THREATS TO CENTRAL BANK INDEPENDENCE:
HIGH-FREQUENCY IDENTIFICATION WITH TWITTER

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ABSTRACT

This paper presents market-based evidence that President Trump influences expectations about monetary policy. The main estimates use tick-by-tick fed funds futures data and a large collection of Trump tweets criticizing the conduct of monetary policy. These collected tweets consistently advocate that the Fed lowers interest rates. Identification in our high-frequency event study exploits a small time window around the precise time stamp for each tweet. The average effect of these tweets on the expected fed funds rate is strongly statistically significant and negative, with an average cumulative effect of around -10 bps with a peak of -18.5 bps at the longest horizon. Therefore, we provide evidence that market participants do not perceive the Fed as a fully independent institution.

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1 Introduction

A general consensus for the effective conduct of monetary policy that emerged over the past few decades is to allow central banks to freely pursue objectives independently of political influence. Narrative accounts over the past century suggest that establishing central bank independence was pivotal for containing inflation by curbing political incentives for expansionary monetary policy. Indeed, cross-country evidence finds that a monetary authority with greater autonomy is associated with lower and more stable inflation.[1] In the 1960s and 1970s, the Johnson and Nixon administrations pressured the Federal Reserve chairman to keep interest rates low, eschewing price stability. 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.[2] 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 threaten the autonomy established in the previous decades. President Trump has been voracious in his frequent attacks on Fed policy. For instance, 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!" Figure 1 illustrates the impact of the message on the expected fed funds rate implied by futures prices in a 30-minute window. The futures contracts are stratified based on the number of FOMC announcements occurring before the corresponding expiration month. The change in expected rates is measured as percentage points of the average absolute change in expected rates following an FOMC announcement (around 2.2

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[1]Some examples include Alesina and Summers (1993) and Grilli, Masciandaro, and Tabellini (1991).
[2]Kohn (2013) discusses the erosion of confidence in the Fed in the aftermath of the financial crisis measured by public polls.

bps). The expected fed funds rate decreases noticeably across all three groups of contracts, with an increasing magnitude with respect to maturity, indicating that market participants expect that the President impacts monetary policy persistently.

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 are examined by using tick-by-tick data on fed funds futures contracts.

Our identification scheme exploits a small time window around a single second precision time-stamp on the tweets. The payoff of these futures contracts depend on the average federal funds rate 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 futures 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 run a linear regression of the expected fed funds rate, implied by the futures price, on a dummy variable indicating five seconds before and five minutes after a tweet, including a time fixed effect to control for all other factors that influence expectations about future monetary policy. For the contracts whose payoffs occur strictly after one or more future meetings, the tweets have a negative and statistically significant impact on the expected fed funds target. The average effect across all contracts is around -0.25 bps per tweet and the cumulative effect is -10 bps, which is sizable considering that the typical change in the target rate at each FOMC meeting is ± 25 bps. The expected fed funds rates at longer horizons are more negatively affected by the tweets than the shorter horizon ones, with a peak of -18.5 bps at the longest horizon. These results illustrate how markets believe that the President is influencing the conduct of monetary policy in a persistent way.

In alternative specifications, event windows ranging from 5 to 60 minutes and a different criteria for selecting tweets are considered, all yielding similar results in terms of significance and magnitude as our benchmark specification. As 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 which further support how political pressure from the President is causing changes market expectations about monetary policy.

A joint estimation is conducted in which the impact of the tweets on the term structure of expected target rates is obtained by considering a linear system of pricing equations that collectively uses information from contracts of different maturities. This estimation procedure also finds that the effect of the tweets is sizable and increases with the horizon, highlighting the persistence in the revisions of expectations. Comparing the changes in expectations at different horizons provides valuable information to discern if the tweets impact the expected timing of an anticipated monetary policy change or if they instead lead to a comprehensive revision in the expected course of monetary policy. We find evidence for the latter scenario, both in the contract-specific estimation and in the joint estimation.

We document that the tweets criticizing the Fed are not systematically related to changes in stock market valuations. An insignificant stock market response helps to assuage the potential concern that the revision in expected interest rates around the selected events arise through the dependency of the target rate on output and the stock market through the Fed reaction function, as opposed to through direct political influence. Tweets by the president that comment on trade and tariff policy have, on average, a negligible effect on expectations of the fed funds rate at all horizons, reflecting how his views on these policies vary substantially depending on the trade partner, industry, or time period. In contrast, the tweets directed at Fed policy unequivocally advocate lower interest rates, allowing for sharper identification in our main empirical analysis examining threats to central bank independence.

Overall, we find strong evidence that the consistent pressure applied by President Trump to pursue more expansionary monetary policy is manifested in market expectations of a lower target rate, implying a steady erosion in central bank independence over the course of his presidency. Our findings that market participants do not perceive the Federal Reserve as fully independent from the executive branch has indirect, but important, consequences

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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 does not directly influence Fed decisions, his political pressure can still affect policy indirectly by changing market expectations regarding the Fed.

The methodological approach of our paper relates to the literature identifying monetary policy shocks using high-frequency data (e.g., Kuttner (2001), Cochrane and Piazzesi (2002), Faust, Swanson, and Wright (2004), Gürkaynak, Sack, and Swanson (2007), and Nakamura and Steinsson (2018)) and papers studying the effect of these shocks on interest rates using a high-frequency approach (e.g., Gürkaynak, Sack, and Swanson (2005a), Gürkaynak, Sack, and Swanson (2005b), Beechey and Wright (2009), Swanson (2011), Hanson and Stein (2015), Gertler and Karadi (2015), Krishnamurthy and Vissing-Jorgensen (2011), Swanson (2017), Gilchrist, Yue, and Zakrajšek (2019)). We follow a similar methodology as these papers, but the objective of our paper is to identify violations of central bank independence. Like these papers we measure expectations of the fed funds target using high-frequency futures prices. The unique approach of our paper is to use tweets by President Trump that pressure the Fed to lower interest rates as the news component. Constructing a tight window around the precise time-stamp of each tweet, we identify the impact of the tweet on expectations of the target fed funds rate with an event study approach. In ongoing work, the effect of a broader set of Trump tweets are examined on different asset classes.

Alesina (1988), Grilli, Masciandaro, and Tabellini (1991), Cukierman, Web, and Neyapti (1992), Alesina and Summers (1993), Acemoglu, Johnson, Querubin, and Robinson (2008), and Binder (2018) 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 literature examines the impact of the degree of independence on macroeconomic outcomes. We differ from this literature in that we identify precise threats to central bank independence using high-frequency financial data and messages from the social media account of the President.

Our findings complement the literature examining the effect of informal communication of policymakers between FOMC meetings on equity markets. Lucca and Moench (2015)

document a pre-announcement drift in stock returns Cieslak, Morse, and Vissing-Jorgensen (2018) study returns over the FOMC cycle, and Ai and Bansal (2018) provide a revealed preference theory for explaining the equity premium around the announcements. The focal point of our paper is to identify particular instances of how direct pressure from the President affects expected policy decisions in future FOMC meetings.

The paper is structured as follows. Section 2 describes the data used in our analysis. Section 3 characterizes the high-frequency identification procedure and presents the baseline estimates. Section 4 presents the joint estimation results. Section 5 compares the relative importance of Fed tweets with respect to FOMC announcements and trade tweets and presents external corroborating evidence. Section 6 concludes.

2   Data Description

Our main empirical analysis uses three high-frequency data sources: Tweets by President Trump, prices on fed funds futures contracts, and prices on the S&P 500 index.

The set of tweets are collected from the personal Twitter account of President Trump (@realDonaldTrump). Each observation includes the text and the accurate to the second time-stamp. The benchmark analysis focuses on critical tweets by the President directed at the Fed that explicitly or implicitly advocate lower interest rates. To this end, the following selection criteria is implemented. First, tweets with at least one of the following keywords are selected: 'fed', 'rate', 'jerome', 'jay', 'powell'. Word extensions stemming from the keywords are also included (e.g., 'federal reserve' and 'fed chairman' are both captured by the keyword 'fed'). Second, the following filters are then applied to the selected tweets. Tweets unrelated to the conduct of monetary policy (e.g., trade, appointment of Fed board members) are eliminated. Tweets that occur after an initial tweet, release of related news articles, or interviews by the President within the narrow event window used in our event study are dropped to avoid double counting and potential contamination. Appendix A provides additional details of the tweet selection criteria.

Following the methodology of Gürkaynak, Sack, and Swanson (2005b) and Nakamura and Steinsson (2018), market expectations of the future fed funds rate are extracted using tick-

by-tick trade data of 30-day federal funds 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).

Intraday prices for the S&P 500 index ETF SPY (S&P 500 from now on) 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). Our sample period starts on the announcement day of the presidential campaign of Donald Trump (June 16, 2015) and ends on the last day for observations on futures prices are available in our dataset (November 2019).

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 at the second accurate time-stamp of each tweet and the tick-by-tick federal funds futures prices across varying maturities. Related news articles and interviews are not used in our tests given that these formats typically contain a wide range of topics that can potentially contaminate the analysis. Our selection criteria also excludes tweets for which such news arrives in the event window.

Market expectations of the fed funds rate are inferred from the traded price of the corresponding futures contracts. Fed funds futures are contracts that reflect the market opinion of what the average federal funds rate will be in the future. The price quotation for this type of contract is 100 minus the arithmetic average of the daily effective federal funds rate during the expiration month. Federal funds future contracts are financially settled on the

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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 federal funds rate is the weighted average of all transactions for a group of federal funds brokers.

The federal funds future rate associated with a contract that expires $i-$month ahead in the future can be decomposed into two components:

$$FFF_{t,i} = \mathbb{E}_t \overline{FFR}_i + \alpha_{t,i},$$

where $FFF_{t,i}$ is the $i-$month ahead futures rate at time t, $\mathbb{E}_t$ 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 funds rate due to regulation requirements.

We are interested in measuring the revision of expectations about the behavior of the Federal Reserve 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 Federal Funds rate in the final month of the futures contract:

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

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

rates:

$$\mathbb{E}_t\left[\Delta\overline{FFT}_i\right] = \Delta FFF_{t,i}. \tag{2}$$

Thus, futures rates can be used to recover changes in expectations at different horizons.

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 2 highlights how two trades are selected for measuring changes in the expected federal funds rate target. The symbols ×, ○, □ 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 two subsets, $[T_0, T_1]$ and $[T_2, T_3]$, the prices that satisfy $arg\max_t\{p_t\}_{t=T_0}^{t=T_1}$ and $arg\min_t\{p_t\}_{t=T_2}^{t=T_3}$ are selected ×. The observations obtained are the closest trades before and after the tweet occurring at time 0.

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

We chose a relatively short time window for our benchmark analysis to make sure to isolate the effects of the tweets that we are interested in. President Trump can sometimes engage in a long series of tweets related to different topics. A short time window minimizes the possibility that other tweets fall inside the window. We also considered alternative windows and found very similar and in many cases stronger results. The results are reported in Subsection 3.4 below.

3.2   Benchmark Estimates

We estimate revisions in expectations across different horizons caused by the selected tweets. The horizon is measured in terms of the number of FOMC meetings a certain contract is exposed to. Analyzing the term structure of expectations is an important dimension of

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

As the federal funds target is set on eight predetermined FOMC meetings per year, we categorize futures contracts across different maturities based on the number of FOMC meetings between the time of the tweet and the contract expiration.[3] 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 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 federal funds rate across time horizons can be obtained from contracts of varying maturities that are exposed to a different number of FOMC meetings or by pooling all contracts together in the statistical analysis.

A contract classified by exposure number j is selected to simultaneously have the shortest time to expiration and at least the corresponding number of FOMC meetings j scheduled before the beginning of the expiration month. This criterion makes sure that the shortest maturity contract that is exposed to at least j FOMC meetings is selected. Then, for each tweet and FOMC exposure, two trades are chosen to measure the change in the expected federal funds rate. The first observation is the last trade five seconds before the tweet and

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[3]The times and dates of the FOMC meetings are obtained from the Federal Reserve Board website.

the second observation is the earliest trade five minutes after the tweet. For those trades, the average distance to the pre-event window, T_1, is seven minutes. The average distance between T_2 and the post-event trade is 14 minutes. This highlights that most selected trades occur within a narrow time window, validating the high-frequency approach taken. The average number of trades in the pre-event outer window is 54 and 67 in the post-event outer window.

For each FOMC meeting exposure, the event study regresses the expected federal funds rate, implied by the futures prices, on a dummy variable indicating whether the observation is before or after a tweet, including fixed effects, according to:

$$E_{t-i\pm\Delta}[r_t] = \alpha + \beta D_\pm + \text{Fixed Effects} + \varepsilon, \tag{3}$$

where $E_{t-i\pm\Delta}[r_t]$ is the market expectation of the federal funds rate for the month when the corresponding future contract expires. The subscript $\pm\Delta$ indicates whether the observation is from the pre- or post-event outer window. For this benchmark specification, we only include time fixed effect to control for all other factors that can affect the interest rate at a particular point in time. The time fixed effect is the same right before and right after the tweet. This guarantees that the estimated coefficient β captures the marginal effect of the tweet, controlling for all other information available around the time of the tweet.

The regression results sorted by contract exposure to the number of FOMC meetings j are reported in Table 1. A column labelled j corresponds to the contract with the earliest expiration month that is fully exposed to at least j meetings at each point in time. The coefficient of interest, β, captures the average revision in expectations of the federal funds rate around each tweet for a particular horizon. The coefficient is negative for all contracts exposed to at least one meeting, with an increasing magnitude as the meeting exposure j rises. The results for the short maturity contracts exposed to only one FOMC meeting imply that the expected interest rate declines by 0.175 bps following a tweet. The change in the expected interest rate for a contract exposed to ten FOMC meetings (a contract that expires more than one year later), declines by 0.578 bps. For seven out of ten contracts, the coefficients are statistically different from zero at the 5% level. Excluding zero maturity

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contract, every coefficient is statistically different from zero at the 10% level, and three of them are statistically different from zero at the 1% level. Contracts that expire before the next FOMC meeting provide a useful control group for potential microstructure and liquidity effects that are potentially correlated with the tweets. The estimated coefficient for the zero exposure contract is not statistically different from zero, ruling out potential microstructure effects driving our main results. Overall, these estimates across contract categories provide strong evidence that our selected tweets by President Trump influence market expectations about the future path of interest rates.

To interpret the economic magnitude of these effects, note that the typical change in the fed funds target is ± 25 bps. Consider an example with two possible scenarios: The rates will remain unchanged or they will be cut by 25 bps. Then, a decline of 0.578 bps corresponds to a 2.3% increase in the probability of a 25 bps target cut, which is a relevant change in the probability assigned to an expansionary monetary policy change. Furthermore, the reported coefficient is the average effect of each tweet. The average cumulative effect is around -10 bps, with a peak of -18.5 bps at the longest horizon (i.e., contracts exposed to 10 meetings). We will return to the issue of the relative magnitude of these effects in Section 5.

In Table 2, we extend the analysis pooling all contracts together and studying the effects on the stock market. Panel A of Table 2 reports the estimates of the average change in expectations of the fed funds rate pooling across all ten contracts with a nonzero meeting exposure at each point in time. The event study regresses the expected federal funds rate across different horizons on a dummy variable indicating if the observation is before or after a tweet:

$$E_{t-i\pm\Delta}[r_t] = \alpha + \beta D_\pm + \text{Fixed Effects} + \varepsilon \tag{4}$$

$E_{t-i\pm\Delta}[r_t]$ is the market expectation of the federal funds rate for the month when the corresponding future contract expires and the subscript $\pm\Delta$ denotes whether the observation is from the pre- or post-event outer window. Fixed effects control for the event time and the contracts across varying meeting exposures. We find that the average effect is negative and highly statistically significant in the pooled estimation. The cumulative average effect

implied by the pooling regression is around -10 bps, consistent with the contract-specific regressions.

Panel B of Table 2 contains the estimates of the average effect of the tweets on the stock market using intraday transaction price data for the S&P 500 index. Similar to Panel A, the regression projects the log index price on a dummy variable which indicates whether the observation is before or after a tweet. The regression using extended trading hours include tweets between 4:00 am and 8:00 pm Eastern Standard Time (EST). The second specification only considers tweets during trading hours between 9:30 am and 4 pm EST. In both specifications, the average stock price reactions to the tweets are not statistically significant, which contrasts with the significant negative interest rate reactions reported in Panel A (and by contract meeting exposure in Table 1).

Panel C of Table 2 reports the correlations between the change in the stock price and the change in expected federal funds rate in the event window around the selected tweets. This is obtained by regressing the change in the expected fed funds rate on the change in the stock market. For each contract meeting exposure, the correlation is close to zero and not statistically significant. An insignificant stock market reaction that is also uncorrelated with the change in expected fed funds rates around the selected events 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 rates attributed directly to political pressure.

3.3   Economic Interpretation

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

Suppose that right before the tweet markets expect that the Fed will cut rates in six

months, but not in the near future. If a tweet only induces a change in expectations about the timing of the already anticipated interest rate cut, a revision in expectations would be observed at only short horizons. Panel A of Figure 3 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. Panel B of Figure 3 provides a depiction of this alternative example. As in the previous case from Panel A, before the tweet, markets expect that the Fed will cut interest rates in six months. However, now the tweet generates a decline in expectations both at short and long horizons, implying that the tweet does not merely change the timing of an already anticipated decline.

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. It is beyond the scope of this paper to test the veracity of these beliefs. The objective of our empirical exercise is to use a high-frequency identification strategy with a short time window around the tweets to control for the many factors that can cause changes in expectations about the conduct of monetary policy. Testing if the Fed *actually* succumbed to the requests of the President is a substantially more challenging task in light of the multitude of factors that the central bank analyzes prior to setting policy.

The fact that market participants may not perceive the Fed as autonomous from the executive branch can nevertheless influence Fed actions. Faust (2016) and Vissing-Jorgensen (2019) show that the Federal Reserve pays close attention to market expectations about its own actions. FOMC members often discuss the importance of not deviating from such expectations. Indeed, one of the cited reasons behind the interest rate cut in July was that markets were anticipating a cut, and not following through would effectively be a stance of contractionary monetary policy (Timiraos (2019)). Therefore, even if the Trump 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. Vissing-Jorgensen (2019) argues that FOMC members have an interest in moving market expectations to gain

the upper hand in internal policy meetings and the tweets from the President might have a similar effect.

3.4 Robustness

This section illustrates the robustness of our main results to alternative specifications. Table 3 presents estimates using different event windows (i.e., varying the inner window, $[T_1, T_2]$, defined in Section 3.1) for the regressions of each contract meeting exposure in Equation 3. Panels A to F report the estimates from windows where the pre-event window ranges from 0.1 minutes to 10 minutes before and the post-event window varies between 5 minutes to 60 minutes after. Like the benchmark, in all of the alternative specifications we find negative and statistically significant estimates for the majority of the slope coefficients across contract meeting exposures, with an increasing pattern across horizon.

We also consider a less stringent tweet selection relative to the benchmark case. For example, under the alternative selection criteria, tweets that do not directly criticize the conduct of monetary policy, but are indirectly related are included. Appendix A contains a detailed description of the selection criteria for both the benchmark and the alternative case. Table 4 reports estimates of Equation 3 for each contract meeting exposure with the benchmark event window but under the alternative tweet selection criteria. The slope coefficients are also negative and most are statistically significant with a generally increasing magnitude across horizon, similar to the benchmark case.

Finally, Table 5 considers a placebo test where 100 randomly selected tweets in the same sample period but excluding tweets that are selected under the benchmark and alternative criteria are used to estimate Equation 3. We repeat the random selection 100 times and report the average of the 100 estimation results. We find that the slope coefficients across contract meeting exposure 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.

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4 Joint Estimation

Section 3.1 estimates a term structure of expectations at each horizon *individually* by using futures contracts sorted on the number of FOMC meetings affecting the payoff of a contract. For each tweet, we estimate the revision in the expected fed funds rate for a particular contract whose payoff is fully exposed to a certain number of FOMC meetings. In this section, we estimate the revision in expectations by considering the price movements of all contracts *jointly*. The revision in expectations implied by a contract that is exposed to four FOMC meetings is not independent of the revision of expectations implied by a contract that is exposed to only three FOMC meetings. Thus, we can extract more information about the change in expectations by analyzing all price movements collectively. This joint estimation procedure also allows us to infer the shadow price of contracts for which a price movement is not observed because the change in expectations for a certain month can be inferred by the movement in the prices of contracts with contiguous maturities.

4.1 Methodology

Contracts with different maturities provide evidence on the term structure of expectations. The joint estimation needs to account for the number of scheduled FOMC meetings, before and within the settlement month, but also for the relation between prices of contracts with different maturities. Following the decomposition in Section 3.1, the fed funds future rate is expressed as:

$$FFF_{t,i} = \mathbb{E}_t \left[\overline{FFT}_i \right] + \mathbb{E}_t \left[\overline{FFR}_i - \overline{FFT}_i \right] + \alpha_i,$$

where i is the month of interest. Importantly, we use $i = 0$ to denote the current month, $i = 1$ to denote the next month, and so on. There are four distinct cases to consider which depend on the time between the tweet occurring at time t and the next FOMC meeting.

1. Time t is included in month i and no FOMC meeting occurs during month i or the FOMC meeting for month i already occurred when the tweet was observed. This case

is possible only if $i = 0$. Thus, we have:

$$FFF_{t,0} = \frac{d_t}{m_0}\overline{FFR}_{0,t-} + \frac{m_0 - d_t}{m_0}\mathbb{E}_t\left[\overline{FFR}_{0,t+}\right] + \alpha_0,$$

where d_t marks the day and time of the tweet, m_0 is the number of days in month 0, $\overline{FFR}_{0,t-}$ is the realized average FFR for the days before the tweet, and $\mathbb{E}_t\left[\overline{FFR}_{0,t+}\right]$ is the expected average fed funds rate over the remaining part of the month. Given that the realized average rate up to time t cannot change in response to the tweet, the term $\overline{FFR}_{0,t-}$ cancels out when taking the difference.

2. Time t is included in month i and the FOMC meeting occurs during month i. This case is possible only if $i = 0$. Thus, we have:

$$FFF_{t,0} = \frac{d_t}{m_0}\overline{FFR}_{0,t-} + \frac{d_0 - d_t}{m_0}\mathbb{E}_t\left[\overline{FFR}_{0,t+}\right] + \frac{m_0 - d_0}{m_0}\mathbb{E}_t\left[\overline{FFR}_0'\right] + \alpha_0,$$

where d_0 marks the day of the FOMC meeting scheduled to occur in the current month, $\mathbb{E}_t\left[\overline{FFR}_{0,t+}\right]$ is the expected average FFR over the remaining part of the month but before the FOMC meeting scheduled for that month, and $\mathbb{E}_t\left[\overline{FFR}_0'\right]$ is the expected average FFR over the period between the FOMC meeting scheduled for the month and the end of the month.

3. Time t is not included in month i and no FOMC meeting occurs during month i:

$$FFF_{t,i} = \mathbb{E}_t\left[\overline{FFR}_i\right] + \alpha_i,$$

where $\mathbb{E}_t\left[\overline{FFR}_i\right]$ is the expected average effective federal funds rate over month i formed at time t.

4. Time t is not included in month i and month i includes an FOMC meeting:

$$FFF_{t,i} = \frac{d_i}{m_i}\mathbb{E}_t\left[\overline{FFR}_i\right] + \frac{m_i - d_i}{m_i}\mathbb{E}_t\left[\overline{FFR}_i'\right] + \alpha_i,$$

where $\mathbb{E}_t\left[\overline{FFR}_i\right]$ is the expected average effective federal funds rate in month i for the

period before the FOMC meeting, d_i is the day in month i during which the FOMC meeting is scheduled, m_i is the number of days in month i, and $\mathbb{E}_t\left[\overline{FFR}'_i\right]$ is the expected average effective federal funds rate in month i for the period between the FOMC meeting and the end of the month.

As in the individual contract regressions from Section 1, the identifying assumption is that the term α_i and the difference between the effective federal funds rate and the target rate are not affected by the tweet. Under this assumption, we can then take the difference of the federal funds rate immediately before and after the tweet to derive the implied change in expectations. The four cases described above lead to the following four conditions that can be used to infer the change in expectations at different horizons:

1. Time t is included in month i and no FOMC meeting occurs during month i or the FOMC meeting for month i had already occurred when the tweet was released:

$$\Delta FFF_{t,0} = 0.$$

   This condition implies that we should not observe a price jump for the contract that expires in the current month if in the month of the tweet there is not an FOMC meeting scheduled to occur after the tweet. We saw in Table 1 that this result holds in the data: The tweets do not move the price of the contracts that are not exposed to any FOMC meeting.

2. Time t is included in month i and the FOMC meeting occurs during month i:

$$\Delta FFF_{t,0} = \frac{m_0 - d_0}{m_0}\mathbb{E}_t\left[\Delta\overline{FFT}'_0\right].$$

   This condition implies that if a tweet occurs in a month in which an FOMC meeting is scheduled to occur after the tweet, we can use the change in the federal funds rate for the a contract that expires in the current month to derive what markets expect will occur in the FOMC meeting.

3. Time t is not included in month i and no FOMC meeting occurs during month i:

$$\Delta FFF_{t,i} = \mathbb{E}_t \left[\Delta \overline{FFT}_i \right].$$

In this case, given that there is no FOMC meeting in month i, any revision in expectations is necessarily driven by a change in the target FFT implemented in the previous month. Therefore,

$$\Delta FFF_{t,i} = \mathbb{E}_t \left[\Delta \overline{FFT}'_{i-1} \right],$$

where $\mathbb{E}_t \left[\Delta \overline{FFT}'_{i-1} \right]$ is the change in the expected average FFT following the FOMC meeting of the previous month, $i - 1$ (there are not two months in a row without a FOMC meeting).

4. Time t is not included in month i and the FOMC meeting occurs during month i:

$$\Delta FFF_{t,i} = \frac{d_i}{m_i} \mathbb{E}_t \left[\Delta \overline{FFT}_i \right] + \frac{m_i - d_i}{m_i} \mathbb{E}_t \left[\Delta \overline{FFT}'_i \right].$$

Because of cases 1 and 2, if month i is the first month with an FOMC meeting since the tweet, the equation above simplifies to:

$$\Delta FFF_{t,i} = \frac{m_i - d_i}{m_i} \mathbb{E}_t \left[\Delta \overline{FFT}'_i \right].$$

Instead, if the most recent FOMC meeting was k months ago, the equation becomes

$$\Delta FFF_{t,i} = \frac{d_i}{m_i} \mathbb{E}_t \left[\Delta \overline{FFT}'_{i-k} \right] + \frac{m_i - d_i}{m_i} \mathbb{E}_t \left[\Delta \overline{FFT}'_i \right].$$

Therefore, the four set of equilibrium conditions can all be expressed in terms of expectations about policy decisions that will be taken in future FOMC meetings. The four sets of conditions above can then be combined in a system of equations and used to derive changes in expectations at horizons corresponding to the scheduled FOMC meetings:

$$\mathbf{\Delta FFF}_t = \mathbf{M} * \mathbf{E}_t \left[\mathbf{\Delta \overline{FFT}'} \right] \tag{5}$$

where $\mathbf{\Delta FFF}_t$ is a $(m \times 1)$ vector of changes in federal funds futures rates, $\mathbf{E}_t \left[\mathbf{\Delta} \overline{FFT}' \right]$ is a vector with $(f \times 1)$ vector with revisions in expectations, $\mathbf{M}$ is a $(m \times f)$ matrix mapping beliefs about changes in the FFT into federal funds futures rates, m is the number of federal funds futures contracts, and f is the number of FOMC meetings. In general, there are more conditions than unknowns $(m > f)$ because there are only eight FOMC meetings in one year, while there are contracts for each month. The equilibrium conditions generally do not exactly hold in the data for at least two reasons. First, the price of the future contracts can only move in discrete steps (multiples of .5 bps, .25 bps for the nearest expiring contract month), which cannot perfectly accommodate small variations in expectations. Second, the contracts might not be all traded at exactly the same time in response to a tweet. Thus, the prices might reflect small fluctuations in beliefs about the impact of the tweet between trades.

To accommodate the fact that the equilibrium relations do not hold exactly, we allow for observation error. Specifically, we first compute the residuals of the equilibrium relations described above by taking the difference between the left and right hand sides of equation 5. If the equilibrium relations held exactly, the residuals would be zero. We then compute the sum of squared residuals and find the vector of revisions in expectations $\mathbf{E}_t \left[\mathbf{\Delta} \overline{FFT}' \right]$ that minimize the sum of squared residuals. Using a generalized inverse to solve for the vector $\mathbf{E}_t \left[\mathbf{\Delta} \overline{FFT}' \right]$ delivers the same results for the cases considered in this paper.

Instances in which some contracts are not traded around a particular tweet are treated as missing observations. The only exception to this rule applies to the contracts that are not exposed to any FOMC meeting. This occurs when the President tweets during a month in which there is no FOMC meeting or if he tweets after the meeting. In this case, it is fair to assume that the absence of any trade for a contract that is not exposed to any FOMC meeting reflects the fact that for this particular contract nothing has really changed, given that the tweet cannot affect the contract. In this case, we treat the missing observation as evidence that the price of the contract has not changed setting the change in the FFF rate to zero. We also tried treating these observations as missing values with similar results.

4.2 Simple Example

For illustration, consider the example outlined in Figure 4. A tweet occurs at time t in March. The first subsequent FOMC meetings are scheduled for March, after the tweet, and May. No FOMC meeting is scheduled to occur for April and June. Thus, the four corresponding equations are:

$$
\begin{aligned}
\Delta FFF_{t,0} &= \frac{d_0 - d_t}{m_0} \mathbb{E}_t\left[\Delta\overline{FFT}_0\right] + \frac{m_0 - d_0}{m_0} \mathbb{E}_t\left[\Delta\overline{FFT}'_0\right] = \frac{m_0 - d_0}{m_0} \mathbb{E}_t\left[\Delta\overline{FFT}'_0\right], \\
\Delta FFF_{t,1} &= \mathbb{E}_t\left[\Delta\overline{FFT}_1\right] = \mathbb{E}_t\left[\Delta\overline{FFT}'_0\right], \\
\Delta FFF_{t,2} &= \frac{d_2}{m_2} \mathbb{E}_t\left[\Delta\overline{FFT}_2\right] + \frac{m_2 - d_2}{m_2} \mathbb{E}_t\left[\Delta\overline{FFT}'_2\right] \\
&= \frac{d_2}{m_2} \mathbb{E}_t\left[\Delta\overline{FFT}'_0\right] + \frac{m_2 - d_2}{m_2} \mathbb{E}_t\left[\Delta\overline{FFT}'_2\right], \\
\Delta FFF_{t,3} &= \frac{d_3}{m3} \mathbb{E}_t\left[\Delta\overline{FFT}_3\right] + \frac{m_3 - d_3}{m_3} \mathbb{E}_t\left[\Delta\overline{FFT}'_3\right] = \mathbb{E}_t\left[\Delta\overline{FFT}_3\right] = \mathbb{E}_t\left[\Delta\overline{FFT}'_2\right].
\end{aligned}
$$

where in the first row we used the fact that $\mathbb{E}_t\left[\Delta\overline{FFT}_0\right] = 0$. Using matrix notation, we have:

$$
\begin{bmatrix} \Delta FFF_{t,0} \\ \Delta FFF_{t,1} \\ \Delta FFF_{t,2} \\ \Delta FFF_{t,3} \end{bmatrix} = \begin{bmatrix} \frac{m_0 - d_0}{m_0} & 0 \\ 1 & 0 \\ \frac{d_2}{m_2} & \frac{m_2 - d_2}{m_2} \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \mathbb{E}_t\left[\Delta\overline{FFT}'_0\right] \\ \mathbb{E}_t\left[\Delta\overline{FFT}'_2\right] \end{bmatrix}.
$$

This system of equations can be solved using a generalized inverse of the matrix or by defining the sum of squared residuals of the equilibrium conditions. The two approaches deliver the same result for the cases considered in this paper. In this example, four equations are used to derive $\mathbb{E}_t\left[\Delta\overline{FFT}'_0\right]$ and $\mathbb{E}_t\left[\Delta\overline{FFT}'_2\right]$. The terms corresponding to $i = 1, 3$ can then be obtained by using the zero restrictions that imply that expectations can change only at horizons corresponding to FOMC meetings: $\mathbb{E}_t\left[\Delta\overline{FFT}'_0\right] = \mathbb{E}_t\left[\Delta\overline{FFT}'_1\right]$ and $\mathbb{E}_t\left[\Delta\overline{FFT}'_2\right] = \mathbb{E}_t\left[\Delta\overline{FFT}'_3\right]$. A similar logic holds for longer horizons and different assumptions about the timing of the tweet and of the FOMC meetings.

4.3 Estimation Results

We conduct two exercises in this section. The first one is similar to our benchmark regression of Section 3.2. We ask how large the revision of expectations at different horizons is based on the number of FOMC meetings that have already occurred. The difference with respect to the analysis conducted in Section 3.2 is that now the revision in expectations takes into account all contracts jointly, as opposed to focusing individually on the contracts that were exposed to a certain number of FOMC meetings. Table 6 reports results based on this approach for both the benchmark time window and for the alternative time windows considered in Section 3.4.[4] The results confirm our findings from Table 1: We find strong evidence that the tweets criticizing the Fed lower market expectations about the future fed funds rate. The average effect across horizons is around $-.21$ basis points and the magnitude grows with the time horizon. All coefficients except for one are statistically significant. The alternative time windows are consistent with these estimates. In fact, the effect increases with respect to the event window, suggesting that our benchmark time window delivers conservative estimates.

The joint estimation gives us the jumps in expectations that coincide with the scheduled FOMC meetings. We can then directly analyze the revision in expectations associated with the different FOMC meetings. Expectations measured by our sample of futures contracts should only change at the horizons that correspond to an FOMC meeting because this is when the target can be changed. For example, in the simple scenario discussed above, we are interested in the revision of expectations associated with the first (March) and the second (May) FOMC meeting after the tweet, $\mathbb{E}_t\left[\Delta\overline{FFT}'_0\right]$ and $\mathbb{E}_t\left[\Delta\overline{FFT}'_2\right]$. Thus, we can ask what is the expected jump in correspondence of a particular FOMC meeting, as opposed to the jump in expectations implied by a contract that is fully exposed to a certain number of FOMC meeting.

The results are reported in Table 7. This alternative approach also provides strong evidence that the tweets affect market expectations of the fed funds rate, with an average effect of -0.21 basis points. All coefficients are statistically significant and longer horizons are associated with larger effects, in line with our benchmark estimates from Table 1. The

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[4]The results are based on exposure to up to eight FOMC meetings because the joint estimation requires a terminal condition given by a month without any FOMC meeting.

alternative event windows confirm these results. As the event window increases, the effects are generally larger at all horizons and the increasing pattern in slope coefficients with respect to horizon gets stronger. A wider event window with more trades occurring makes it more likely that the theoretical restrictions linking different maturities are satisfied. Thus, our benchmark results based on the narrower event window can be considered a conservative estimate of the effects of the tweets.

5   Additional Analysis

This section presents additional evidence highlighting the importance of tweets by the President criticizing the Fed. We first compare the effect of our selected tweets in which the President criticize monetary policy to his tweets targeted at trade and tariffs, two other important economic policies that he has frequently commented on. We then present some external validation of our results.

5.1   Fed Tweets and Trade-Tariff Tweets

Trade and tariff tweets by the President are selected using the following criteria. First, we search for tweets containing either a word stemming from set $A = \{$trade, tariff, export, import$\}$ or tweets than contain at least one word stemming from set $B_1 = \{$china, mexico, canada, japan, germany$\}$ and $B_2 = \{$deal, buy, purchase, farmer, industry$\}$. Second, we refine the search by dropping all tweets that are not directly related to the subject of trade and tariff policy and those that coincide with other tweets within the event window. The remaining tweets are classified into three categories: Positive (e.g., the announcement of a new trade agreement), negative (e.g., criticizing a trading partner or threatening tariffs), or ambiguous (i.e., does not fit clearly into positive or negative categories).

The positive and negative tweets do not necessarily need to correspond to actual changes in trade or tariff policy. For example, a tweet is classified as negative even if it simply criticizes the trade situation because it sends a negative signal to markets about the resolution of trade disputes. Analogously, a tweet that mentions a positive meeting with a foreign leader about trade is classified as positive. Our classification here is similar to our tweet selection criteria

in the benchmark analysis, in which all tweets contain criticism of policy, but not necessarily correspond to explicit policy changes. In contrast to the multifaceted nature of the trade and tariff tweets, the tweets directed at the Fed unequivocally advocate expansionary monetary policy in our sample period.

We compare the relative importance of tweets criticizing the Fed in Table 8 by reporting the mean and standard deviation of changes in the fed funds rate in response to FOMC announcements (Panel A), the critical tweets about the Federal Reserve (Panel B), and the tweets on trade and tariffs (Panel C) in the benchmark event window. Changes in the fed funds futures rate are computed as the average difference in the fed funds futures rates across all horizons. For the trade and tariffs tweets, the statistics are reported for all related tweets, positive tweets, and negative tweets. The sample size for the FFF rates reflect the fact that we have multiple horizons for each tweet.

The mean change in the fed funds futures rate around the Fed tweets is approximately half of mean change around the FOMC announcements, highlighting the sizable effect of the Fed tweets on market expectations regarding the conduct of monetary policy. Conversely, the magnitude of the changes around the trade and tariffs tweets is quite small, even when these tweets are separated into positive and negative news. The positive and negative trade and tariff tweets are associated with opposite movements in the fed funds rate, contributing to a noticeably smaller average change when both categories are pooled together. Significant heterogeneity in the trade and tariff tweets often involving multiple dimensions besides only interest rate policy weakens the average effect on market expectations of fed policy. In contrast, the unified nature of the Fed tweets concentrated on lower interest rates yields stronger effects on expected target rates.

Table 9 reports the impact of trade and tariff tweets based on the pooled regression specification given in Equation 4 and the benchmark event window. Panel A reports the average effect of the tweets on the expected funds rate. When all trade and tariff tweets are used, the effect is positive but not statistically significant, reflecting how the trade and tariff tweets can contain both positive or negative news, depending on the trade partner, industry, or time period. In contrast, the stance of the President on monetary policy unequivocally advocates lower interest rates, allowing for sharper identification and strong statistical sig-

nificance in our benchmark analysis that focuses on his critical tweets of Fed policy. When only positive trade and tariff news is considered, we find a positive and statistically significant effect on the expected federal funds rate, but a negative and insignificant effect when only negative news is considered. These patterns are mirrored in the stock market, where statistically significant responses are only observed for positive trade and tariff news that raise stock market valuations. We interpret the dichotomy in the statistical significance of the effects between positive and negative trade and tariff news is that President Trump uses twitter very often to complain about other countries, but comments less frequently to convey news about new tariffs. As a consequence, many negative tweets do not contain additional informational content, lowering the significance of the average effect.

In Panel C of Table 9, we inspect the relation between changes in the expected fed funds rate and changes in the stock market. We adopt the same approach used for the tweets criticizing the Fed (Panel C of Table 2). For each tweet, we compute the revision in the expected fed funds rate and the change in the stock market. We then run a regression of the changes in the expected fed funds rate on the changes in the stock market. As in our benchmark analysis, we look at the behavior of expectations at different horizons by grouping contracts based on the exposure to FOMC meetings. The change in prices of futures contracts with zero exposure to FOMC meetings are not significantly correlated with changes in stock market movement around trade and tariff tweets. Instead, the correlation is positive and statistically significant for all exposed contracts with the effect intensifying with respect to the time horizon.

The correlation patterns around trade and tariff tweets are consistent with a narrative in which such tweets move expectations about the fed funds rate through the dependency of interest rates to the macroeconomic outlook (and the stock market itself) through the reaction function. Tweets about trade translate into news about future real activity, encoded in stock market valuations. Revisions in expected future growth prospects, reflected in changes in stock market prices, lead to changes in expectations about future monetary policy. Conversely, recall that the correlation between changes in the expected fed fund rate and changes in the stock market around Fed tweets are not statistically significant (reported in Table 2), suggesting that the trade and tariff tweets work through different economic

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channels than the Fed tweets.

5.2   Corroborating Evidence

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

On June 18th, 2019, Bloomberg posted an article describing how President Trump had asked lawyers at the White House about the possibility of removing Powell. The 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 5 shows the response of expected interest rates at different horizons to this news. The change is reported as a percentage of the average absolute change in federal fund futures following FOMC meetings announcement since June 2015 (around 2.2 bps). A decline in interest rates is observed across all maturities, with a more pronounced effect at longer maturities. At long horizons, the change in expectations is even larger than the typical response to FOMC announcements.

The observation that longer maturity futures contracts are more affected than shorter maturity ones is consistent with the fact that regardless of the legal feasibility of replacing the 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.

Figure 6 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 as explained above 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 fed funds futures. 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 that the President is looking into the legal aspects of firing Powell (June 18th, 2019) 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.[5] The price has naturally been trending down as the end of 2019 approaches given that the bet only pertains to the removal of Powell in 2019.

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 – 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, President 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

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

cover the period between August 10, 2011 - August 7, 2012, when economic conditions were arguably substantially weaker than in 2018-2019. For example, the unemployment rate was 9% in August 2011, when he was advocating for tighter monetary policy, while it was 3.9% in April 2018, when he started tweeting that the Fed should keep rates low (Data from FRED II, BLS). 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 views 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.

6 Conclusion

This paper presents novel market-based evidence that President Trump impacts expected monetary policy. Our high-frequency identification approach relies on a large collection of unique tweets from the President criticizing the conduct of monetary policy in conjunction with tick-by-tick fed funds futures prices over the past two years. The collected tweets ardently pressure the fed to lower interest rates. High-frequency changes in expectations of the fed funds target across horizons are extracted from the futures prices of different maturities. An event study is conducted by constructing a small time window around the precise at the second timestamps of each tweet to assess the reaction of the expected fed funds target before and after each tweet. The cumulative effect of the collected tweets implied by our estimation is around -10 bps since his first tweet attacking the Fed in April 2018. The effect grows over the time horizon, with a peak of -18.5 bps at the longest horizon. Our

findings suggest that market participants believe in the possibility of an erosion in central bank independence due to persistent political pressure.

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Table 1: Regressions Sorted on Contract Meeting Exposure

This event study regresses the expected federal funds rate, implied by the futures prices, on a dummy variable indicating whether the observation is before or after a tweet by President Trump which criticizes the Federal Reserve. The table reports the average change in the expected federal funds rate across time horizons implied by contracts of varying maturities. For each tweet and FOMC exposure, two trades of the same contract are chosen to measure the change in the expected federal funds rate around each tweet. The selected contract for the exposure to j FOMC meetings has the shortest time to expiration and simultaneously at least j FOMC meetings before the month of expiration. The regression specification reads

$$E_{t-i\pm\Delta}[r_t] = \alpha + \beta D_{\pm} + \text{Fixed Effects} + \varepsilon,$$

where $E_{t-i\pm\Delta}[r_t]$ is the market expectation of the federal funds rate for the month when the corresponding future contract expires. The rate is measured in basis points. The subscript $\pm\Delta$ indicates whether the observation is from the pre or post-event outer window. β captures the average revision in expectations of the federal funds rate around each tweet.

Variable						Exposure to FOMC Meetings					
	0	1	2	3	4	5	6	7	8	9	10
Panel A: Regression Coefficients											
Intercept α	212.9***	193.9***	183.7***	173.6***	166.7***	161.8***	158.3***	154.6***	151.7***	148.2***	151.9***
std. err.	2.94	3.61	4.43	5.44	6.19	6.70	7.18	7.67	8.22	8.51	10.25
t-stat.	72.33	53.74	41.47	31.93	26.92	24.15	22.04	20.17	18.46	17.42	14.81
Dummy Coef. β	0.012	−0.175***	−0.163**	−0.163*	−0.225***	−0.187**	−0.250**	−0.200**	−0.333***	−0.321*	−0.578*
std. err.	0.024	0.061	0.072	0.088	0.095	0.087	0.109	0.099	0.133	0.168	0.319
t-stat.	0.53	−2.88	−2.24	−1.84	−2.38	−2.15	−2.30	−2.01	−2.51	−1.91	−1.81
Panel B: Regression Properties											
N	40	40	40	40	40	40	40	40	39	39	32
T_0 [min]	240	240	240	240	240	240	240	240	240	240	240
T_1 [min]	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
T_2 [min]	5	5	5	5	5	5	5	5	5	5	5
T_3 [min]	120	120	120	120	120	120	120	120	120	120	120

Table 2: Regressions Pooling Contracts and the Stock Market

This table reports the impact of tweets threatening central bank independence on the expected federal funds rate and the stock market. Panel A estimates the average change in expectations of the federal funds rate pooling across ten contracts with a nonzero meeting exposure at each point in time. The event study regresses the expected federal funds rate across different maturities, implied by the futures prices, on a dummy variable indicating whether the observation is before or after a tweet

$$E_{t-i\pm\Delta}[r_t] = \alpha + \beta D_\pm + \text{Fixed Effects} + \varepsilon$$

$E_{t-i\pm\Delta}[r_t]$ is the market expectation of the federal funds rate for the month when the corresponding future contract expires. The rate is measured in basis points. The subscript $\pm\Delta$ denotes whether the observation is from the pre or post-event outer window. Fixed effects control for the event time and contracts across different expiration months.

Panel B estimates the average effect on the stock market. Similar to Panel A, the regression projects the variable log-S&P 500 on a dummy variable which indicates whether the observation is before or after a tweet. The regression using extended trading hours include tweets between 4:00 a.m. and 8:00 p.m. ET. The regression without pre-market and after-hours trading includes tweets between 9:30 a.m. and 4 p.m. ET.

Panel C investigates the correlation between changes in log-S&P 500 and changes in the expectations of the Federal Funds Rate in the event window around the selected tweets. For each FOMC exposure, changes in the expected FFR from the respective contract are regressed on a constant and the changes in log-S&P 500. Panel C includes the extended trading hours sample.

	Coef. α	t-stat$_\alpha$	Coef. β	t-stat$_\beta$	N
Panel A: FFF Regression					
	164.8	72.2	-0.253	-6.10	390
Panel B: S&P 500 Regression					
Extended hours	566.3	669.0	-0.016	-1.29	39
Trading hours	567.1	464.0	-0.005	-0.32	18
Panel C: FFF & S&P 500 Regression					
FOMC 0	0.02	0.67	-0.21	-0.68	39
FOMC 1	-0.16	-2.54	1.37	1.69	39
FOMC 2	-0.14	-1.84	0.99	1.0	39
FOMC 3	-0.15	-1.65	0.79	0.65	39
FOMC 4	-0.22	-2.19	-0.09	-0.06	39
FOMC 5	-0.18	-1.93	1.00	0.83	39
FOMC 6	-0.23	-2.01	1.91	1.29	39
FOMC 7	-0.19	-1.79	1.16	0.85	39
FOMC 8	-0.31	-2.27	1.50	0.84	39
FOMC 9	-0.32	-1.86	-0.22	-0.10	39
FOMC 10	-0.60	-1.76	-0.73	-0.18	32

Table 3: Alternative Event Windows

This table reports the event study results based on six alternative inner time window specifications. Each panel reports the estimation results for a different pre window T_1 and post window T_2. Each panel regresses the expected federal funds rate, implied by the futures prices, on a dummy variable indicating whether the observation is before or after a tweet by President Trump which criticizes the Federal Reserve. The table reports the average change in the expected federal funds rate across time horizons implied by contracts of varying maturities. For each tweet and FOMC exposure, two trades of the same contract are chosen to measure the change in the expected federal funds rate around each tweet. The selected contract for the exposure to j FOMC meetings has the shortest time to expiration and simultaneously at least j FOMC meetings before the month of expiration. The regression specification reads

$$E_{t-i\pm\Delta}[r_t] = \alpha + \beta D_{\pm} + \text{Fixed Effects} + \varepsilon,$$

where $E_{t-i\pm\Delta}[r_t]$ is the market expectation of the federal funds rate for the month when the corresponding future contract expires. The rate is measured in basis points. The subscript $\pm\Delta$ indicates whether the observation is from the pre or post-event outer window. β captures the average revision in expectations of the federal funds rate around each tweet.

Variable		Exposure to FOMC Meetings									
	0	1	2	3	4	5	6	7	8	9	10
Panel A: [1 min, 5 min]											
Dummy Coef. β	0.000	−0.175***	−0.125	−0.163*	−0.263***	−0.212***	−0.237**	−0.175	−0.295**	−0.295	−0.547*
t-stat.	0.00	−2.88	−1.61	−1.84	−2.72	−2.38	−2.18	−1.62	−2.00	−1.64	−1.68
Panel B: [0.1 min, 15 min]											
Dummy Coef. β	0.000	−0.169**	−0.213***	−0.212*	−0.250*	−0.263*	−0.313**	−0.462**	−0.462**	−0.513**	−0.591*
t-stat.	0.00	−2.23	−2.38	−1.81	−1.75	−1.82	−2.15	−2.26	−2.19	−2.17	−1.84
Panel C: [5 min, 5 min]											
Dummy Coef. β	0.006	−0.238***	−0.175***	−0.175*	−0.313***	−0.237***	−0.237**	−0.231*	−0.333***	−0.218	−0.422
t-stat.	0.27	−3.83	−2.33	−1.69	−3.01	−2.42	−1.98	−1.92	−2.23	−1.21	−1.27
Panel D: [10 min, 30 min]											
Dummy Coef. β	−0.077	−0.275**	−0.437***	−0.575***	−0.612***	−0.637***	−0.725***	−0.756***	−0.724***	−0.566*	−0.676**
t-stat.	−0.73	−2.07	−3.23	−3.07	−2.82	−2.76	−2.95	−2.71	−2.83	−1.94	−1.97
Panel E: [10 min, 60 min]											
Dummy Coef. β	−0.125	−0.262	−0.437**	−0.625**	−0.725***	−0.725***	−0.800***	−0.885***	−0.789***	−0.618*	−0.614
t-stat.	−1.18	−1.44	−2.15	−2.30	−2.48	−2.38	−2.60	−2.78	−2.48	−1.72	−1.63

Table 4: Alternative Tweet Selection Criteria

This table reports the results 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 directly criticize the federal reserve directly. Furthermore, the study includes tweets that criticize the Federal Reserve but also contain news on trade. The event study regresses the expected federal funds rate, implied by the futures prices, on a dummy variable indicating whether the observation is before or after a tweet by President Trump. The table reports the average change in the expected federal funds rate across time horizons implied by contracts of varying maturities. For each tweet and FOMC exposure, two trades of the same contract are chosen to measure the change in the expected federal funds rate around each tweet. The selected contract for the exposure to j FOMC meetings has the shortest time to expiration and simultaneously at least j FOMC meetings before the month of expiration. The regression specification reads

$$E_{t-i\pm\Delta}[r_t] = \alpha + \beta D_\pm + \text{Fixed Effects} + \varepsilon,$$

where $E_{t-i\pm\Delta}[r_t]$ is the market expectation of the federal funds rate for the month when the corresponding future contract expires. The rate is measured in basis points. The subscript $\pm\Delta$ indicates whether the observation is from the pre or post-event outer window. β captures the average revision in expectations of the federal funds rate around each tweet. The number of observations N are twice the number of tweets.

						Exposure to FOMC Meetings					
Variable	0	1	2	3	4	5	6	7	8	9	10
Panel A: Regression Coefficients											
Intercept α	211.2***	193.3***	183.8***	173.7***	166.8***	161.6***	160.1***	154.2***	153.9***	149.4***	155.7***
std. err.	4.09	4.34	4.67	5.24	5.74	6.04	6.15	6.72	7.06	7.21	8.83
t-stat.	51.63	44.58	39.35	33.14	29.04	26.75	26.05	22.95	21.78	20.72	17.64
Dummy Coef. β	0.014	−0.170**	−0.222***	−0.204**	−0.287***	−0.287***	−0.340***	−0.204	−0.314	−0.288	−0.720***
std. err.	0.020	0.075	0.083	0.093	0.107	0.102	0.113	0.190	0.244	0.247	0.305
t-stat.	0.68	−2.27	−2.67	−2.19	−2.68	−2.81	−3.02	−1.07	−1.29	−1.17	−2.36
Panel B: Regression Properties											
N	54	53	54	54	54	54	53	54	51	52	41
T_0 [min]	240	240	240	240	240	240	240	240	240	240	240
T_1 [min]	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
T_2 [min]	5	5	5	5	5	5	5	5	5	5	5
T_3 [min]	120	120	120	120	120	120	120	120	120	120	120

Table 5: Placebo Tests

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, tariffs, and trade are excluded. The event study is conducted 100 times (100 times 100 tweets) and the table reports the average of the 100 estimation results. Each event study regresses the expected federal funds rate, implied by the futures prices, on a dummy variable indicating whether the observation is before or after a tweet by President Trump. The table reports the average change in the expected federal funds rate across time horizons implied by contracts of varying maturities. For each tweet and FOMC exposure, two trades of the same contract are chosen to measure the change in the expected federal funds rate around each tweet. The selected contract for the exposure to j FOMC meetings has the shortest time to expiration and simultaneously at least j FOMC meetings before the month of expiration. The regression specification reads

$$E_{t-i\pm\Delta}[r_t] = \alpha + \beta D_{\pm} + \text{Fixed Effects} + \varepsilon,$$

where $E_{t-i\pm\Delta}[r_t]$ is the market expectation of the federal funds rate for the month when the corresponding future contract expires. The subscript $\pm\Delta$ indicates whether the observation is from the pre or post-event outer window. β captures the average revision in expectations of the federal funds rate around each tweet. The number of observations N are twice the number of tweets.

Variable		Exposure to FOMC Meetings									
	0	1	2	3	4	5	6	7	8	9	10
Panel A: Regression Coefficients											
Intercept α	60.5***	61.2***	62.2***	64.1***	66.1***	69.5***	70.4***	74.0***	75.4***	78.7***	80.7***
std. err.	11.04	10.09	9.78	9.83	9.92	9.95	9.88	9.99	10.13	10.36	10.51
t-stat.	5.46	6.04	6.34	6.5	6.65	6.98	7.12	7.43	7.46	7.62	7.73
Dummy Coef. β	0.000	0.001	0.004	-0.008	-0.005	-0.024	-0.022	-0.017	-0.002	-0.008	0.011
std. err.	0.032	0.047	0.051	0.063	0.071	0.086	0.099	0.111	0.129	0.138	0.155
t-stat.	-0.01	0.03	0.11	-0.21	-0.10	-0.31	-0.27	-0.14	-0.03	-0.07	0.03
Panel B: Regression Properties											
N	50	58	59	59	59	59	59	57	55	52	50
T_0 [min]	240	240	240	240	240	240	240	240	240	240	240
T_1 [min]	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
T_2 [min]	5	5	5	5	5	5	5	5	5	5	5
T_3 [min]	120	120	120	120	120	120	120	120	120	120	120

Table 6: Joint Estimation Based on Minimal FOMC Exposure

This table reports the regression results for changes in the expected federal funds rate at different maturities. The revision in expectations is computed by using the change in futures rates for contract of different maturities. Each column considers the revision of expectations that occurs after a minimal number of FOMC meetings has occurred (from 1 to 8). The rate is measured in basis points.

Variable	Exposure to FOMC Meetings							
	1	2	3	4	5	6	7	8
Panel A (Benchmark): [0.1 min, 5 min]								
Dummy Coef. β	−0.148**	−0.13	−0.207**	−0.225***	−0.233**	−0.265***	−0.251**	−0.246*
std. err.	0.073	0.079	0.101	0.091	0.102	0.111	0.124	0.142
t-stat.	−2.026	−1.632	−2.056	−2.483	−2.272	−2.393	−2.027	−1.733
N	39	39	39	39	39	39	39	34
Panel B: [1 min, 5 min]								
Dummy Coef. β	−0.160**	−0.118	−0.198*	−0.236***	−0.216**	−0.256**	−0.226*	−0.218
std. err.	0.074	0.081	0.104	0.095	0.107	0.117	0.133	0.149
t-stat.	−2.144	−1.467	−1.915	−2.478	−2.024	−2.199	−1.697	−1.466
N	39	39	39	39	39	39	39	34
Panel C: [0.1 min, 15 min]								
Dummy Coef. β	−0.163*	−0.178*	−0.331***	−0.314**	−0.298*	−0.280	−0.378*	−0.505***
std. err.	0.098	0.104	0.138	0.139	0.154	0.174	0.198	0.190
t-stat.	−1.660	−1.721	−2.395	−2.259	−1.936	−1.606	−1.905	−2.663
N	39	39	39	39	39	39	39	34
Panel D: [5 min, 5 min]								
Dummy Coef. β	−0.236***	−0.206***	−0.264***	−0.302***	−0.192*	−0.230*	−0.286**	−0.265*
std. err.	0.071	0.078	0.109	0.100	0.116	0.127	0.144	0.155
t-stat.	−3.342	−2.656	−2.413	−3.029	−1.658	−1.816	−1.99	−1.709
N	39	39	39	39	39	39	39	34
Panel F: [10 min, 30 min]								
Dummy Coef. β	−0.345***	−0.345***	−0.523***	−0.515***	−0.54***	−0.602***	−0.685***	−0.734***
std. err.	0.118	0.126	0.181	0.190	0.212	0.218	0.255	0.285
t-stat.	−2.933	−2.738	−2.891	−2.715	−2.547	−2.756	−2.687	−2.573
N	38	38	38	38	38	38	38	34
Panel G: [10 min, 60 min]								
Dummy Coef. β	−0.341*	−0.324	−0.575**	−0.625**	−0.638**	−0.719***	−0.801***	−0.887***
std. err.	0.191	0.205	0.275	0.273	0.287	0.283	0.297	0.314
t-stat.	−1.784	−1.583	−2.093	−2.286	−2.224	−2.545	−2.697	−2.825
N	38	38	38	38	38	38	38	34

Table 7: Joint Estimation Based on Exact FOMC Exposure

This table reports the regression results for changes in the expected federal funds that occur in correspondence of different FOMC meetings. The revision in expectations is computed by using the change in futures rates for contract of different maturities. Each column considers the revision of expectations that occurs in correspondence of the 1st, 2nd, . . . 8th FOMC meeting after the tweet.

				FOMC Meeting				
Variable	1st	2nd	3rd	4th	5th	6th	7th	8th
Panel A (Benchmark): [0.1 min, 5 min]								
Dummy Coef. β	−0.139***	−0.152**	−0.175*	−0.222***	−0.172*	−0.251***	−0.197**	−0.335**
std. err.	0.057	0.075	0.095	0.093	0.092	0.105	0.100	0.145
t-stat.	−2.450	−2.016	−1.848	−2.387	−1.858	−2.395	−1.973	−2.303
N	39	39	39	39	39	39	39	38
Panel B: [1 min, 5 min]								
Dummy Coef. β	−0.148***	−0.124	−0.164*	−0.26***	−0.194**	−0.231**	−0.162	−0.309**
std. err.	0.056	0.078	0.092	0.097	0.094	0.111	0.116	0.155
t-stat.	−2.643	−1.575	−1.775	−2.692	−2.069	−2.086	−1.393	−1.993
N	39	39	39	39	39	39	39	38
Panel C: [0.1 min, 15 min]								
Dummy Coef. β	−0.151*	−0.188**	−0.219*	−0.261*	−0.267*	−0.299**	−0.438**	−0.510***
std. err.	0.078	0.095	0.123	0.141	0.147	0.151	0.194	0.209
t-stat.	−1.925	−1.972	−1.786	−1.844	−1.818	−1.976	−2.255	−2.438
N	39	39	39	39	39	39	39	38
Panel D: [5 min, 5 min]								
Dummy Coef. β	−0.204***	−0.188***	−0.21**	−0.303***	−0.209**	−0.212*	−0.200	−0.326**
std. err.	0.061	0.076	0.105	0.100	0.100	0.121	0.125	0.157
t-stat.	−3.342	−2.482	−1.997	−3.025	−2.084	−1.755	−1.603	−2.072
N	39	39	39	39	39	39	39	38
Panel F: [10 min, 30 min]								
Dummy Coef. β	−0.123	−0.343***	−0.462***	−0.487***	−0.517***	−0.591***	−0.612***	−0.746***
std. err.	0.076	0.119	0.169	0.179	0.208	0.215	0.263	0.271
t-stat.	−1.609	−2.891	−2.734	−2.713	−2.482	−2.754	−2.328	−2.748
N	38	38	38	38	38	38	38	37
Panel G: [10 min, 60 min]								
Dummy Coef. β	−0.115	−0.343*	−0.500*	−0.593**	−0.615**	−0.660**	−0.756***	−0.817***
std. err.	0.157	0.198	0.264	0.273	0.294	0.294	0.300	0.322
t-stat.	−0.735	−1.736	−1.891	−2.174	−2.093	−2.242	−2.521	−2.534
N	38	38	38	38	38	38	38	37

Table 8: Comparing Magnitudes

This table reports the summary statistics for the changes in the Federal Funds Futures for all available maturities around FOMC announcements, tweets on the federal reserve, and tweets on trade and tariffs. The rate is measured in basis points. We provide the mean, standard deviation, and the number of observations in our data sample. To construct the statistics for FOMC announcements, we create an inner time window of 0.1 min prior to the announcement and 5 min after the announcement.

	mean	std.dev.	N
FOMC Announcements	−0.428	3.247	672
Tweets on the Federal Reserve	−0.212	0.914	715
Tweets on Trade & Tariffs: All Tweets	0.018	1.091	4526
Tweets on Trade & Tariffs: Positive Tweets	0.165	1.339	1356
Tweets on Trade & Tariffs: Negative Tweets	−0.053	1.081	2297

Table 9: Trade and Tariff Tweets

This table reports the impact of tweets discussing trade and tariffs on the expected federal funds rate and the stock market. Tweets that contain either a word from set A or tweets than contain at least one word from set B_1 and B_2 are considered. Set $A = \{trade, tariff, export, import\}$, $B_1 = \{china, mexico, canada, japan, germany\}$, and set $B_2 = \{deal, buy, purchase, farmer, industry\}$. Tweets which are not related to the subject of trade and tariffs are dropped, as well as tweets which occur within a narrow time-window after another. The remaining tweets are classified into three categories: Positive (such as the announcement of a new trade agreement), negative (such as criticizing a trading partner or threatening tariffs), or ambiguous tweets which do not fit clearly into one category. Conditional on a set on the categorized tweets, panel A estimates the average change in expectations of the federal funds rate pooling across ten contracts with a nonzero meeting exposure at each point in time. The event study regresses the expected federal funds rate across different maturities, implied by the futures prices, on a dummy variable indicating whether the observation is before or after a tweet

$$E_{t-i\pm\Delta}[r_t] = \alpha + \beta D_\pm + \text{Fixed Effects} + \varepsilon.$$

$E_{t-i\pm\Delta}[r_t]$ is the market expectation of the federal funds rate for the month when the corresponding future contract expires. The rate is measured in basis points. The subscript $\pm\Delta$ denotes whether the observation is from the pre or post-event outer window. Fixed effects control for the event time and contracts across different expiration months.

Panel B estimates the average effect on the stock market. Similar to Panel A, the regression projects the variable log-S&P 500 on a dummy variable which indicates whether the observation is before or after a tweet. The regression using extended trading hours include tweets between 4:00 a.m. and 8:00 p.m. ET. The regression without pre-market and after-hours trading includes tweets between 9:30 a.m. and 4 p.m. ET.

Panel C investigates the correlation between changes in log-S&P 500 and changes in the expectations of the Federal Funds Rate in the event window around the selected tweets. For each FOMC exposure, changes in the expected FFR from the respective contract are regressed on a constant and the changes in log-S&P 500. Panel C includes the extended trading hours sample.

	All			Positive			Negative		
	Coef. β	t-stat$_\beta$	N	Coef. β	t-stat$_\beta$	N	Coef. β	t-stat$_\beta$	N
Panel A: FFF Regression									
	0.027	1.32	2543	0.174	3.89	761	-0.022	-0.77	1293
Panel B: S&P 500 Regression									
Extended hours	0.003	0.40	255	0.029	2.31	78	-0.013	-1.06	127
Trading hours	-0.017	-0.08	82	-0.117	-0.17	25	-0.039	-1.07	38
Panel C: FFF & S&P 500 Regression									
FOMC 0	-0.02	-0.13	216	-0.29	-1.11	68	-0.05	-0.33	108
FOMC 1	1.16	5.12	243	1.83	4.76	72	1.50	5.00	122
FOMC 2	1.40	4.93	249	2.08	5.58	76	1.66	4.03	126
FOMC 3	1.71	4.65	248	2.32	5.01	75	1.94	3.84	126
FOMC 4	2.03	4.53	246	2.97	5.17	75	2.3	3.72	125
FOMC 5	2.25	4.3	244	2.87	2.66	75	2.58	4.44	122
FOMC 6	2.25	3.81	243	2.81	2.26	72	2.67	3.81	123
FOMC 7	2.66	4.01	238	3.43	2.11	74	3.27	4.84	117
FOMC 8	2.76	3.91	223	2.95	1.41	69	3.51	7.42	116
FOMC 9	3.45	4.52	226	4.58	2.33	69	4.16	5.41	115
FOMC 10	3.29	4.8	219	4.49	3.90	65	4.88	8.07	111

Figure 1: First Tweet Criticizing the Fed

This plot shows the changes in expected federal funds rates at different horizons with respect to the first tweet that threatens central bank independence. The contracts are color-coded by their exposure to prior FOMC meetings before expiration. Contracts in the first group are exposed to between 1 and 4 FOMC meetings, contracts in the second group are exposed to between 5 and 8 FOMC meetings, and contracts in the third group are exposed to at least 9 FOMC meetings. Changes are reported as a percentage of the average absolute change in federal fund futures following FOMC meetings announcement since June 2015 (2.226 bps).

"Russia and China are playing the Currency Devaluation game as the U.S. keeps raising interest rates. Not acceptable!" - Donald J. Trump on the 16th of April 2018 via Twitter
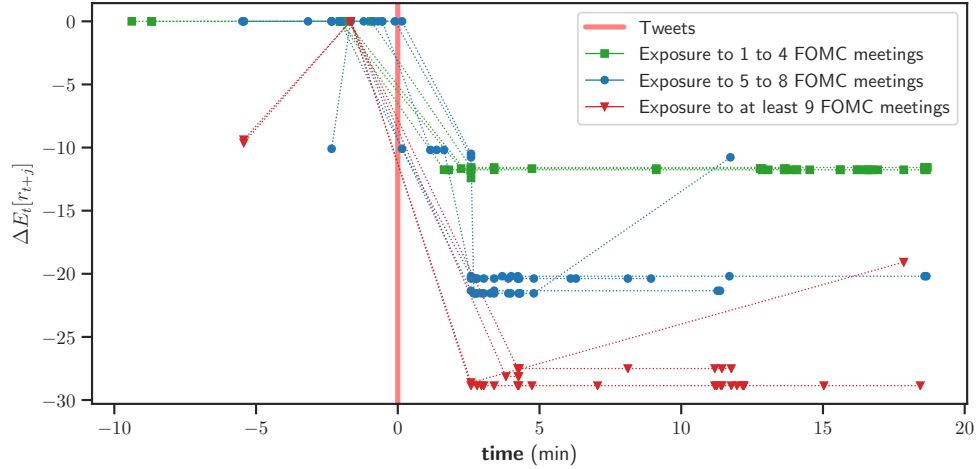
Figure 2: Event Window

This figure illustrates the selection of trades to study the impact of an even 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. Within each subset, $[T_0, T_1]$ and $[T_2, T_3]$, the trades satisfing $arg\max_t\{p_t\}_{t=T_0}^{t=T_1}$ and $arg\min_t\{p_t\}_{t=T_2}^{t=T_3}$ are selected, i.e. trades that minimize the distance to the inner window.
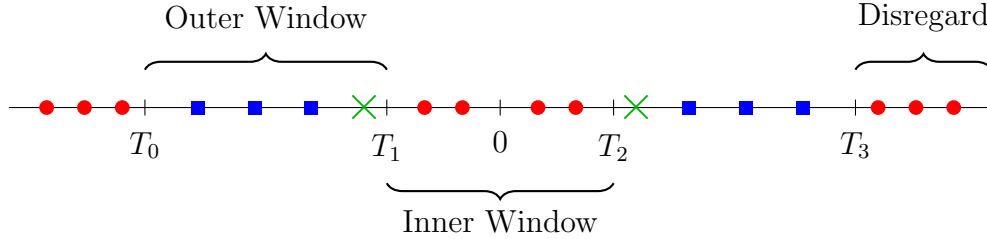
Figure 3: Interest Rate Cut Timing

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.
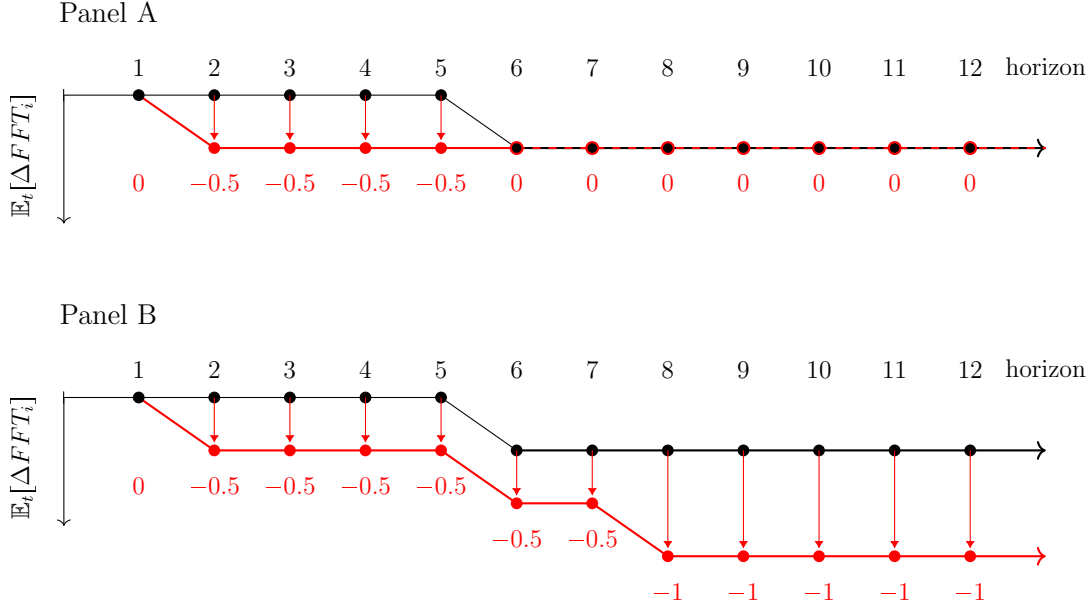
Figure 4: Time Horizons for Joint Estimation

This figure provides an illustration of the four distinct cases considered in our joint estimation of the term structure of expectations with respect to the time horizon.
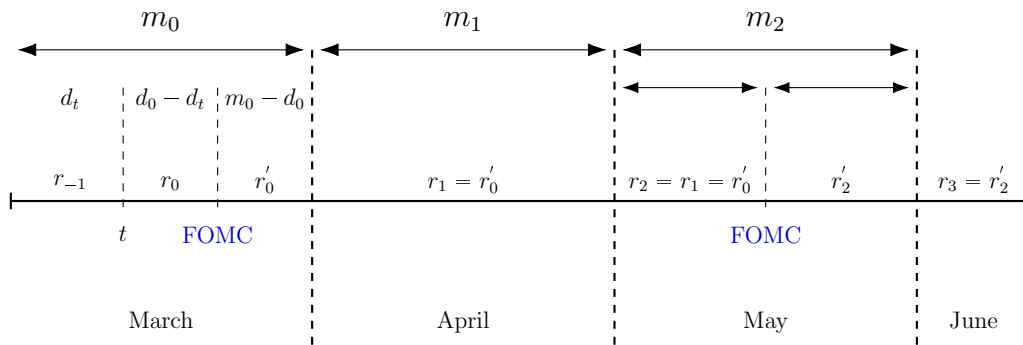
Figure 5: News Threatening the Removal of Powell

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.
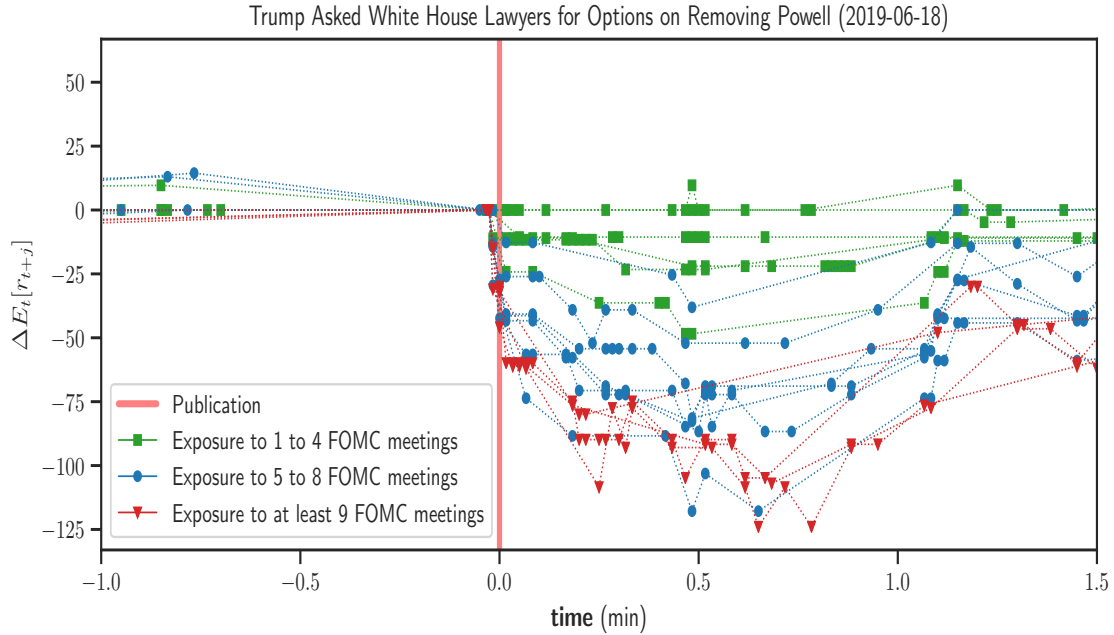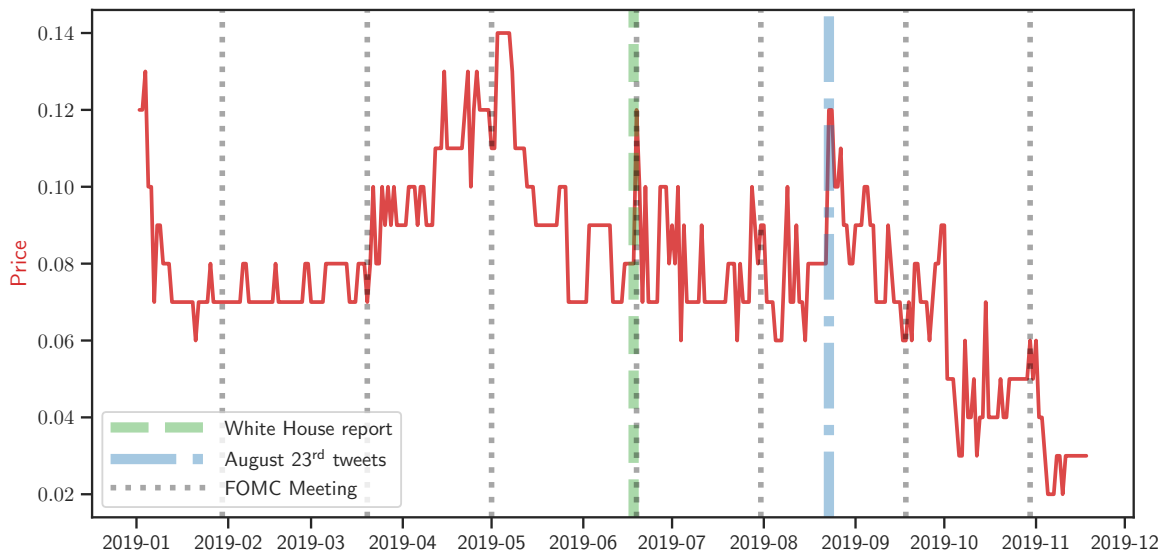

Figure 6: Bets on the Removal of Powell

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.

A Data

A.1 Asset prices

Futures Contracts
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. This dataset covers the period of January 1995 to October 2019. 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.

S&P500 index ETF SPY
The stock market dataset consists of intraday transaction prices for the S&P500 index ETF SPY. The tick-by-tick observations 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 last day for observations on futures prices are available in our dataset.

A.2 Event Selection

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 between the Terminal News Ticker from Bloomberg and the Twitter accounts @cnbc, @cnbcnow, @zerohedge, and businessinsider.

Tweets
The entire set of tweets are collected from the Twitter account of President Trump from his personal account (@realDonaldTrump). Each observation includes the text, the accurate to the second timestamp, and a classification of the tweet into either a reply or a retweet. All tweets issued after the announcement of his presidential campaign in June 2015 are considered. The last observation is from November 2019. 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, rate, jerome, jay, powell*. This includes tweets which contain word extensions such as the word 'federal' is captured by 'fed'. Next, the obtained set of tweets is cleaned according to

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

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

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

4. Retweets
   Drop tweets which do not contain new information other than the reiteration of the President of a tweet by someone else and are indicated by quotation marks.
   Example: *"If the Fed backs off and starts talking a little more Dovish, I think we're going to be right back to our 2800 to 2900 target range that we've had for the S&P 500." Scott Wren, Wells Fargo.*

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

6. Trade & Tariffs
   Drop tweets which include other information about the economy, in particular, comments on trade or tariffs 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!*

In the robustness section 3.4, an alternative selection criteria is considered. The results in table 4 are based on the same set of tweets which include the keywords *fed, rate, jerome, jay, powell*. Tweets are dropped according to the technical criteria 1-4, i.e. tweets which are off-topic, doubles, announcements, or retweets. In contrast to the benchmark specification we include tweets which were classified as irrelevant or which did contain information on trade or tariffs.

Section 5.1 implements the following selection criteria for tweets on tariffs and trade by President Trump's Twitter account. Select a tweet which contains either a word from set A_0 or at least one word from set B_1 and simultaneously at least one word from set B_2. Set A_0 contains the words *china, mexico, canada, japan, germany*. Set B_1 is a list with the words *china, mexico, canada, japan, germany* and B_2 includes *deal, buy, purchase, farmer, industry*. This selection ensures that all relevant tweets are selected while minimizing the number of tweets which are off-topic. Next, the obtained set of tweets is cleaned by removing any off-topic tweets which do not refer to the topic of interest. An example is *The U.S., together with Mexico and Canada, just got the World Cup. Congratulations - a great deal of hard work!* In addition, tweets which occur within a narrow time-window after another are dropped. The remaining tweets are classified into three categories: Positive (such as the announcement of a new trade agreement), negative (such as criticizing a trading partner or threatening tariffs), or ambiguous tweets which do not fit clearly into one category. For example, the tweet *My meeting in Argentina with President Xi of China was an extraordinary one. Relations with China have taken a BIG leap forward! Very good things will happen. We are dealing from great strength, but China likewise has much to gain if and when a deal is completed. Level the field!* is classified as positive. The tweet *I have just authorized a doubling of Tariffs on Steel and Aluminum with respect to Turkey as their currency, the Turkish Lira, slides rapidly downward against our very strong Dollar! Aluminum will now be 20% and Steel 50%. Our relations with Turkey are not good at this time!* is classified as negative.