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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 a cumulative effect of around negative 10 bps. Therefore, we provide evidence that market participants believe that the Fed will succumb to the political pressure from the President, which poses a significant threat to central bank independence.

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1 Introduction

A general consensus for the effective conduct of monetary policy 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] For example, 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 prior to expiry. 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.

[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.

We systematically investigate 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 Fed policy which unequivocally advocate looser monetary policy, harkening 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 using tick-by-tick data on fed funds futures prices.

Our identification scheme exploits a small time window around a single second precision timestamp 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 category, we run a linear regression of the expected fed funds rate, implied by the futures price, on a dummy variable indicating before and after a tweet in a one minute pre- and five minute post-window, including fixed effects. 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 -0.30 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. 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 of 3 to 30 minutes are considered, yielding similar results in terms of significance and magnitude as our benchmark specification. As the target rate is only changed during the FOMC meetings, short maturity futures contracts outstanding 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. The impact of the tweets on the term structure of expected target rates is jointly estimated with a linear system of pricing equations using information from contracts of varying maturities. Results from the joint estimation similarly finds that the effect of the tweets increases with horizon, highlighting the persistence in the revisions of expectations.

Overall, we find strong evidence that the consistent pressure applied by President Trump to pursue more expansionary monetary policy is manifested in the market expectations of a lower target rate, forecasting 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 independent from the executive branch has indirect, but important, consequences for the actual autonomy of the central bank. Evidence that the Fed closely monitors and is affected by market expectations of its own actions (e.g., Faust (2016) and Vissing-Jorgensen (2019)) implies that even if President Trump 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., 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 timestamp of each tweet, we identify the impact of the tweet on expectations of the target fed funds rate with discontinuity-based estimation. 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 of 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 diret 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. Section 4 presents the baseline results. Section 5 provides an interpretation of the results. Section 6 discusses the joint estimation of the term structure of expectations.

2 Data

This section describes the four main datasets used in our analysis: tweets from the Twitter account of President Trump, federal funds futures provided by the CME Group, news stories from the Bloomberg Terminal, and the FOMC Meeting calendar from the Federal Reserve.

2.1 Twitter

The entire set of tweets are collected from the Twitter account of President Trump (`@realDonaldTrump`). Each observation includes the text, the accurate to the second timestamp, and a classification of the tweet into either a reply, retweet, or media content. The number of retweets, favorites, and replies are also observed.

For the benchmark analysis, all tweets issued after the announcement of his presidential campaign in June 2015 are considered. The last observation is from August 2019. Out of those tweets, every statement that uses the key words ‘Federal Reserve’, ‘interest rates’, or ‘Jerome Powell’ are first selected. Second, any tweets that meet the following criteria are disregarded. Any tweets that were made when markets for the federal funds futures were closed, or, when no trades occurred within our selected time window (e.g., during extended trading hours) are eliminated. Any comments that are not directly an instruction or criticism for the Fed policies are dropped (e.g., announcing a new nomination such as the tweet ”It is my please to announce that @StephenMoore, a very respected Economist, will be nominated to serve on the Fed Board”). Also, any tweets that provide new information about the state of the economy or trade deals are dropped. This insures that our results are less likely driven by changes in market expectations about future state of the economy or the likelihood of successful trade negotiations which could impact the interest rate decision taken by the Federal Reserve.

2.2 Futures Contracts

Following the methodology of Gurkaynak, Sack, and Swanson (2004) and Nakamura and Steinsson (2018), market expectations of the future fed funds rate are backed out 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 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.

This dataset covers the period of January 1995 to August 2019. The length of this time sample allows us to compare the effects of President Trump's tweets before and after he became President of the United States of America. We show that after his election, his statements lead to a significant revision in market expectations about the future path of the federal funds rates.

2.3 News

In extended analysis contained in the Appendix, additional press statements and news articles unique from our tweets are analyzed in which President Trump criticized the Fed or its Chairman, Jerome Powell. Precise timestamps of articles referenced in Condon (2019) using the Bloomberg Terminal are collected. When President Trump gives an interview on the Federal Reserve via a News Outlet (such as Fox News, CNBC, etc.), the first observation is taken that displays his comment in the headline of the Bloomberg Terminal News Ticker. The timestamp is cross-referenced with Factiva to get the earliest point in time where investors were made aware of his statement. The dataset is extended to any additional original comments, using the key words 'Federal Reserve', 'interest rate', or 'Jerome Powell'. Statements which do not advocate lower interest rates (e.g., *"I maybe regret appointing Powell to head the Fed but I'm not going to fire him"*) are dropped from the analysis, but are instead used in robustness exercises for testing statements that possibly strengthen independence.

2.4 FOMC Announcements

All past and future FOMC meeting days are collected from the website of the Federal Reserve Bank. The approach described in Section 2.3 is used to obtain precise timestamps for the FOMC announcements: Use the first item in the Terminal News Ticker from Bloomberg, cross reference the time with Factiva, and take the minimum of the two sources. For future FOMC announcements, the time is set to the average announcement time of the past year.

3 Identification Strategy

This section presents the methodology for identifying the impact of the tweets by President Trump on the target fed funds rate using high-frequency data. First, the procedure of inferring the target rate using fed funds futures prices is described. The second part outlines the window construction for identifying high-frequency changes.

3.1 Federal Funds Rate Target

The federal funds futures cash settlement price is 100 minus the arithmetic average of the daily effective federal funds rate during the month of expiration. The effective federal funds rate is the weighted average of all transactions for a group of federal funds brokers.

The federal funds future rate 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 α_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. An identification assumption in our baseline estimation requires that this bias component is not directly affected by information conveyed in the tweets, but the main results do not rely on these assumptions as discussed below.

We are interested in 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 future 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:

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

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:

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

As explained below, futures rates can be used to recover changes in expectations at different horizons. Our main results are robust to relaxing these assumptions, as presented in the Appendix.

3.2 Time Window

The identifying assumption of the high-frequency approach is that no other systematic shocks to market expectations about future federal funds rates occur within a particular time window. Figure 2 highlights how two trades are selected for measuring changes in the expected federal funds rate target. The symbols $\times$, $\circ$, $\square$ represent an observed price due to a trade. All trades that fall outside the outer windows, $t < T_0$, $t > T_3$, or within the inner window, $T_1 < t < T_2$, are disregarded. Of the 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 ($\times$). The observations obtained are the closest trades before and after the tweet occurring at time 0. In the benchmark case, the pre-event outer window is between $T_0 = 180$ min and $T_1 = 1$ min before the tweet. This ensures that the last observation before the tweet is not impacted by the event itself, but yet as recent as possible. In contrast to other high-frequency studies, there is less concern for news to arrive beforehand, as 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 $T_0 - T_1 = 180$ min and $T_3 - T_2 = 120$ min ensure that only contracts with recent trades are considered. Table 1 provides an overview on the federal funds contracts that fall in this time window. Panel A provides the statistics on the federal funds return and its changes, irrespective of the time to expiration. The average contract duration is 289 days and on average, over five FOMC meetings occur before the contract expires. Panel B and Panel C report the statistics of contracts split at the median FOMC meeting exposure. The exposure is measured by the number of meetings before the first day of the expiration month. If an FOMC meeting occurs within the expiration month, the fraction of days left in that month is added.

In alternative specifications, event windows between 3 and 30 minutes are also examined. The different windows yield similar results in terms of significance and magnitude as the benchmark specification of 5 minutes.

4 Main Results

This section describes the main results regarding the revision in expectations across short and long horizons. For each FOMC meeting, estimates are presented using the contracts with an expiration such that the computation of the payoff (i.e., the final month of the contract) follows the FOMC meeting. We find that the tweets by President Trump criticizing the Federal Reserve lead to a persistent decline in expected target rates with a magnitude that increases with horizon. The effect of the tweets in the latter part of the sample are stronger.

Analyzing the entire term structure of prices and expectations is a particularly important component of our analysis because tweets do not typically coincide with FOMC meetings. Many tweets occur either after the FOMC meetings or in a month without FOMC meetings. In those two cases, there is not a jump in the federal funds rate associated with the zero maturity contract. Analyzing the change in expectations at different horizons provides information on whether tweets only affect the expected timing of a monetary policy change that is already anticipated, or, whether tweets imply a comprehensive revision in the expected course of monetary policy.

4.1 Estimated Effects by Contract Exposure

This subsection focuses on the revision in expectations conditional on the number of FOMC meetings between the time of the tweet and contract expiration. 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 expect no rate changes in the next meeting, but that downward adjustments occur in subsequent meetings, 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.

The average change in the expected federal funds rate is obtained for each level of FOMC exposure. The contract is selected which simultaneously has the shortest time to expiration and at least the corresponding number of FOMC meetings scheduled before the beginning of the expiration month. 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 one minute before the tweet and the second observation is the earliest trade five minutes after the tweet (see Section 3.2). 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 fixed FOMC 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:

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

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.

The regression results are shown in Table 2. Each column reports the minimal number of FOMC meetings to which the contract is exposed. The coefficient of interest, β, captures the average revision in expectations of the federal funds rate around each tweet. As expected, the coefficient for the zero maturity contract is essentially zero as the payoff of this contract is not exposed to any FOMC meeting. The coefficient is negative for all contracts, with an increasing magnitude as maturity increases. The results for the short maturity contracts exposed to one FOMC meeting imply that the expected interest rate declines by 0.181 bps following a tweet. This number grows as the horizon increases. The change in the expected interest rate for a contract exposed to 10 FOMC meetings (a contract that expires one year later), declines by 0.5 bps. For six out of ten contracts, the coefficients are statistically different from zero at the 1% level. Excluding the zero maturity contract, only one coefficient is not statistically different from zero. These estimates provide strong evidence that the Trump tweets lower market expectations about future interest rates.

The estimated revision in expectations might appear small, but it is important to keep in mind that the typical change in the FFR target is 25 bps. A back-of-the-envelope calculation based on two scenarios shows that a decline of 0.5 bps corresponds to a 2% increase in the probability of a 25 bps FFR 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 cumulative effect is quite large when taking into account the total number of tweets. Finally, it is worth emphasizing that the typical size of a monetary policy *shock* is also small, especially in a period of near zero interest rates.

Table 3 reports the additional regressions with different time windows to demonstrate that our results are not driven by the particular time window used in the event study. The general pattern for the estimates across contracts is unchanged using the different windows. The estimated coefficients are always negative and tend to increase with horizon. Across all possible timeframes used, all contracts exposed to between 5 and 9 FOMC meetings are always statistically significant from zero at the 1% level, providing strong evidence that markets revise upward the probability assigned to an interest rate cut within the year. If anything, these alternative specifications deliver even stronger results. The [5,5] minute window has nine out of ten revisions statistically different from zero at the 1% level and the [10,20] minute window presents revisions in expectations that are substantially larger and all statistically different from zero at the 1% level. Thus, the results based on our benchmark specification (presented in Table 4) are conservative. Overall, the results illustrate how markets believe that the President is significantly influencing the conduct of monetary policy.

4.2 Estimated Effects by Pooling Contracts

The previous section illustrated that the tweets by President Trump criticizing the Federal

Reserve induce an overall decline in the expected path of interest rates, with the magnitude of the effects increasing by horizon. The analysis was conducted within individual contract categories based on the number of FOMC meetings preceding the payoff of the contract. In this subsection, the information contained in the revision of expectations about the single contracts to study the average change in expectations across contracts and the different revision for short- and long-term expectations is aggregated. To this end, a panel regression is run that includes all fixed FOMC exposure contracts from Section 4.1 with at least one FOMC meeting prior the expiration month.

The expected fed funds rate across different maturities is first regressed on a dummy variable indicating whether the observation is before or after a tweet:

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

Panel A of Table 4 reports the parameter estimates. Consistent with the results above, a tweet that criticizes the Fed induces a statistically significant negative response in the expected funds rate. We find a 0.282 bps average decline in the path of expected future interest rates in the pooled regression, which can be interpreted as a level shift in the expected fed funds rate across horizons.

To test if the revision in expectations changes between short and longer horizons, the subsequent regression considers two contracts, a contract that is exposed to exactly one FOMC meeting and a contract with an expiration date past one year such that the payoffs are computed after the next eight FOMC meetings. The expected federal funds rate is regressed on a dummy variable indicating if the observation is before or after a tweet, an additional dummy signifying whether the contract is exposed to one or eight FOMC meetings, and the interaction between the two dummies:

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

where δ captures the slope of the term structure of expectations.

The regression result from the specification above is reported in Panel B of Table 4. Both the level and slope effects are negative and statistically significant. As in the individual contract regressions, a tweet criticizing the Fed lowers expected interest rates across horizons. The fact that the coefficient δ is large and negative highlights that with longer time to expiration the revision in expectations is stronger than short term expectations, highlighting how markets expect the effects to build up persistently over time.

4.3 Subsample Analysis

President Trump mounted his first attack of the Fed on April 2018 through a tweet in the middle of a monetary policy cycle that witnessed the Fed moving away from the zero lower (see Figure 5). The Fed increased rates during December 2018 meeting then proceeded to keep rates constant until the meeting in July of 2019, when the they decided on a 25 bps cut. Since December 2018, the frequency of the President's tweets have increased and it could be argued that some of the most critical tweets occurred during the Summer of 2019. We ask if this turning point in the conduct of monetary policy on the July 2019 meeting had an impact on the attention that markets devote to related Trump tweets used in our estimation. The observation that the Fed reversed the policies that started in early 2016 and that gained momentum in 2018 is consistent with the narrative that the the Fed is bending to the unrelenting political pressure from President Trump.

We estimate the average and slope effect of the tweets in the pooled regressions separately across two subsamples, the period before and the period after the most recent FOMC meeting on the 31st of July 2019. Table 5 reports the results. In both subsamples, the tweets generate a decline in the expected path of the fed funds rate. However, the effects for the post-July 2019 period are substantially larger, both for the level and slope. In the level specification, the estimated coefficient is almost twice as large in magnitude. In the second specification that accounts for the timing of the change, the level effect is three times larger, while the slope effect is unchanged. Some of the coefficients are now only marginally statistically significant given that the number of observations are substantially reduced compared to the full sample.

The subsample analysis highlights how the severity of the threats to central bank autonomy perceived by market participants is potentially intensifying. The fact that the Federal Reserve made a dramatic shift in the conduct of monetary policy in less than one year after the rate increase in December 2018 might have induced market participants to believe that the tweets by President Trump influenced recent monetary policy decisions. As a result, now a tweet that harshly criticizes the Federal Reserve could be more likely to move market expectations.

5 Discussion

Our main results demonstrate that political pressure in the form of tweets from the President criticizing the Fed for keeping interest too high significantly affect expectations about the future path of the Federal Funds rate. The effect is present both at short and long horizons as the revision in expectations caused by these tweets grows 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 markets expect that the Fed will cut rates in six months, but not in the near future. If a tweet induces markets to believe that the cut will occur earlier, a revision in expectations would be observed at short, but not long horizons. An example is illustrated in Panel A of Figure 3. Instead, our results point in a different direction. The fact that the revision in expectations keeps growing over time indicates that markets are not sure whether the Federal Reserve will succumb to the political pressure in the immediate future (e.g., during the next FOMC meeting), but they assign a sizable probability to this outcome occurring at some point in the future. Panel B of Figure 3 provides an example to illustrate this point. As in the previous case, before the tweet, markets expect that the Fed will cut interest rates in six months. After the tweet, an alternative scenario arises. Once again, expected rates move down in the short run, but the expected decline continues over time, implying that the tweet does not merely change the timing of an already anticipated decline.

The subsample analysis demonstrated that the effects of the tweets on expected monetary policy are stronger after the Fed decided to cut rates at the end of July 2019. In the official statements and communications, the Fed explained the reasons behind the interest rate cut. However, markets might have perceived that pressure from the tweets by President Trump played a role in the change of the monetary policy phase. In this paper, we cannot establish the exact motives for the rate cut, but only that markets might doubt that the Federal Reserve acted purely in response to changes in the economic outlook, especially in light of the positive outlook for the state of US economy at the time of the decision.

Our results suggest that markets do not perceive the Federal Reserve Bank as a fully independent institution immune from political pressure. It is beyond the scope of this paper to test the veracity of these beliefs. Our empirical exercise is to use a clean identification strategy relying on high frequency data with a short time window around the tweets to control for the many factors that can cause changes in the conduct of monetary policy. Testing if the Fed actually succumbed to the requests of the President Trump is a substantially more challenging task in light of the multitude of factors that the central bank analyzes prior to setting policy.

Nevertheless, the fact that market participants might not perceive the Federal Reserve as autonomous from the executive branch can have important implications for the actual independence of the central bank. 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 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 tweets 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.

6 Term Structure of Expectations

The estimation presented in Section 4.1 studies a term structure of expectations by contracts sorted on the number of FOMC meetings that affect a particular contract. In this section, we conduct a robustness check by studying the revision of expectations based on the term structure of expectations with respect to time. If the Federal Reserve had an FOMC meeting every month that exactly coincided with the maturity of each futures contracts, the information contained in the contracts sorted by exposure to future FOMC meetings and by time would be the same. As explained above, the behavior of the term structure of expectations plays a key role in our analysis because it is possible that a tweet creates expectations of lower interest rates in the more distant future, even if investors do not expect any change in the next FOMC meeting. On the other hand, it could also be possible that agents already expect lower rates and they believe that the tweet will simply anticipate the time of the cut. In this case, a change in expectations would be expected at short horizons, but not at longer horizons.

Contracts with different durations 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. Following the decomposition in Section 3.1, the fed funds future rate is expressed as:

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

where i is the month of interest. Examining the entire term structure of expectations is important as tweets typically do not coincide with FOMC meetings as in the case of Gurkaynak, Sack, and Swanson (2004) and Nakamura and Steinsson (2018). A tweet can occur in a month without an FOMC meeting scheduled. Consequently, the revision in expectations only occurs on contracts with longer maturities. There are four distinct cases to consider which depends on the time between the tweet at time t and the next FOMC meeting.

1. Time t is included in month i and no FOMC meeting occurs during month i:

$$FFF_{t,i} = \frac{d_t}{m_i} r_{-1} + \frac{m_i - d_t}{m_i}\mathbb{E}_t\left[r_i^0\right] + \alpha_i,$$

   where d_t marks the day and time of the tweet and m_i is the number of days in month i. Under the assumption that the tweet only affects the expected federal funds target rate, the term $\mathbb{E}_t\left[r_i^0\right]$ cancels out when taking the difference.

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

$$FFF_{t,i} = \frac{d_t}{m_i} r_{-1} + \frac{d_i - d_t}{m_i} \mathbb{E}_t \left[r_{i,t} \right] + \frac{m_i - d_i}{m_i} \mathbb{E}_t \left[r_i' \right] + \alpha_i,$$

where d_i marks the day and time of the FOMC meeting scheduled to occur in month i. This can be rewritten as:

$$FFF_{t,0} = \frac{d_t}{m_0} r_{-1} + \frac{d_0 - d_t}{m_0} \mathbb{E}_t \left[r_{0,t} \right] + \frac{m_0 - d_0}{m_0} \mathbb{E}_t \left[r_0' \right] + \alpha_0$$

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

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

where r_i is the average effective federal funds rate over the month.

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

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

where r_i is the average effective federal funds rate for the period before the FOMC meeting, d_i is the number the days before the FOMC meeting, and m_i is the number of days in month i.

The difference is taken right before and right after the tweet. The assumption that the difference between the effective federal funds rate and the target rate is not affected by the tweet implies:

1. Time t is included in month i and no FOMC meeting occurs during month i:

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

which can be rewritten as $\Delta FFF_{t,0} = 0$.

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

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

which can be rewritten as

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

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

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

Note that the assumptions imply that the revision in expectations about the target drive the change in the effective FFR. Therefore,

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

where $\mathbb{E}_t\left[\Delta r'_{i-1}\right]$ is the change in the expected post-FOMC meeting FFR target for the previous month (assuming that 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:

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

If month i is the first month with an FOMC meeting since the tweet, the condition is:

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

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

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

Changes in forward rates can be mapped to changes in the expected FFR target by solving a linear system of equations. Reconstructing the term structure of expectations identifies the time horizon for which the revisions occur. Instances in which some contracts are not traded around a particular tweet are treated as missing observations.

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 and May. No FOMC meeting is scheduled to occur for April and June. Thus, the four corresponding equations are:

$$\begin{aligned}
\Delta FFF_{t,0} &= \frac{d_0 - d_t}{m_0}\mathbb{E}_t\left[\Delta r_0\right] + \frac{m_0 - d_0}{m_0}\mathbb{E}_t\left[\Delta r'_0\right] \\
&= \frac{m_0 - d_0}{m_0}\mathbb{E}_t\left[\Delta r'_0\right], \\
\Delta FFF_{t,1} &= \mathbb{E}_t\left[\Delta r_1\right] = \mathbb{E}_t\left[\Delta r'_0\right], \\
\Delta FFF_{t,2} &= \frac{d_2}{m_2}\mathbb{E}_t\left[\Delta r_2\right] + \frac{m_2 - d_2}{m_2}\mathbb{E}_t\left[\Delta r'_2\right] \\
&= \frac{d_2}{m_2}\mathbb{E}_t\left[\Delta r'_0\right] + \frac{m_2 - d_2}{m_2}\mathbb{E}_t\left[\Delta r'_2\right], \\
\Delta FFF_{t,3} &= \frac{d_3}{m3}\mathbb{E}_t\left[\Delta r_3\right] + \frac{m_3 - d_3}{m_3}\mathbb{E}_t\left[\Delta r'_3\right] \\
&= \mathbb{E}_t\left[\Delta r_3\right] = \mathbb{E}_t\left[\Delta r'_2\right].
\end{aligned}$$

The underlying assumption for the first row is $\mathbb{E}_t\left[\Delta r_0\right] = 0$. In total, three equations derive $\mathbb{E}_t\left[\Delta r'_0\right]$ and $\mathbb{E}_t\left[\Delta r'_2\right]$ which requires a non-linear solver. This example can be generalized and extended to longer horizons. A numerical solution minimizing the total error is obtained if the cross-equation restrictions do not hold exactly. The system in matrix notation becomes

$$\begin{bmatrix} \Delta FFF_{t,0} \\ \Delta FFF_{t,1} \\ \Delta FFF_{t,2} \\ \Delta FFF_{t,3} \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} \frac{m_0-d_0}{m_0} & 0 & 0 & 0 \\ \frac{d_1}{m_1} & \frac{m_1-d_1}{m_1} & & \\ & \frac{d_2}{m_2} & \frac{m_2-d_2}{m_2} & \\ & & \frac{d_3}{m_3} & \frac{m_3-d_3}{m_3} \\ -1 & 1 & & \\ & & -1 & 1 \end{bmatrix} \begin{bmatrix} \mathbb{E}_t\left[\Delta r'_0\right] \\ \mathbb{E}_t\left[\Delta r'_1\right] \\ \mathbb{E}_t\left[\Delta r'_2\right] \\ \mathbb{E}_t\left[\Delta r'_3\right] \end{bmatrix}.$$

Using the appropriate restrictions, the equations simplify to

$$\begin{bmatrix} \Delta FFF_{t,0} \\ \Delta FFF_{t,1} \\ \Delta FFF_{t,2} \\ \Delta FFF_{t,3} \end{bmatrix} = \begin{bmatrix} \frac{m_0-d_0}{m_0} & 0 \\ 1 & 0 \\ \frac{d_2}{m_2} & \frac{m_2-d_2}{m_2} \\ & 1 \end{bmatrix} \begin{bmatrix} \mathbb{E}_t\left[\Delta r'_0\right] \\ \mathbb{E}_t\left[\Delta r'_1\right] \\ \mathbb{E}_t\left[\Delta r'_2\right] \\ \mathbb{E}_t\left[\Delta r'_3\right] \end{bmatrix}.$$

The estimation results are shown in Table 6. In the first month, the average change on the expected fed funds rate is around three times smaller compared to the effect on the one year ahead contract. Thus, the tweets have persistent effects on expectations about the federal funds rate. As explained above, if the tweets were simply creating expectations that cuts expected further in the future will occur earlier on, large changes observed at short horizons would be expected, but with no accompanying revisions at longer horizons. Instead, our evidence points in the opposite direction. The tweets imply a revision in expectations that builds over time. One interpretation is that markets might think that in the immediate future the Fed might be reluctant to immediately follow through with a cut in interest rates, but that the pressure from President Trump will lead to an eventual decline in the FFR.

The results from the joint estimation presented here are in line with results from Section 4.1. The term structure estimates based on classifying contracts by the exposure to the number of FOMC meetings is presented as our benchmark results because it is more closely related to previous contributions and because the results are easier to interpret. A two month horizon is not an homogeneous concept in the term structure of expectations based strictly on time because in the two months there could be one or two FOMC meetings depending on the date of the tweet. Instead, the term structure of expectations built with respect to the number of FOMC meetings controls for the exposure to future monetary policy decisions.

7 Conclusion

This paper presents novel market-based evidence that President Trump impacts expected monetary policy with a strong expansionary bias typical of politically motivated agendas. 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 our estimation is around negative 10 bps over the past year, with the effect growing over time and horizon. Our findings suggest that market participants believe that the erosion to central bank independence is significant and persistent.

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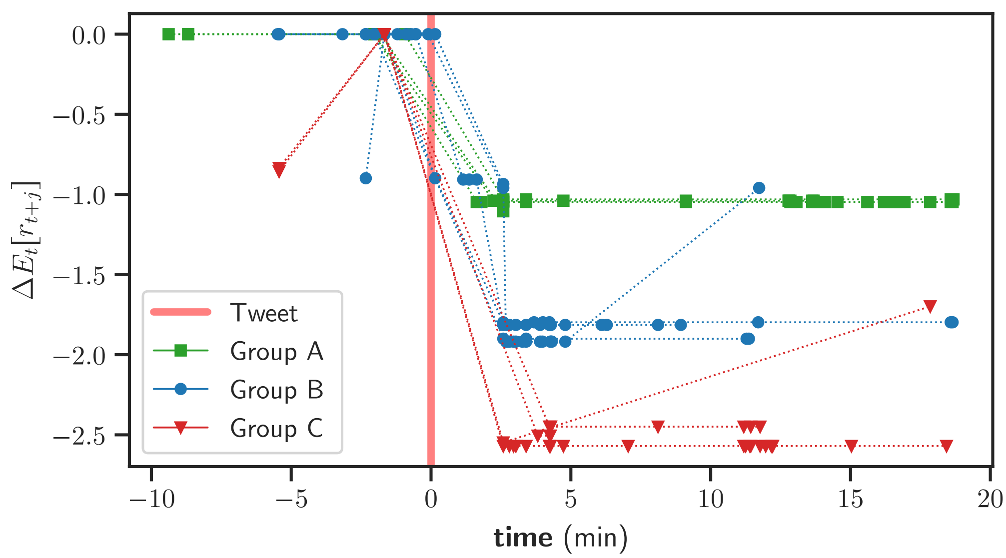
Figure 1: We plot the change in expected federal funds rate for different horizons. The changes are color-coded via the number of FOMC meetings before the contract expires. Group A is exposed up to 4 FOMC meetings, Group B up to 8, and Group C to at least 9 meetings. The changes are reported as changes in percent from 25 Basis Points.

"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



"As usual, the Fed did NOTHING! It is incredible that they can 'speak' without knowing or asking what I am doing, which will be announced shortly. We have a very strong dollar and a very weak Fed. I will work 'brilliantly' with both, and the U.S. will do great... ...My only question is, who is our bigger enemy, Jay Powell or Chairman Xi?" - Donald J. Trump on the 23rd of August 2019 via Twitter

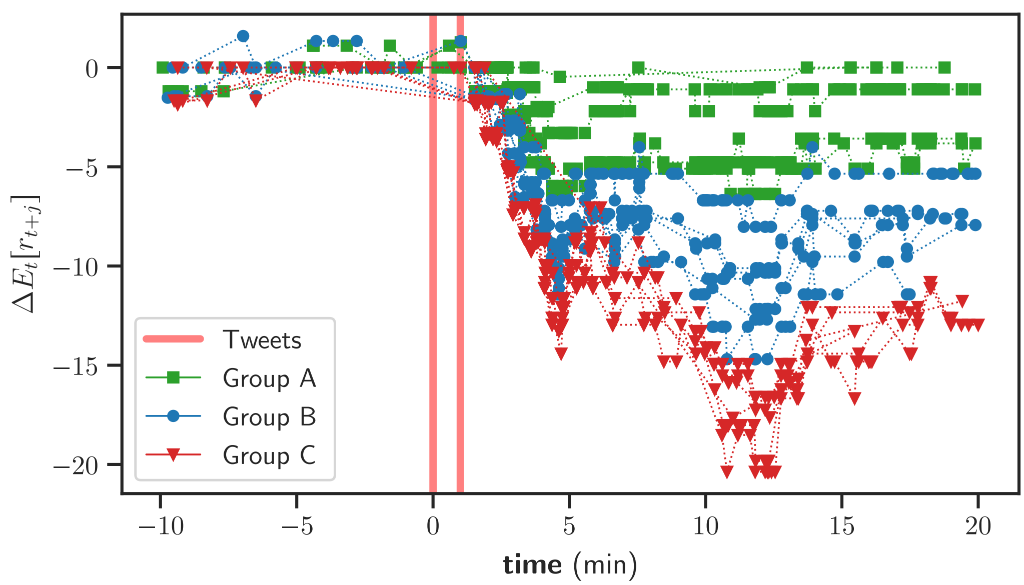


Figure 2: This figure illustrates the time window for how two trades are selected for measuring changes in the expected federal funds rate target in our high-frequency event study.

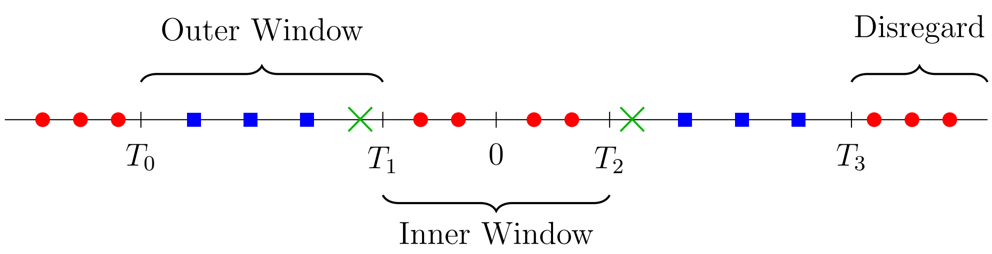


Figure 3: This figure provides two examples highlighting the importance of the timing of the interest rate cuts in relation to our benchmark estimates.

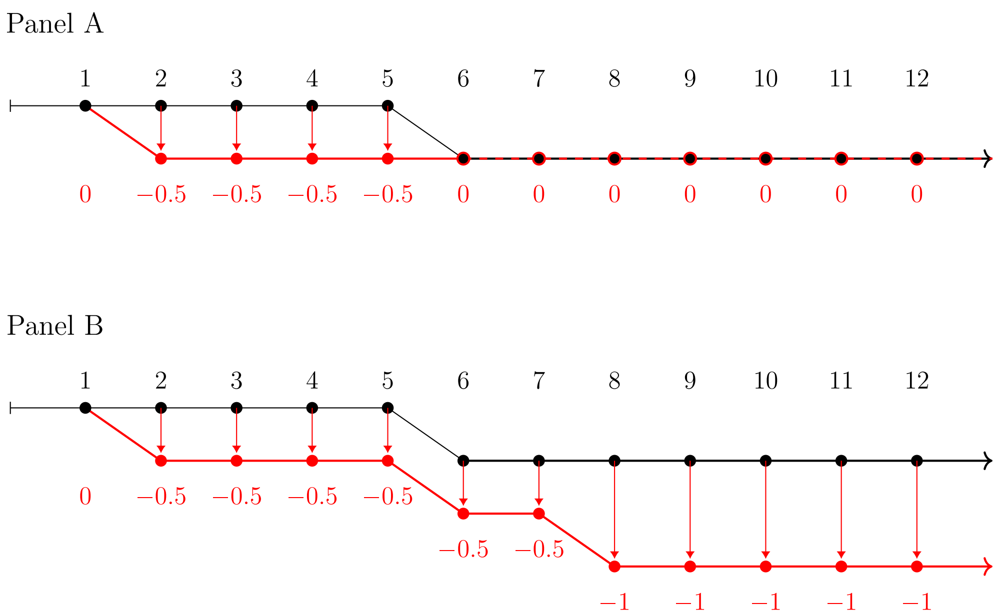


Figure 4: This figure provides an illustration of the four distinct cases considered in our joint estimation of the term structure of expectations with respect to the time horizon.

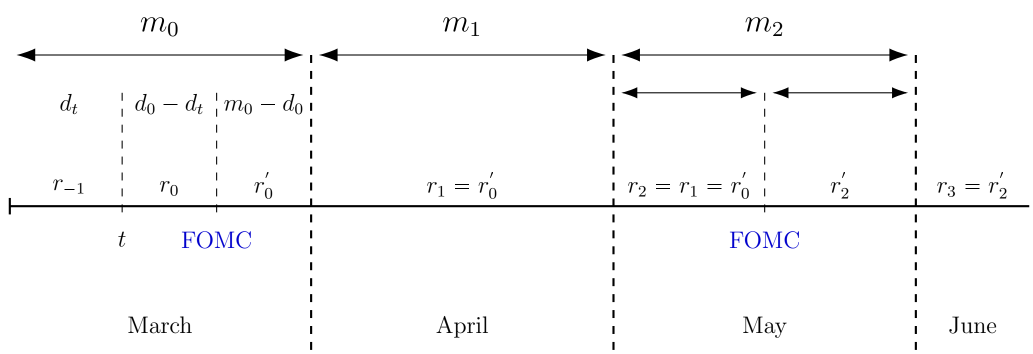


Figure 5: Federal Funds Upper Limit Target

This figure reports the federal funds upper limit target together with four event types: All FOMC meetings, the inauguration of Donald Trump on the on the 20th of January 2017, the nomination Jerome Powell for the Fed Chair position on the 1st of November 2017, and the first critical Tweet by Donald Trump which promotes lower interest rates on the 16th of April 2018.

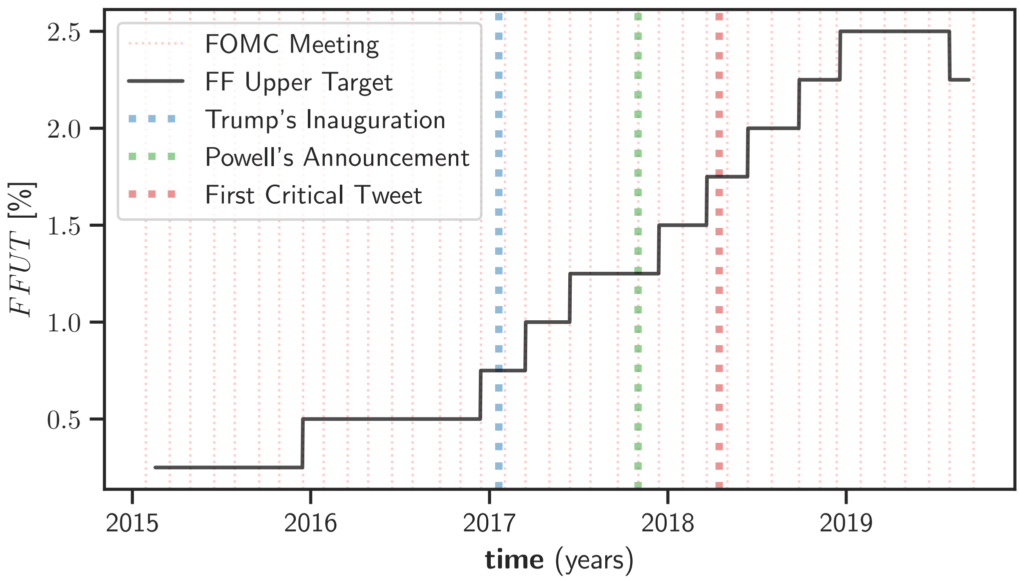


Table 1: Summary Statistics: All Contracts

This table reports the summary statistics on trades of all contracts that fall within the baseline window. Panel A calculates the the statistics on the total set of observations while Panel B and C compare contracts split at the median FOMC meeting exposure (i.e. the number of FOMC meetings occurring before contract expiration).

Variable	Mean (1)	Std. Dev. (2)	Minimum (3)	Maximum (4)
Panel A: Pooled Statistics				
Federal Funds Rate	2.41	0.22	1.69	2.83
ΔFederal Funds Rate	-0.0034	0.01	-0.03	0.02
Contract Duration [days]	289.0	171.0	1.0	655.0
Number of FOMC Meetings	6.0	3.78	0.0	14.06
Panel B: FOMC Meetings - Below Median				
Federal Funds Rate	2.318	0.221	1.69	2.68
ΔFederal Funds Rate	-0.002	0.003	-0.01	0.005
Panel C: FOMC Meetings - Above Median				
Federal Funds Rate	2.503	0.166	2.195	2.83
ΔFederal Funds Rate	-0.005	0.008	-0.035	0.015

Table 2: Fixed FOMC Exposure: Baseline Specification

This table reports the regression results for changes in the expected federal funds rate at different maturities. Each column considers contracts with a minimal number of FOMC meetings (from 0 to 10) to which a contract is exposed. 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

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

$E_{t-i\pm\Delta}[r_t]$ is the market expectation of the federal funds rate for the month when the corresponding future contract expires and the subscript $\pm\Delta$ indicates whether the observation is from the pre or post-event outer window.

	Exposure to FOMC Meetings										
Variable	0	1	2	3	4	5	6	7	8	9	10
Panel A: Regression Coefficients											
Intercept α	2.23***	2.04***	1.93***	1.82***	1.75***	1.70***	1.66***	1.62***	1.59***	1.56***	1.62***
std. err.	0.03	0.03	0.04	0.06	0.07	0.07	0.07	0.08	0.09	0.09	0.11
t-stat.	76.66	59.23	43.93	32.57	26.74	24.55	22.36	20.59	18.27	17.36	14.53
Dummy Coef. β	−0.00015	−0.00181**	−0.00139	−0.0020*	−0.0030***	−0.00347***	−0.00333***	−0.00347***	−0.00456***	−0.00338**	−0.005*
std. err.	0.0002	0.0008	0.0011	0.0012	0.0011	0.0011	0.0012	0.0013	0.0017	0.0015	0.0028
t-stat.	−0.627	−2.127	−1.281	−1.719	−2.756	−3.305	−2.714	−2.633	−2.713	−2.207	−1.794
Panel B: Regression Properties											
N	68	72	72	70	70	72	72	72	68	68	52
T_0 [min]	180	180	180	180	180	180	180	180	180	180	180
T_1 [min]	1	1	1	1	1	1	1	1	1	1	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 3: Fixed FOMC Exposure: Robustness

This table reports the regression results for changes in the expected federal funds rate at different maturities for different inner time windows. Each column considers contracts with a minimal number of FOMC meetings (from 0 to 10) to which a contract is exposed. 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

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

$E_{t-i\pm\Delta}[r_t]$ is the market expectation of the federal funds rate for the month when the corresponding future contract expires and the subscript $\pm\Delta$ indicates whether the observation is from the pre or post-event outer window.

	Exposure to FOMC Meetings										
Variable	0	1	2	3	4	5	6	7	8	9	10
Panel A: [1 min, 3 min]											
Dummy Coef. β.	−0.00015	−0.00097*	−0.00042	−0.00114	−0.00143	−0.00278***	−0.00208**	−0.00292**	−0.00368**	−0.00309**	−0.00558**
t-stat.	−0.627	−1.745	−0.475	−1.214	−1.537	−3.247	−2.163	−2.428	−2.243	−2.342	−2.152
Panel B: [1 min, 5 min]											
Dummy Coef. β	−0.00015	−0.00181**	−0.00139	−0.002*	−0.003***	−0.00347***	−0.00333***	−0.00347***	−0.00456***	−0.00338**	−0.005*
t-stat.	−0.627	−2.127	−1.281	−1.719	−2.756	−3.305	−2.714	−2.633	−2.713	−2.207	−1.794
Panel C: [5 min, 5 min]											
Dummy Coef. β	$7e-05$	−0.00194**	−0.00181*	−0.00271**	−0.00329***	−0.00347***	−0.00333***	−0.00343**	−0.00441***	−0.00338**	−0.00365
t-stat.	0.329	−2.348	−1.844	−2.138	−2.793	−2.954	−2.582	−2.528	−2.703	−2.073	−1.276
Panel D: [1 min, 15 min]											
Dummy Coef. β	−0.00015	−0.00118	−0.00139	−0.00171	−0.00271**	−0.00333***	−0.00292**	−0.00443***	−0.00485***	−0.005***	−0.00389*
t-stat.	−0.529	−1.606	−1.405	−1.503	−2.111	−2.714	−2.084	−2.624	−2.719	−2.807	−1.646
Panel E: [1 min, 30 min]											
Dummy Coef. β	−0.00118	−0.00222*	−0.00167	−0.00292*	−0.005***	−0.005**	−0.00571***	−0.00443**	−0.00606***	−0.00561***	−0.00667**
t-stat.	−1.034	−1.776	−1.261	−1.854	−2.586	−2.575	−2.644	−2.55	−2.973	−2.675	−2.461
Panel F: [10 min, 20 min]											
Dummy Coef. β	−0.00109	−0.00257*	−0.00319**	−0.00333**	−0.00403**	−0.00528***	−0.00458**	−0.00456***	−0.00561**	−0.00455**	−0.00593**
t-stat.	−0.913	−1.845	−2.36	−2.029	−2.004	−2.664	−2.151	−3.074	−2.47	−2.473	−2.107

Table 4: Level and Slope

The regression studies the average change in expectations across contracts and different revision for short- and long-term expectations. The regression in panel A includes all fixed FOMC exposure contracts with at least one FOMC meeting prior the expiration month. 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 and the subscript $\pm\Delta$ denotes whether the observation is from the pre or post-event outer window.
Panel B considers two contracts to test whether the revision in expectations changes between short and longer horizon. A contract that is exposed to exactly one FOMC meeting and a contract one year later. The expected federal funds rate is regressed on a dummy variable which signifies whether the observation is before or after a tweet and extended by an additional dummy which indicates whether the contract is exposed to one or eight FOMC meetings, as well as the interaction between the two dummies:

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

The subscript SL indicates whether the contract is exposed to one or eight FOMC meetings prior the month of expiration.

	Intercept α	Post-Pre β	Long-Short γ	Post-Pre & Long-Short δ
Panel A: Level Regression				
Coefficient	1.78	-0.00282		
std. err.	0.0605	0.00106		
t-stat.	29.38	-2.66		
Panel B: Slope Regression				
Coefficient	2.04	-0.00181	-0.44556	-0.00275
std. err.	0.03442	0.00085	0.06716	0.00141
t-stat.	59.21	-2.13	-6.63	-1.96

Table 5: Pre and Post the most Recent FOMC Meeting

The first set of results is based on a subsample before the most recent FOMC meeting (31st of July 2019) and the second set considers only tweets that occurred after the meeting. For each subsample, the regression studies the average change in expectations across contracts and different revision for short- and long-term expectations. The regression in panel A includes all fixed FOMC exposure contracts with at least one FOMC meeting prior the expiration month. 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 and the subscript $\pm\Delta$ indicates whether the observation is from the pre or post-event outer window.
Panel B considers two contracts to test whether the revision in expectations changes between short and longer horizon. A contract that is exposed to exactly one FOMC meeting and a contract one year later. The expected federal funds rate is regressed on a dummy variable which denotes if the observation is before or after a tweet and extended by an additional dummy which signifies whether the contract is exposed to one or eight FOMC meetings, as well as the interaction between the two dummies:

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

The subscript SL denotes whether the contract is exposed to one or eight FOMC meetings prior the month of expiration.

Before the 31st July 2019

	Intercept α	Post-Pre β	Long-Short γ	Post-Pre x Long-Short δ
Panel A: Level Regression				
Coefficient	1.99	−0.00213		
std. err.	0.07077	0.00108		
t-stat.	28.07	−1.98		
Panel B: Slope Regression				
Coefficient	2.17	−0.00095	−0.29377	−0.0028
std. err.	0.03744	0.00066	0.10016	0.00187
t-stat.	57.95	−1.45	−2.93	−1.49

After the 31st July 2019

	Intercept α	Post-Pre β	Long-Short γ	Post-Pre x Long-Short δ
Panel A: Level Regression				
Coefficient	1.48	−0.00381		
std. err.	0.02411	0.00204		
t-stat.	61.24	−1.87		
Panel B: Slope Regression				
Coefficient	1.85	−0.003	−0.66617	−0.00271
std. err.	0.01212	0.00181	0.0194	0.00221
t-stat.	152.94	−1.65	−34.34	−1.23

Table 6: Term Structure of Expectations

This table reports the results on the multi contract estimation based on the linear system of equations developed in section 6. Using different contact expirations, changes in market expectations on the federal funds rate for each month till one year ahead are obtained. For robustness, panel B provides results on the term structure of expectations for different horizons from five to ten months.

	Months															
Variable	0	1	2	3	4	5	6	7	8	9	10	11	12	mean	12-0	12-1
Panel A: Baseline [1 min, 5 min]																
$\mathbb{E}_t[\Delta r_i]$	0.020	−0.139	−0.066	−0.073	−0.114	−0.183	−0.209	−0.212	−0.250	−0.268	−0.274	−0.323	−0.307	−0.184	−0.327	−0.168
Panel B: Different Horizons																
$\mathbb{E}_t[\Delta r_i]$	0.018	−0.134	−0.074	−0.091	−0.148	−0.214								−0.107	−0.231	−0.080
$\mathbb{E}_t[\Delta r_i]$	0.018	−0.133	−0.074	−0.092	−0.144	−0.206	−0.268							−0.128	−0.287	−0.135
$\mathbb{E}_t[\Delta r_i]$	0.021	−0.138	−0.065	−0.079	−0.143	−0.185	−0.221	−0.242	−0.216					−0.141	−0.237	−0.079
$\mathbb{E}_t[\Delta r_i]$	0.016	−0.144	−0.070	−0.092	−0.125	−0.191	−0.225	−0.220	−0.253	−0.272	−0.289			−0.170	−0.304	−0.145