel B: Daily event window

		Exposure to FOMC Meetings				
	All	0	1–4	5–8	9–10	11–12
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{a}$	−0.10	0.02	−0.07	−0.08	−0.13	−0.43
	[−1.94]	[0.99]	[−1.11]	[−0.73]	[−0.60]	[−1.63]
$\hat{b}$	−0.25	−0.03	−0.05	−0.28	−0.35	−0.68
	[−5.19]	[−0.94]	[−1.90]	[−2.89]	[−2.70]	[−2.96]
$\hat{a}+\hat{b}$	−0.35	−0.01	−0.12	−0.36	−0.48	−1.11
Observations	4010	157	1156	1146	434	321

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: 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. Panel A uses an inner event window of 0.1 min before the tweet and five minutes after, while the outer event window is four hours before and two hours after. Panel B uses an inner event window of 0.1 min before the tweet and 24 h after, while the outer event window is four hours before and 36 h after. Our sample period starts in June 2015 and ends in December 2019.

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. The estimated effect is about six times smaller in magnitude for both event windows.

Figure 3 extends this analysis by showing the average effect of the 50 most relevant macroeconomic indicators on interest rate expectations using our benchmark event window. 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.[10] The figure plots on the y-axis the average effect 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.[11] 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.

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.

[10] On 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.

[11] Table 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.

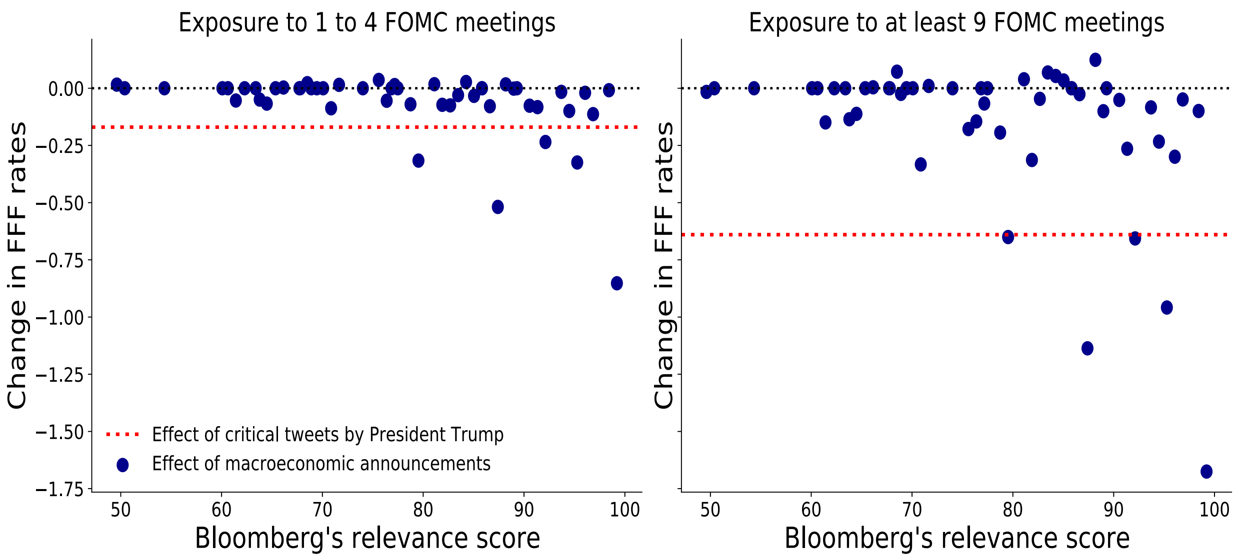

Fig. 3. Effect of macro announcements on interest rate expectations. *Notes*: This figure shows the average effect of macroeconomic news releases on interest rate expectations. For each macroeconomic indicator k, we run the following regression: $(E_t - E_{t-\Delta t})[r_j] = a_{kj} + b_{kj}S_{kt} + \varepsilon_j$, 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.

Table 4
Estimated effects of Trump tweets on bonds and stocks.

Panel A: Effects of Trump tweets on U.S. Treasury futures				
	(1) 2-Year	(2) 5-Year	(3) 10-Year	(4) 30-Year
α	−0.18	−0.07	−0.18	−0.08
	[−1.58]	[−2.74]	[−1.91]	[−4.94]
Panel B: Effects of Trump tweets criticizing QE policies on U.S. Treasury futures				
α	−0.10	−0.06	−0.16	−0.07
	[−1.36]	[−2.78]	[−1.84]	[−3.93]
β_{QE}	−0.38	−0.04	−0.57	−0.12
	[−1.07]	[−0.35]	[−1.82]	[−2.88]
Panel C: Effects of Trump tweets on stocks				
	High freq. (1)	Daily freq. (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 changes in yields of U.S Treasury futures on a constant around the tweets:
where Δy_j is the change in the log of U.S. Treasury future yields around each tweet in the event window and α_j measures it's average effect. Panel B regresses Δy_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:
In Panel A and B, the inner event window is 0.1 min 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 min window around the tweet, while the daily frequency considers a 24 h 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).

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 yield changes in the U.S. Treasury futures contract on a constant term, similar to our specification in Eq. (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.[12] We, however, convert log futures price changes into yield changes by dividing the futures returns by the negative of duration as in Cieslak and Schrimpf (2019). The daily duration data is obtained from Bloomberg. 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 1.90. 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.

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 yield 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.[13]

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).[14, 15]

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.[16] Our VAR analysis below confirms this interpretation of the results. cannot rule out that some information effect (as far as one thinks that the public updates its views about the economy based on the tweets) can be present in the estimates

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

[12] The 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.

[13] We thank the referee for this suggestion.

[14] For 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.

[15] A possible explanation for the smaller stock price responses could be attributed to institutional decay weakening the credibility of the Fed, creating greater macroeconomic uncertainty that partially offsets the expansionary effects of lower interest rate expectations.

[16] We cannot completely rule out that some information effect can be present in the estimates.

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. 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.

In the Online Appendix, we also 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.

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.

Table 5
Change in FFF pricing errors around Trump tweets .

		Exposure to FOMC Meetings				
	All	0	1–4	5–8	9–10	11–12
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: High frequency						
Regression Const. α	−1.75	0.02	−0.46	−1.85	−2.26	−6.22
t − stat	[−2.53]	[1.14]	[−0.98]	[−2.05]	[−2.22]	[−2.64]
Observations	636	30	230	234	96	46
Panel B: Daily frequency						
Regression Const. α	−18.00	0.00	−17.53	−17.22	−26.61	−22.75
t − stat	[−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:
where $\mathrm{FE}(ff)_{jt}$ denotes 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 min (four hours) before and five minutes (two hours) after). In panel B, we use the daily estimation window that goes from 0.1 min before the tweet to 24 h 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.

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

$$(E_t - E_{t-\Delta t})\left|\mathrm{FE}_{jt}\right| = a_j + \epsilon_{jt}, \tag{7}$$

where $(E_t - E_{t-\Delta t})\left|\mathrm{FE}_{jt}\right|$ 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. Column (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 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 et al. (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 that 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 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 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

[17] The 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.

[18] To obtain a monthly series of real GDP, we follow Jarociński and Karadi (2020) and interpolate real GDP and GDP deflator to a monthly frequency using the methodology described in Stock and Watson (2017). The monthly series is constructed by using a Kalman filter to distribute the quarterly GDP and GDP deflator series across months using a dataset of monthly variables that are closely related to economic activity and prices.

[19] We find this feature desirable to the extent that the FFR is under the direct control of the Federal Reserve while yields of longer maturities are affected by inflation expectations and movements in risk premia. Results based on using 1-year constant Treasury yields are qualitatively similar, but tend to be noisier.

[20] The 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.

[21] The 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.

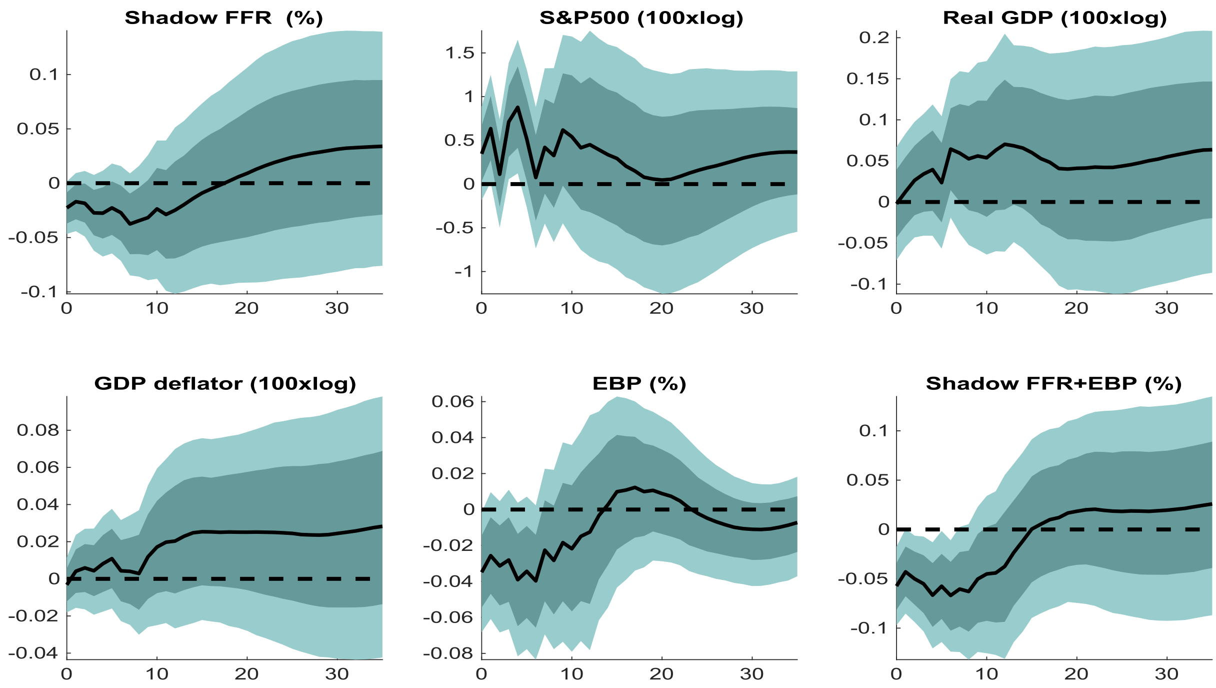

Fig. 4. VAR analysis: impulse responses to a tweet shock. *Notes*: This figure reports impulse responses to a one standard deviation tweet shock obtained using VAR analysis. The impulse responses are obtained using a Bayesian VAR estimated over the period October 2001 to February 2020.

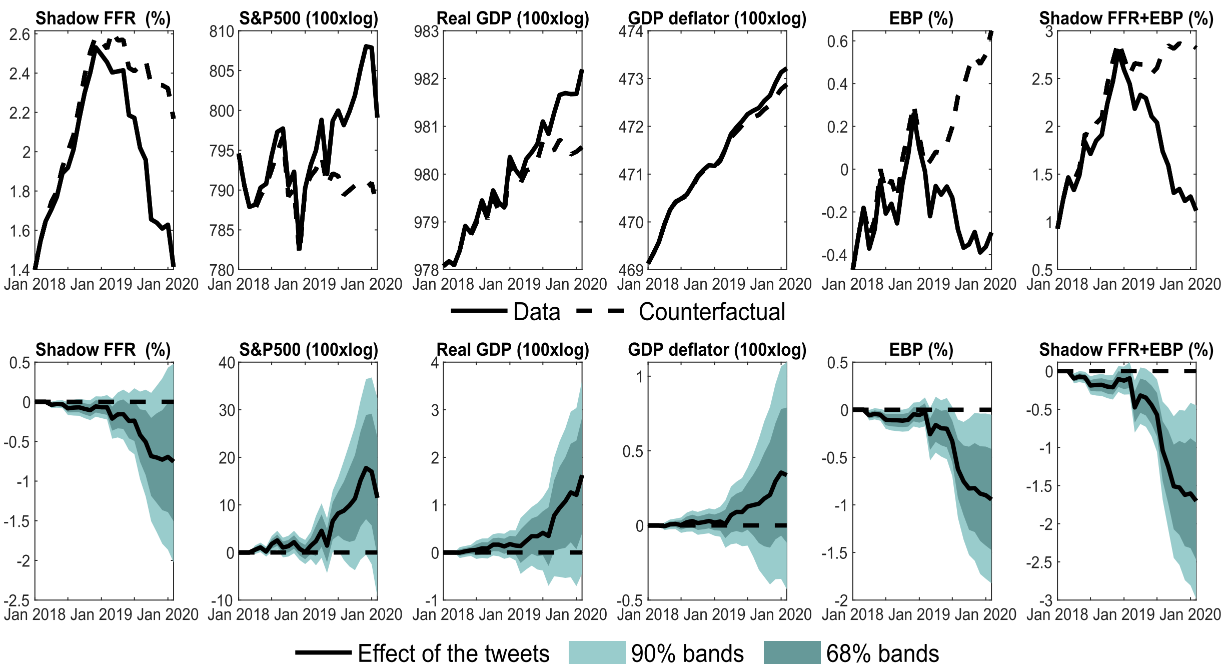

Fig. 5. VAR analysis: cumulative effect of the tweets on realized variables. *Notes*: The first row reports the realized data (black line) and a counterfactual simulation that removes all tweet shocks (black dashed line). The second row reports the differences between the realized data and a counterfactual 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 October 2001 to February 2020.

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 Fig. 5 shows the actual path and the counterfactual path, while the second row of Fig. 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 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 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.

Data Availability

Some of the data have been purchased and we cannot share them. However, we will share of the codes and publicly available data in a way that it will be possible for other to replicate our results.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jmoneco.2023.01.001.

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[22] The credible sets for the impulse responses are relatively wide for the macro variables. This should not be surprising given that we are looking at a series of events that unfolded over a short period of time (unlike when analyzing the effects of monetary policy shocks).

[23] The 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.

[24] Consistent with the stock price responses documented in Fig. 5, Bianchi et al. (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.

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