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Social media, high-frequency trading, and market making after-hours – Evidence from presidential tweets

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Abstract

I analyze differences between the core and extended trading sessions in the high-frequency reaction of equity markets to potential news. Using presidential tweets as unanticipated, potentially market-stirring events, I find that volatility increases and liquidity deteriorates within fractions of a second after a tweet. The speed of quote adjustments indicates that algorithmic traders monitor social media sources around the clock and automatically trade upon this information. Compared to the core trading session, the reduction in market quality is much stronger and faster during the extended trading hours, when liquidity is lower and designated market maker participation is optional.

JEL CLASSIFICATION
G10, G12, G14, G23

1 | INTRODUCTION

Financial markets operate increasingly fast, with much of trading activity driven by algorithms. Additionally, exchange opening hours have lengthened, reflecting the need and willingness to continuously trade. Taken together, these changes impact trading in general and market making in particular. While trading activity is mostly automated nowadays, so is much of the information processing leading up to these trades. For example, algorithmic traders process and trade on public news, such as macroeconomic announcements, at speeds orders of magnitude faster than any human trader could. Moreover, they can monitor multiple sources simultaneously and around the clock, thereby particularly benefiting from longer exchange opening hours.

In the race to incorporate news into prices first, algorithmic and high-frequency traders increasingly look beyond established sources and rely on alternative ones. One such alternative is social media data, which can take two basic forms: The first form comprises a wide cross-section of social media posts by a large group of individuals. This type of data is suited to study the sentiment of a broad investor base. The other form is narrower, focusing on social media posts by important individuals or institutions. Examples include companies that distribute news via social media, as well as high-ranking individuals from the private or public sectors, such as corporate executives or government officials. In both cases, one of the most important social media platforms is X, formerly known as Twitter, which allows users to post short messages called tweets.

Using tweets by U.S. President Donald Trump during his first term as market-stirring events, I analyze the high-frequency reaction of equity markets to potential news, focusing on the behavior of liquidity providers. While, on average the tweets do not have a directional impact on prices beyond a short window of up to 2 seconds, I find that volatility increases substantially within less than 1 second after a tweet and reduces to its pre-tweet level after about 10 seconds. Likewise, quoted liquidity deteriorates and replenishes at the same pace. With respect to trading liquidity, a spread decomposition indicates that increases in effective spreads are driven by larger price impacts, whereas the profitability of market making, as measured by realized spreads, is not significantly affected. Compared to the core trading session, the reduction in market quality is substantially stronger and faster during the extended trading hours, where liquidity is generally lower and the participation of designated market makers is optional.

Given the speed of quote adjustments within fractions of 1 second after a tweet, it is unlikely that the results are driven by human traders. Instead, the results are consistent with the notion that algorithms monitor social media platforms around the clock and automatically trade based on this information. The notable reduction in liquidity during the extended hours is likely due to voluntary liquidity providers withdrawing from the market during tweet-induced uncertainty, with no designated market makers obliged to keep providing liquidity and stabilizing prices.

Algorithmic trading, and particularly its subset of high-frequency trading (HFT), is at the center of a debate regarding its externalities and social benefits (Goldstein et al., 2014). The effect of such trading activity likely depends on the specific strategies chosen. On the one hand, HFTs have been shown to enhance market quality by providing liquidity and making markets (Hagströmer & Nordén, 2013). On the other hand, some HFTs might engage in predatory activity by using their speed advantage to adversely select slower traders.[1]

While in order-driven markets, any trader submitting a limit order acts as a liquidity provider, many exchanges choose to have designated market makers (DMMs). These commit to continuously providing liquidity by quoting prices on both sides of the order book, typically subject to some maximum spread and minimum quoted size. The literature on DMMs has mostly found positive effects of DMMs on market quality and liquidity (Anand et al., 2009; Bessembinder et al., 2020; Clark-Joseph et al., 2017; Menkveld & Wang, 2013; Venkataraman & Waisburd, 2007). The positive effect is particularly pronounced during times of market turbulence (Anand & Venkataraman, 2016; Chung et al., 2022; Theissen & Westheide, 2020). Today, most DMMs are HFTs, since these specialized market makers have to quickly react to information from the trading process and from external sources in order to stay profitable by avoiding adverse selection. In this study, one of the primary differences between the core and extended trading hours is that during the latter, market maker participation is strictly optional. I hence contribute to the literature on DMMs by providing indirect evidence of their positive effect during periods of market uncertainty.

The literature on after-hours trading so far has documented lower liquidity and trading volume as well as higher volatility outside of the core trading session (Barclay & Hendershott, 2004; Giannetti et al., 2006; McInish et al., 2002). However, there appears to be significant price discovery after-hours (Barclay & Hendershott, 2003;

[1]For a survey of the literature on HFT and its effects, see Menkveld (2016).

Dungey et al., 2009; Jiang et al., 2012). Cui and Gozluklu (2025) compare market reactions to earnings announcements, insider trades, and index reconstitutions between the core trading hours and the after-hours session. They show that both scheduled and unscheduled news after-hours trigger increased trading activity. Specifically looking at HFT activity during the various trading phases, Cole et al. (2015) conclude that HFTs are not very active during the extended trading hours and contribute little to price discovery during these times. Finally, Jain et al. (2019) document increased short-selling activity in the after-hours session following earnings announcements released after hours. By studying differences between trading sessions throughout the day in how prices and liquidity react to unscheduled news, I also contribute to the literature on after-hours trading.

Regardless of the strategy chosen, HFTs monitor not only data on the trading process itself but also information from other sources, such as macroeconomic announcements (Brogaard et al., 2014; Scholtus et al., 2014). When it comes to alternative data sources in a high-frequency context, the empirical evidence is still scarce. Agrawal et al. (2018) present findings that social media news lead to increases in liquidity. Using intraday data, they show that momentum turns to mean reversion at the time of the peak of social media sentiment. Behrendt and Schmidt (2018) use intraday data and find a statistically significant but economically small correlation between Twitter activity and equity volatility. However, while some of the documented effects might be due to algorithms monitoring social media channels, the data frequency of 5 minutes might be too low to study high-frequency trading activity. Gan et al. (2024) compare the impact of overnight social and news media across several international markets using a high-frequency measure of media sentiment. While they find an effect of social media news on overnight stock returns, this effect is mostly limited to the United States.[2] By documenting the high-speed reaction to potentially market-moving tweets, I contribute to this stream in the literature on how investors in general and algorithmic traders in particular use social media data.

A growing stream within the literature considers how government officials use social media to directly communicate with the public. A natural question, then, is how these modern types of information releases impact financial markets and, in particular, how algorithmic traders incorporate them into their trading strategies. Closely related to this study are Abdi et al. (2023), Gjerstad et al. (2021), and Nishimura et al. (2021). All three studies look at how the S&P 500 reacts to President Donald Trump's tweets and thus consider the same index also used in this study. However, their studies focus on larger windows around each tweet and thus use a lower frequency of 1- or 5-minute intervals, and do not consider market making activity or effects on liquidity. Abdi et al. (2023) find that the tweets do not provide new information, but rather react to pre-existing market conditions. Gjerstad et al. (2021) find that the prices tend to decline after tweets while volume and volatility increase. Nishimura et al. (2021) similarly document that tweets positively affect volatility. Using minutely intraday data, Machus et al. (2022) find that individual companies mentioned in tweets experience abnormally high trading volume. Prices increase after positive news and decrease after negative news, but this price change is subsequently reversed and thus only temporary. While the previously mentioned studies focus on equity markets, others have documented an effect of tweets by Donald Trump on expected interest rates (Bianchi et al., 2023) and exchange rates (Filippou et al., 2025). There are several further studies that investigate the effect of presidential tweets on financial markets, but most do not consider high-frequency market reactions (Born et al., 2017; Burggraf et al., 2020; Ge et al., 2019; Huynh, 2021; Klaus & Koser, 2020; Pham et al., 2022; Salem et al., 2019; Zhang et al., 2024). Instead, they document longer-term effects. By examining how market making and trading activity evolve immediately after a tweet, I provide evidence on the mechanisms behind the market's overall reaction to presidential communication via social media. To summarize, several studies have documented increased volatility after presidential tweets, but the evidence regarding the direction of price movements is less clear. In any case, Donald Trump's tweets serve as exogenous shocks to study unanticipated increases in uncertainty at high frequency. Since presidential tweets are unscheduled, mostly unpredictable, occur throughout the day, and are precisely timestamped, they provide an opportunity to test for

[2]Several other studies analyze social media data and how it affects financial markets, but typically at lower frequencies (see, e.g., Dredze et al., 2016 for a survey).

differences in high-frequency market reactions between different trading sessions, which is not equally feasible using other types of news.

2 | INSTITUTIONAL BACKGROUND

2.1 | Trading hours

Trading at the New York Stock Exchange (NYSE) Archipelago Exchange (Arca), the relevant exchange for this study, is split into three sessions: The pre-market session (4:00 a.m. to 9:30 a.m.), the core trading session (9:30 a.m. to 4:00 p.m.), and the after-hours session (4:00 p.m. to 8:00 p.m.). Taken together, the pre-market and after-hours sessions constitute the extended trading hours. Additionally, there are call auctions at the beginning of each of the three sessions.

There are three types of participants on the trading platform: Market Makers, Lead Market Makers, and Order Routers. All three are required to hold NYSE Arca equity trading permits; individual investors, however, are not eligible to trade directly on the exchange. Both market makers and lead market makers are designated market makers in the context of this study. Lead market makers differ from regular market makers in that they have stricter requirements to participate in off-exchange trading, although all designated market makers have certain quoting obligations. In particular, they must provide continuous, displayed quotes on both sides of the order book and adhere to limits on the maximum bid-ask spread (NYSE Arca, 2019). Designated market makers, in turn, are incentivized by more favorable trading fee schedules. However and importantly for this study, market maker participation is strictly voluntary during the extended hour, potentially leading to less liquidity and more volatile stock prices. In fact, the Financial Industry Regulatory Authority, a self-regulatory body for exchanges and brokers, requires its members to communicate the risks of lower liquidity and potential price jumps during the extended hours to their clients (FINRA, 2009).

2.2 | Algorithmic trading and social media

Personal tweets by government officials are particularly suited to study how traders automatically process alternative information sources and react by trading. Firstly, there is evidence that at least some presidential tweets contain information which potentially moves markets (Bianchi et al., 2023; Klaus & Koser, 2020). Moreover, such tweets increase uncertainty, especially since their content is mostly unpredictable at high frequencies, requiring advanced algorithms to react on the spot. In contrast, scheduled announcements allow for greater anticipation while traditional news reports often elicit slower, more deliberate adjustments. Secondly and contrary to, for example, macroeconomic announcements, the tweets are unscheduled, and their timing and frequency likewise unpredictable. However, similar to official macroeconomic news releases, but in contrast to many other sources of news, such as newspaper articles, the tweets can be timestamped with very high accuracy, down to a millisecond precision. Thirdly, the tweets occur throughout the day (and night) and thus practically randomly fall into all different trading sessions, facilitating a comparison of the impact of the same news source between the different market hours. Finally, these tweets originate directly from a single influential source and are directly available to a wide audience, bypassing traditional intermediaries and reducing ambiguity about authorship. The combination of immediacy, brevity, and direct authorship thus provides a mechanism through which tweets can trigger the sharp and short-lived market reactions documented in this study.

That algorithms monitor Twitter for this purpose is also supported by anecdotal evidence. Although most algorithmic traders do not disclose their trading strategies and systems, there are reports of algorithms monitoring Donald Trump's social media accounts and automatically trading based on tweets. For example, National Public

Radio's (NPR) Planet Money discusses building such a trading "bot" (i.e., a trading algorithm). Importantly, they mention that this was achieved with the support of the head of investments at the time of the high-frequency trading firm Tradeworx (NPR, 2017). Similarly, there are trading algorithms that automatically perform sentiment analysis on the President's tweets and short-sell stocks of companies mentioned in negative-sentiment tweets within seconds (Forbes, 2017).

3 | DATA AND METHODOLOGY

The data used in this study comes from two main sources: Tweets from the Trump Twitter Archive[3] and exchange-traded fund (ETF) data from Refinitiv. The sample ranges from January 1 to November 6, 2020—the day most media outlets had declared that Donald Trump had lost the 2020 presidential election.

3.1 | Tweet data

During his presidency, Donald Trump actively used Twitter to communicate with the public. The data used in this study contains all his tweets (@realDonaldTrump) during the sample period, including subsequently deleted tweets. Long tweets that are split into multiple shorter tweets are combined if they occurred within 5 minutes and the next tweet begins with three dots. An advantage of using Twitter data is that very precise timestamps are available. Every tweet is assigned a unique identifier, called Snowflake ID, that contains a timestamp in millisecond precision, allowing for a high-frequency analysis of market reactions.[4]

There are possible differences between how markets react to tweets and to retweets. The latter might reveal less about Donald Trumps' personal opinions or their content might be more difficult for an algorithm to analyze. Building on this notion, I drop all retweets.[5] In a similar vein, even though tweeted from his official account, some tweets might not have been written by Trump personally. However, while the authorship of tweets is not directly observable, his staffers are substantially more likely to use hashtags. I hence drop all tweets that contain a hashtag (Almond & Du, 2020; McGill, 2017). Likewise, I drop all tweets not sent from an iPhone (e.g., those sent via Twitter Media Studio), although none of these steps meaningfully impact the results.

To further analyze tweet content, I employ several approaches. Firstly, I classify tweets as economic tweets if they contain one of the keywords from Baker et al. (2026). Their dictionary contains terms from general economic and policy-related categories and should thus capture tweets where the President's influence on future economic conditions is especially relevant. Secondly, I classify the sentiment expressed in the tweet by employing a pre-trained machine learning model. In particular, I use the 2022 updated version of Twitter-roBERTa-base. The model has been trained on more than 120 million tweets covering several years, including my sample period. The model has been finetuned for sentiment analysis with the TweetEval benchmark (Barbieri et al., 2020; Camacho-Collados et al., 2022; Loureiro et al., 2022). I pre-process the tweets by removing numbers, hyperlinks, and "@mentions", as well as by normalizing whitespaces, turning all letters lowercase, and finally, normalizing each tweet to a length of 128 tokens. To each tweet, the model then assigns either a negative (−1), neutral (0), or positive (1) sentiment. I then combine the two methodologies and obtain the sentiment for economic tweets only. Thirdly, I cluster the tweets based on their topic using a machine learning topic modeling approach further explained in Section 5.3.

[3] I thank Brendan Brown for making the data available at http://www.thetrumparchive.com.

[4] Snowflake IDs have been used by Twitter since November 2010. The first 41 bits of the identifier contain the time in milliseconds since some epoch. In practical terms, Unix epoch timestamps can be extracted by dividing the identifier by 2^{22} and adding 1288834974657 (see also Twitter Inc. 2010).

[5] Repeating the analysis while including retweets yields very similar results. The reactions to tweets and retweets thus does not appear to differ substantially at high frequencies.

3.2 | Equity market data

The equity market dataset contains high-frequency data for the SPDR S&P 500 (SPY) as traded at NYSE Arca, one of the largest and most liquid ETFs worldwide. The data contains all trades as well as quoted prices and quantities at the best bid and offer sampled at a frequency of 1 millisecond. I aggregate the data to 100 millisecond intervals by calculating various measures of trading activity and liquidity: the average quote midpoint log return, the standard deviation of 1 millisecond quote midpoint returns, the total trading volume, the average relative quoted bid-ask spread, and the average depth available at the best bid and ask. To measure trading liquidity, I compute effective spreads and decompose these into realized spreads and the price impact.

$$\text{Effective} = \frac{2D_t(P_t - M_t)}{M_t} \tag{1}$$

$$\text{Realized}_\Delta = \frac{2D_t(P_t - M_{t+\Delta})}{M_t} \tag{2}$$

$$\text{Price Impact}_\Delta = \frac{2D_t(M_{t+\Delta} - M_t)}{M_t}, \tag{3}$$

where P_t is the price of a transaction, M_t is the quote midpoint before the transaction, $M_{t+\Delta}$ is the quote midpoint Δ seconds after the trade, and D_t is +1 or −1 if the trade is initiated by the buyer or the seller, respectively. Similar to Hagströmer (2021), I classify trades into buyer and seller initiated using the Lee and Ready (1991) algorithm. For each 100-millisecond window, I then compute equally weighted averages of these values for Δ = 1 second.[6]

To address potential outliers, the measures are then winsorized at the 99.50% level. However, the winsorization does not meaningfully impact my conclusions.

3.3 | Estimation approach

To study the market reactions to tweets, I use two different approaches. First, I use three sets of regressions with date and intraday fixed effects to show the effect of tweets and how they differ between the individual market sessions. Then, to zoom into the development of how the market reacts, I employ sequences of *t* tests to perform an event study.

As a baseline model, I consider trading and liquidity data in a small window of ±1, ±10, and ±60 seconds around each tweet and run the following fixed effects regression

$$V_{ij} = \beta_0 + \beta_1 \text{Post}_{ij} + \tau_1 d_i + \tau_2 g_{ij} + \varepsilon_{ij}, \tag{4}$$

where V_{ij} is the measure of trading activity or liquidity and Post_{ij} is a binary variable set to 1 if observation j occurred after tweet i, d is the date fixed effect, and g is the intraday fixed effect for every 15-minute interval. The constant captures any pre-tweet levels in the dependent variables. I include intraday fixed effects to control for known patterns in liquidity. For example, several studies have documented U-shaped patterns in illiquidity and volatility (McInish & Wood, 1992; Wood et al., 1985). The date fixed effects control for longer-term trends.

[6]Hagströmer (2021) argues that this methodology of estimating effective spreads and thus realized spreads and price impacts is biased since the quote midpoint is not an unbiased estimate of the fundamental value. However, I obtain similar results when using depth-weighted quote midpoints $\tilde{M} = \frac{P^B Q^A + P^A Q^B}{Q^A + Q^B}$, as suggested by Hagströmer (2021), where P^B and Q^B (P^A and Q^A) are price and quoted quantity at the best bid (ask), respectively.

To estimate the effect of tweets during the extended trading hours, I include the interaction of Post with H_{Core} and H_{Extended}, binary variables set to 1 if the tweet was sent during the core trading session or during the extended trading hours, respectively.

$$V_{ij} = \beta_0 + \beta_1 \text{Post}_{ij} \times H_{\text{Core},i} + \beta_2 \text{Post}_{ij} \times H_{\text{Extended},i} + \tau_1 d_i + \tau_2 g_{ij} + \varepsilon_{ij} \tag{5}$$

Note that the unconditional effect of H_{Extended} is already subsumed in the intraday fixed effects and, hence, not included as a separate regressor.

Finally, I separate the extended trading hours into the pre-market and after-hours trading sessions. Specifically, I include the binary variables H_{Pre} and H_{After}, which are set to 1 for the trading sessions before and after the core trading session, respectively:

$$V_{ij} = \beta_0 + \beta_1 \text{Post}_{ij} \times H_{\text{Core},i} + \beta_2 \text{Post}_{ij} \times H_{\text{Pre},i} + \beta_3 \text{Post}_{ij} \times H_{\text{After},i} + \tau_1 d_i + \tau_2 g_{ij} + \varepsilon_{ij} \tag{6}$$

In all regressions, the standard errors are clustered by tweet.

To analyze the development of the high frequency market reactions in more detail, I then perform sequences of t tests. I first take the average of the measures of trading activity and liquidity in the 1-minute window before a given tweet. For every lag l after the tweet, I then calculate the difference between the measure and the average in the before window. $l = 0$ indicates the 100-millisecond window during which the tweet occurred. Using standard t tests across all tweets, I then test for the significance up to a given lag, using a maximum of 600 lags (1 minute). I then perform these tests separately for the core trading and the extended hours session, where I set the maximum lag to 150 (15 seconds), since most effects diminish after 10 seconds.

4 | HIGH-FREQUENCY MARKET REACTION TO TWEETS

4.1 | Descriptive statistics

In total, I identify 2,392 tweets during exchange opening hours, which translates to about 11 tweets per trading day. Of these, 748 were tweeted during the pre-market phase, 1,054 during the core trading session, and 593 during the after-hours session. Figure 1 shows the weekly average number of tweets across time for the core trading session and the extended hours. Tweeting activity varies substantially across time, peaking at

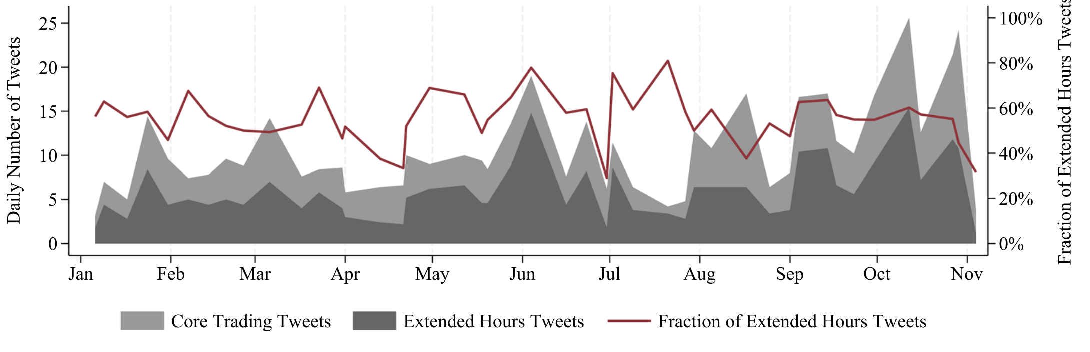

FIGURE 1 Tweeting activity over time. *Note:* This graph shows the stacked weekly averages of the daily number of tweets during the core and extended trading hours. The line indicates the fraction of tweets during the extended trading hours. [Color figure can be viewed at wileyonlinelibrary.com]

an average of about 26 tweets per day at the beginning of October 2020. Relatively speaking, the fraction of tweets during the extended hours is more stable and fluctuates mostly between 40% and 80% with no discernible trend.

Figure 2 shows the total number of tweets during each hour of the day. The pattern is very similar to what has been documented by Almond and Du (2020): There are hardly any tweets during the night between 2 a.m. and 6 a.m. The morning, especially from 7 a.m. to 9 a.m., sees the highest frequency of tweeting activity, while at around noon there are relatively few tweets. Throughout the rest of the day, the number of tweets increases again until midnight. There are thus a significant number of tweets during all trading phases.

Descriptive statistics at the tweet level are presented in Table 1. The number of times a tweet is retweeted is slightly higher during the core trading session, but at a comparable magnitude. Regarding the content of the tweets, none of the approaches show substantial differences between the core trading session and the extended hours. Both the fraction of tweets with economic keywords and the sentiment score are at similar levels. The sentiment of tweets with economic keywords is negative on average and slightly stronger during the core trading session, although the difference is not statistically significant.

The remaining variables are based on the ETF data. For every tweet, I take the average of each respective measure during the 1-minute window before the tweet was sent. While average returns do not differ materially between the core trading session and the extended trading hours, their standard deviation is lower during the latter. The lower volatility after hours can be explained by relatively few quote updates during these times, resulting in a substantial number of zero returns.

At 1.64 basis points (bps), quoted bid-ask spreads are roughly three times as large during the extended trading hours. Effective spreads are on average lower than quoted spreads, but likewise larger during the extended hours than during the core trading session. This is consistent with the mandatory warning regarding low after-hours liquidity that FINRA obliges its members to communicate to their clients (FINRA, 2009). While quoted depth is larger during the extended hours, this has to be interpreted with caution as the data only provides the quantity available at the best bid and ask. Since quoted spreads are substantially wider, the quoted depth during the extended hours might be larger at the top of the book, but the prices at which it is available is much further from the quote midpoint. Expectedly, trading volume is much higher during the core trading session.

Untabulated *t* tests confirm that the differences in volatility, trading volume, and liquidity between the core trading session and the extended hours are statistically significant at the 1% level. However, the same does not hold for the content of the tweets: For sentiment and the use of economic keywords, the differences are statistically insignificant. The differences in returns are likewise insignificant.

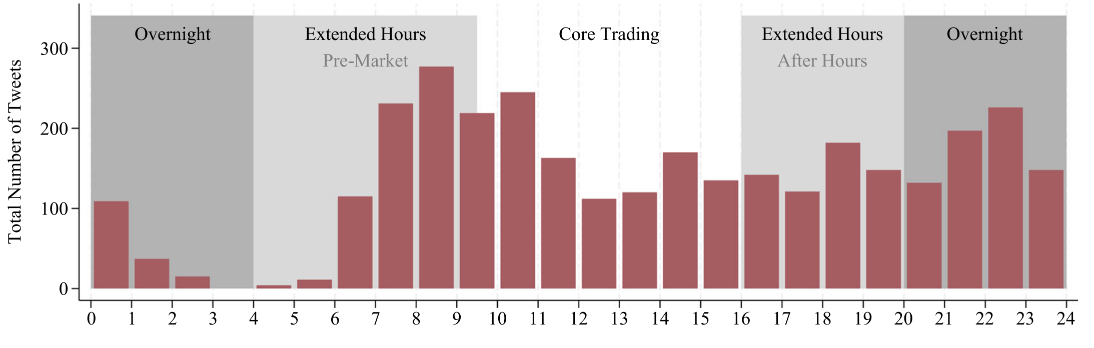

FIGURE 2 Tweeting activity and trading hours. *Note:* This graph shows the distribution of Donald Trump's tweets throughout the day. Each bar provides the total number of tweets in the sample that fall into a given hour of the day. The gray areas indicate the various sessions of the trading hours at NYSE Arca. [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 1 Descriptive statistics.

	Mean	SD	Min	P5	P50	P95	Max	Skew.	Kurt.	N
Panel A: Full trading day										
Retweets	24.12	16.83	0.00	7.11	20.00	56.99	143.07	2.1	9.8	2,392
Economic Tweet	0.14	0.35	0.00	0.00	0.00	1.00	1.00	2.0	5.1	2,392
Sentiment	0.13	0.93	−1.00	−1.00	1.00	1.00	1.00	−0.3	1.2	2,392
Sentiment Economic	−0.21	0.92	−1.00	−1.00	−1.00	1.00	1.00	0.4	1.3	343
Return	−0.02	0.78	−6.04	−1.21	0.00	1.03	6.56	−0.5	14.5	2,392
Volatility	0.95	1.25	0.00	0.02	0.46	3.30	10.18	2.6	11.8	2,392
Volume	7.60	12.31	0.00	0.00	3.07	29.95	166.63	3.9	27.9	2,392
Quoted Spread	1.17	1.03	0.30	0.42	0.92	2.80	9.36	3.7	22.7	2,392
Depth	4.48	3.31	0.66	1.29	3.77	10.26	38.66	3.8	26.3	2,392
Effective Spread	0.71	0.62	0.00	0.22	0.48	1.87	4.31	2.3	9.9	2,257
Realized Spread	0.46	0.79	−3.96	−0.17	0.23	1.70	9.09	3.6	28.4	2,257
Price Impact	0.28	0.47	−3.01	−0.17	0.20	1.12	6.56	2.1	27.5	2,257
Panel B: Core trading session										
Retweets	25.09	17.02	0.00	7.30	21.71	58.10	134.72	1.9	8.7	1,054
Economic Tweet	0.15	0.36	0.00	0.00	0.00	1.00	1.00	1.9	4.8	1,054
Sentiment	0.11	0.93	−1.00	−1.00	0.00	1.00	1.00	−0.2	1.2	1,054
Sentiment Economic	−0.28	0.90	−1.00	−1.00	−1.00	1.00	1.00	0.6	1.5	160
Return	−0.04	1.06	−6.04	−1.78	0.00	1.56	6.56	−0.4	9.3	1,054
Volatility	1.71	1.46	0.09	0.27	1.32	4.74	10.18	2.0	7.9	1,054
Volume	15.19	15.14	0.87	3.08	10.46	44.56	166.63	3.2	19.5	1,054
Quoted Spread	0.59	0.20	0.32	0.40	0.54	0.92	2.29	3.3	18.4	1,054
Depth	3.65	1.94	0.69	1.14	3.35	7.55	12.98	1.3	5.3	1,054
Effective Spread	0.32	0.12	0.12	0.20	0.30	0.54	1.21	2.8	14.4	1,054
Realized Spread	0.10	0.16	−0.55	−0.13	0.10	0.37	0.86	0.5	5.2	1,054
Price Impact	0.22	0.17	−0.29	−0.01	0.20	0.51	1.19	1.4	7.3	1,054
Panel C: Extended trading hours										
Retweets	23.35	16.64	0.00	6.97	19.04	56.02	143.07	2.2	10.9	1,338
Economic Tweet	0.14	0.34	0.00	0.00	0.00	1.00	1.00	2.1	5.5	1,338
Sentiment	0.15	0.93	−1.00	−1.00	1.00	1.00	1.00	−0.3	1.2	1,338
Sentiment Economic	−0.15	0.94	−1.00	−1.00	−1.00	1.00	1.00	0.3	1.2	183
Return	0.00	0.45	−2.66	−0.76	0.00	0.65	2.11	−0.4	7.8	1,338
Volatility	0.35	0.54	0.00	0.01	0.17	1.26	7.43	4.7	39.4	1,338
Volume	1.61	2.99	0.00	0.00	0.70	5.71	48.29	6.9	82.3	1,338

(Continues)

TABLE 1 (Continued)

	Mean	SD	Min	P5	P50	P95	Max	Skew.	Kurt.	N
Quoted Spread	1.64	1.17	0.30	0.69	1.32	3.68	9.36	3.4	17.8	1,338
Depth	5.14	3.95	0.66	1.73	4.13	12.63	38.66	3.5	20.4	1,338
Effective Spread	1.06	0.67	0.00	0.32	0.89	2.50	4.31	1.9	7.7	1,203
Realized Spread	0.77	0.97	−3.96	−0.29	0.63	2.27	9.09	2.8	19.3	1,203
Price Impact	0.33	0.61	−3.01	−0.32	0.24	1.33	6.56	1.4	16.7	1,203

Note: This table shows summary statistics for the key variables. *Retweet* is the number of retweets of a tweet. *Economic Tweet* is a binary variable indicating tweets containing economic keywords. *Sentiment* is the sentiment score as estimated by Twitter-roBERTa-base. *Sentiment Economic* is the sentiment of economic tweets only. The market-based measures as explained in the following are calculated for every 100 milliseconds; an observation in this table is then the average for the 1-minute interval before a tweet. *Return* is the average 1 millisecond logarithmic quote midpoint return in 0.0001 bps. *Volatility* is the average standard deviation of 1 millisecond returns in 0.01 bps. *Volume* is the total traded volume during a 100-millisecond window in $1,000. *Quoted Spread* is the average relative quoted bid-ask spread in bps. *Depth* is the average quoted depth at the best bid and ask in $1,000. *Effective Spread* is the average relative effective spread in bps. *Realized Spread* and *Price Impact* are the relative realized spread and the price impact measured at 1 second after a trade in bps. In panel A, the full trading day is used. In panels B and C, the sample is split into observations during the core trading session and extended trading hours, respectively.

4.2 | Price and trading activity reactions

I now test for short-term changes in prices and trading activity after Donald Trump's tweets using regressions with fixed effects. The results for quote midpoint returns, volatility, and trading volume can be found in Table 2. In panel A, I test for the overall effect of tweets during a window of 1, 10, and 60 seconds around each tweet, respectively. In panel B, this effect is then split into the core trading session and the extended hours. In panel C, the effect during the extended trading hours is further split into the pre-market and after-hours sessions.

Some previous studies have documented significant changes of asset prices after presidential tweets (Burggraf et al., 2020; Klaus & Koser, 2020), although Abdi et al. (2023) argue that these effects are simply the result of Donald Trump reacting to pre-existing market developments. The causality might thus run in the other direction. In my sample – containing data on a broad market index at a substantially higher frequency than other studies and while controlling for intraday effects – I only find very short-lived price impacts of tweets. Over the entire trading day, there is a significant negative effect on returns during the ±1-second window. When splitting the effect into the core and extended trading session, all coefficients are negative during the ±1-second window, but only marginally significantly so during the extended hours and in particular in the pre-market phase. At longer durations, the coefficients are practically zero and usually insignificant. Overall, I conclude that there is some evidence that prices briefly decrease after a tweet, but they quickly return to their previous levels.

While tweets do not appear to substantially impact average returns for longer than a few seconds, they are positively related to return volatility as evident in the middle set of columns. For example, when considering the full trading day, the standard deviation of 1 millisecond quote midpoint returns increases by 0.00089 bps during the 10 seconds after a tweet compared to the 10 seconds before. Since the average volatility before a tweet is 0.0095 bps, this translates to an increase of about 9%. This confirms previous results about the volatility-inducing effect of presidential tweets (Benton & Philips, 2020; Burggraf et al., 2020). However, the high-frequency nature of my dataset allows me to further document the speed of volatility increases, which was not feasible in other studies. The increase in volatility is almost immediate: Compared to 1 second before a tweet, volatility increases by 0.00125 bps, or about 13%. It is thus highly unlikely that this increase in volatility is the result of human traders, but rather points to the activity of algorithms monitoring social media data and adjusting their quoting behavior. When split into the

TABLE 2 Returns, volatility, and trading volume.

	Return			Volatility			Volume		
	±1s	±10s	±60s	±1s	±10s	±60s	±1s	±10s	±60s
Panel A: Full trading day									
Post	−0.351**	−0.012	0.018	0.125***	0.089***	0.026***	−0.135	0.291	0.093
	(−2.09)	(−0.23)	(0.80)	(6.88)	(8.35)	(2.96)	(−0.35)	(1.59)	(0.73)
Panel B: Extended trading hours									
Post × CoreTrading	−0.451	−0.036	0.006	0.023	0.064***	0.000	−0.156	0.451	−0.078
	(−1.38)	(−0.33)	(0.13)	(0.81)	(3.98)	(0.00)	(−0.19)	(1.20)	(−0.30)
Post × ExtHours	−0.272*	0.006	0.028	0.206***	0.109***	0.046***	−0.119	0.165	0.227**
	(−1.75)	(0.14)	(1.44)	(8.74)	(7.65)	(4.02)	(−0.41)	(1.19)	(2.34)
Panel C: Pre-market and after hours									
Post × CoreTrading	−0.451	−0.036	0.006	0.023	0.064***	0.000	−0.156	0.451	−0.078
	(−1.38)	(−0.33)	(0.13)	(0.81)	(3.98)	(0.00)	(−0.19)	(1.20)	(−0.30)
Post × PreMarket	−0.416*	−0.057	0.004	0.277***	0.157***	0.050***	−0.124	−0.006	0.035
	(−1.81)	(−0.88)	(0.14)	(7.56)	(7.03)	(3.20)	(−0.28)	(−0.03)	(0.25)
Post × AfterHours	−0.091	0.104*	0.040	0.116***	0.038***	0.011	−0.113	0.030	−0.032
	(−0.46)	(1.68)	(1.53)	(4.47)	(3.10)	(1.20)	(−0.35)	(0.20)	(−0.25)

Note: This table shows the reactions of returns and their volatility as well as of trading volume. *Return* is the the average 1 millisecond logarithmic quote midpoint return in 0.0001 bps. *Volatility* is the average standard deviation of 1 millisecond returns in 0.01 bps. *Volume* is the total traded volume during a 100 millisecond window in $1,000. Panel A shows the results for the full trading day where the observations are taken from a window of ±1, ±10, and ±60 seconds around each tweet, respectively. *Post* is a binary variable set to 1 for observations after a tweet. Panel B shows the effect split by the core and extended trading hours, indicated by the binary variables *CoreTrading* and *ExtHours*. In panel C, this effect is further separated by the binary variables *PreMarket* and *AfterHours*, which are set to 1 for the trading sessions before and after the core trading session, respectively. All models include day fixed and intraday fixed effects for every 15-minute interval of the day. The standard errors are clustered by tweet and the resulting t statistics are given in parentheses. ***, **, * denotes significance at the 1%, 5%, 10% level, respectively.

core and extended trading session, I find that this finding is mostly driven by a fast and strong increase in volatility during the extended hours. The coefficient for tweets during the extended trading session using the ±1-second window is 0.206, indicating a drastic increase in volatility of about 59% relative to before the tweet. For the core trading session, this increase is less than 1%. Compared to the after-hours market, volatility in the pre-market session increases stronger and the effect lasts longer, although both extended hours sessions see substantial and fast increases in return volatility.

The surge in quote midpoint volatility is unlikely to be driven by actual trades. Looking at trading volume, there is practically no evidence that trading activity increases after a tweet. Likewise, there are no meaningful differences between the core trading and other trading sessions, with the exception of a significantly higher volume during the ±1-minute window in the extended trading hours. I thus conclude that the changes in volatility are at least partially the result of quickly adjusted quotes by liquidity providers, a notion that will be investigated in more detail in Section 4.3.

The regression results so far support the view that market participants react within split seconds to presidential tweets and that the effect diminishes quickly. In Figure 3, I show the development of cumulative returns, volatility, and trading volume in more detail. Each set of graphs visualizes the development of one of the investigated

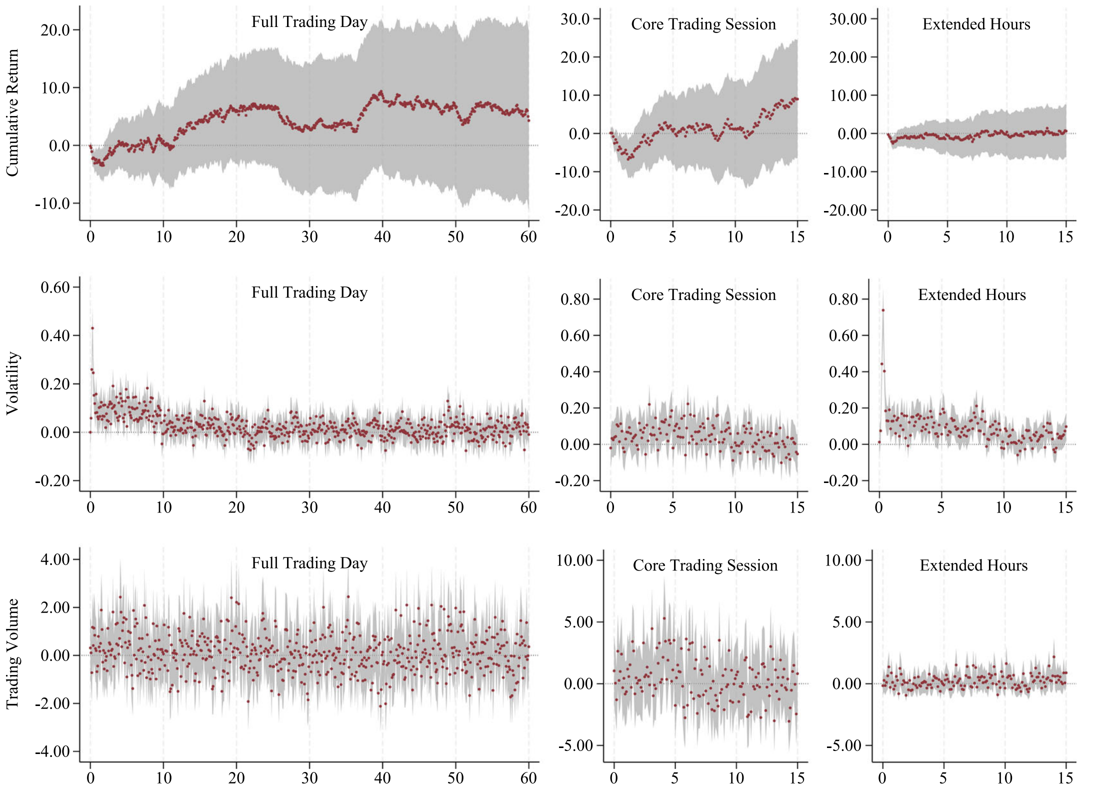

FIGURE 3 Return, volatility, and volume over Time. *Note:* These graphs show average cumulative returns, return volatility, and trading volume for every second after a tweet. Cumulative returns are based on 1 second averages of logarithmic 1 millisecond quote midpoint returns in 0.0001 bps. Volatility is the 100 millisecond standard deviation of the 1 millisecond returns in 0.01 bps. Trading volume is the total trading volume during every second in $1,000. Volatility and Volume are given as the differences to the average of the 60 seconds before each tweet. The gray area shows the 90% confidence interval based on cross-sectional *t* tests for every second after a tweet. The leftmost graphs show the results for the full sample, whereas the other two graphs show the results only based on the core trading session and the extended trading hours, respectively. [Color figure can be viewed at wileyonlinelibrary.com]

measures, where the left graph shows the development for the full sample and the other two graphs for the core and extended trading sessions separately. Since most estimates are statistically insignificant after about 10 seconds, for the sample split the maximum lag considered is 15 seconds. For all measures other than cumulative returns, the respective pre-tweet average during the 1 minute before the tweet has been subtracted, so the graphs show changes to before. The graphs furthermore show the 90% confidence interval based on cross-sectional *t* tests at each 100 milliseconds after the tweet.

Confirming the regression results, cumulative returns are only statistically significantly different from zero during a short period of up to 2 seconds after the tweets. This holds for both the core trading session and the extended trading hours, although the effect lasts slightly longer during the core trading session. Meanwhile, the changes in quote midpoint volatility are much more striking. Volatility increases within less than 1 second the tweet was sent and reaches its maximum increase of 0.0043 bps, or about 45% relative to before, just 300 milliseconds later. After an additional 200 milliseconds, volatility declines but stays at an elevated level of about 0.001 bps (10%) relative to before. Volatility turns back to its pre-tweet level after about 10 seconds. During the core trading session, the increase in volatility is much less pronounced and also less sudden, while during the extended hours the change in volatility is more drastic. Again, the split-second increase in volatility is consistent with the notion that algorithmic traders continuously monitor social media channels and quickly adjust their quotes, since as before, there are no significant changes in trading volume after a tweet. Moreover, the speed of quote adjustments is inconsistent with human or retail traders driving these results.

4.3 | Liquidity

The previous literature has mostly disregarded liquidity effects of news releases after hours. In this section, I present novel evidence on how high-frequency liquidity reactions to market-stirring news differ across the various trading sessions. I first consider quoted liquidity and then analyze trading liquidity.

The results for quoted liquidity in Table 3 indicate substantial short-term liquidity dry-ups following presidential tweets. The reduction in quoted liquidity materializes at a similar pace to the spike in volatility, with quoted bid-ask spreads increasing within 1 second after a tweet. In the 10 seconds afterwards, the highly significant coefficient of 0.171 translates to an average increase in spreads of about 14.6% compared to shortly before the tweet.

TABLE 3 Quoted liquidity.

	Quoted Spreads			Depth		
	±1s	±10s	±60s	±1s	±10s	±60s
Panel A: Full trading day						
Post	0.145***	0.171***	0.044***	−189.37***	−178.31***	−3.236
	(14.85)	(13.80)	(4.80)	(−3.89)	(−3.21)	(−0.07)
Panel B: Extended trading hours						
Post × *CoreTrading*	0.009**	0.006**	−0.002	−89.748	−107.10**	14.706
	(2.29)	(2.33)	(−0.82)	(−1.44)	(−2.29)	(0.46)
Post × *ExtHours*	0.253***	0.300***	0.080***	−267.84***	−234.40**	−17.369
	(15.19)	(14.05)	(4.92)	(−3.73)	(−2.54)	(−0.21)
Panel C: Pre-market and after hours						
Post × *CoreTrading*	0.009**	0.006**	−0.002	−89.748	−106.94**	14.723
	(2.29)	(2.29)	(−0.87)	(−1.44)	(−2.28)	(0.46)
Post × *PreMarket*	0.299***	0.346***	0.065***	−188.57**	−191.62	−7.263
	(14.25)	(13.98)	(3.55)	(−2.06)	(−1.64)	(−0.07)
Post × *AfterHours*	0.195***	0.244***	0.098***	−368.34***	−281.63*	−17.593
	(7.32)	(6.61)	(3.48)	(−3.22)	(−1.91)	(−0.14)

Note: This table shows the reactions of quoted liquidity. *Quoted Spread* is the average relative quoted bid-ask spread in bps. *Depth* is the average quoted depth at the best bid and ask in $1,000. Panel A shows the results for the full trading day where the observations are taken from a window of ±1, ±10, and ±60 seconds around each tweet, respectively. *Post* is a binary variable set to 1 for observations after a tweet. Panel B shows the effect split by the core and extended trading hours, indicated by the binary variables *CoreTrading* and *ExtHours*. In panel C, this effect is further separated by the binary variables *PreMarket* and *AfterHours*, which are set to 1 for the trading sessions before and after the core trading session, respectively. All models include day fixed and intraday fixed effects for every 15-minute interval of the day. The standard errors are clustered by tweet and the resulting *t* statistics are given in parentheses. ***, **, * denotes significance at the 1%, 5%, 10% level, respectively.

Importantly, there are considerable differences between trading sessions: While the reduction in liquidity as measured by quoted spreads is stronger in the pre-market phase than in the after-hours market, it is significant in both cases and orders of magnitude larger than during the core trading session. Even in the core session there is evidence of slightly larger spreads, although the effect is comparatively very small and disappears in the ±1-minute window.

While spreads capture the trading costs of small transactions and thus one dimension of liquidity, depth is inversely related to the price impact of large orders, hence capturing another dimension. Changes in depth following tweets are significantly negative for the ±1- and ±10-seconds window. As previously discussed, the results for the quoted depth available at the best bid and ask have to be interpreted in light of changes in these prices. During the extended trading hours, spreads generally widen substantially, so the overall reduction in depth occurs at prices that are even further from the quote midpoint than before. There is thus a compounding effect on liquidity: The best bid and ask are further from the midpoint and the quantity available at these prices is lower, although not always significantly. There are significant reductions in depth in all trading phases, including the core trading session. However, the reductions in depth are generally stronger during the extended trading hours, especially during after-hours trading.

While quoted liquidity is an important metric of market quality, typically more relevant to traders is the realized liquidity when trading. In particular, effective spreads may be smaller than quoted spreads due to price improvements or liquidity timing. I hence present results for trading liquidity in Table 4. However, the estimates are noisier, presumably because of the lower trading activity during the extended trading hours. Similar to quoted spreads, there is a significant increase in effective spreads. The increase in effective spreads by 0.023 bps in the ±10-seconds window for the full trading day translates to a relative increase by 3.2% compared to pre-tweet averages. The effect is smaller than for quoted spreads, suggesting that some traders strategically manage their order execution costs.

As before, the increase in spreads is much larger during the extended trading hours, but generally not significant in the shortest time window of ±1-second. When decomposing effective spreads into the price impact and realized spreads, I find that the increases in effective spreads are driven by higher price impacts after tweets. For the price impact, the coefficient of 0.064 for the ±10-seconds window during the full trading day reflects an increase of about 22.9% compared to before a tweet. The coefficients for realized spreads are insignificant except for the decrease of 0.243 bps at the ±10-seconds interval during the after-hours market, whereas price impacts increase during the extended hours. Since realized spreads give the revenues of market makers, this finding suggests that liquidity providers are able to quickly react to the tweets and thus mostly protect themselves against the increase in volatility and potentially adverse price movements. Consequently, liquidity demanders that trade shortly after a tweet bear the cost of the reduction in liquidity.

As before, the results are confirmed when the development of liquidity is analyzed for every 100 milliseconds after a tweet separately. Figure 4 shows the striking increase in quoted bid-ask spreads starting within just 200 milliseconds after the tweet. The maximum increase of about 0.24 bps is reached after about 3 seconds. Since during the core trading session, spreads essentially stay at their pre-tweet level, the overall effect is almost exclusively driven by the liquidity reduction during the extended hours. Spreads increase up to 0.40 bps or about 24% compared to their pre-tweet average of 1.65 bps. Similarly to volatility, the reduction in market quality not only starts practically immediately, but is also resolved about 10 seconds later. Likewise, the reduction in depth is clearly visible albeit less smooth. Order book resiliency as measured by the speed of liquidity replenishment after a tweet is similar across the different trading sessions, but the reduction in depth is more pronounced during the extended hours. The results for effective spreads are again much noisier than for quoted liquidity. Still, effective spreads increase almost instantaneously after a tweet.

One of the key institutional differences between the core and extended trading hours is the obligation of designated market makers to provide liquidity and ensure continuous pricing during the core session. This can for example be seen in quoted liquidity: Quoted spreads increase only marginally after a tweet during the core trading

TABLE 4 Trading liquidity.

	Effective Spreads			Price Impact $_{1s}$			Realized Spreads $_{1s}$		
	±1s	±10s	±60s	±1s	±10s	±60s	±1s	±10s	±60s
Panel A: Full trading day									
Post	0.024*	0.023***	0.007*	0.051	0.064**	0.019*	−0.016	−0.033	−0.010
	(1.76)	(3.79)	(1.81)	(0.66)	(2.41)	(1.68)	(−0.20)	(−1.21)	(−0.90)
Panel B: Extended trading hours									
Post × CoreTrading	0.011	0.014***	−0.000	0.055	0.045	0.011	−0.038	−0.029	−0.010
	(1.01)	(3.17)	(−0.03)	(0.67)	(1.59)	(0.90)	(−0.46)	(−1.05)	(−0.89)
Post × ExtHours	0.136	0.092**	0.063***	0.016	0.223***	0.082***	0.173	−0.060	−0.006
	(1.44)	(2.13)	(2.62)	(0.08)	(2.96)	(2.67)	(0.70)	(−0.68)	(−0.19)
Panel C: Pre-market and after hours									
Post × CoreTrading	0.011	0.014***	−0.000	0.055	0.044	0.011	−0.038	−0.029	−0.010
	(1.01)	(3.17)	(−0.07)	(0.67)	(1.57)	(0.89)	(−0.46)	(−1.03)	(−0.89)
Post × PreMarket	0.107	0.137***	0.028	−0.045	0.186*	0.064	0.213	−0.020	−0.024
	(0.86)	(2.94)	(0.76)	(−0.19)	(1.82)	(1.57)	(0.72)	(−0.16)	(−0.53)
Post × AfterHours	0.194	−0.000	0.068**	0.134	0.249**	0.097**	0.096	−0.243*	−0.008
	(1.42)	(−0.01)	(2.19)	(0.33)	(2.58)	(2.16)	(0.22)	(−1.90)	(−0.15)

Note: This table shows the reaction of trading liquidity. *Effective Spread* is the relative effective spread in bps. *Realized Spread* and *Price Impact* are the relative realized spread and the price impact measured at 1 second after a trade in bps. Panel A shows the results for the full trading day where the observations are taken from a window of ±1, ±10, and ±60 seconds around each tweet, respectively. *Post* is a binary variable set to 1 for observations after a tweet. Panel B shows the effect split by the core and extended trading hours, indicated by the binary variables *CoreTrading* and *ExtHours*. In panel C, this effect is further separated by the binary variables *PreMarket* and *AfterHours*, which are set to 1 for the trading sessions before and after the core trading session, respectively. All models include day fixed and intraday fixed effects for every 15-minute interval of the day. The standard errors are clustered by tweet and the resulting *t* statistics are given in parentheses. ***, **, * denotes significance at the 1%, 5%, 10% level, respectively.

session. However, quoted depth decreases substantially even during the core session, indicating that some voluntary liquidity providers (i.e., limit order traders that are not designated market makers) briefly reduce their provided liquidity after a tweet. The sudden reduction in liquidity and the increase in volatility during the extended hours is then consistent with both designated and voluntary market makers withdrawing. In line with Clark-Joseph et al. (2017) and Theissen and Westheide (2020), my results thus provide indirect evidence that designated market makers indeed still matter in today's trading environment, especially in times of heightened uncertainty during which voluntary liquidity providers likely retract.

4.4 | Robustness

While the regression analyses above include date and intraday fixed effects to control for time trends in the data and, importantly, capture pre-tweet average levels of the dependent variables via the constant, I now perform additional robustness checks. Overall, the results of the analyses above are robust to controlling for pre-event trends, employing intraday polynomial filtering, excluding days of macroeconomic announcements, excluding days

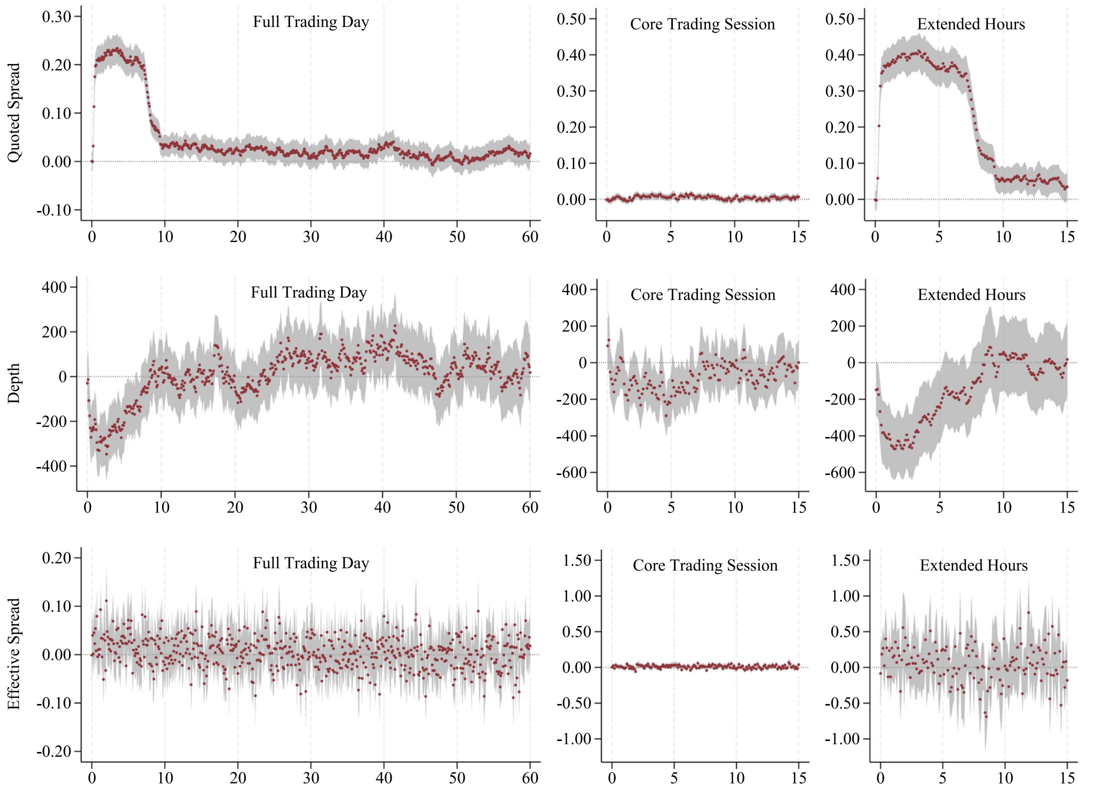

FIGURE 4 Liquidity over time. *Note:* These graphs show measures of liquidity for every second after a tweet. Spreads are the average relative quoted and effective bid-ask spreads in bps, respectively. Depth is the quantity available at the best bid and ask. All measures are given as the differences to the average of the 60 seconds before each tweet. The gray area shows the 90% confidence interval based on cross-sectional *t* tests for every second after a tweet. The leftmost graphs show the results for the full sample, whereas the other two graphs show the results only based on the core trading session and the extended trading hours, respectively. [Color figure can be viewed at wileyonlinelibrary.com]

on which the President travels that might induce differences in latency, and excluding periods when the futures market is closed. Moreover, several placebo tests further confirm the robustness of my findings.

4.4.1 | Reacting to market trends?

Abdi et al. (2023) and Machus et al. (2022) argue that controlling for market trends is important when analyzing the effect of presidential tweets on asset prices. They find most of Donald Trump's tweets to be reactive to market trends, meaning that they do not provide novel information but are rather predictable by prior market conditions. Note that the regressions above already control for pre-tweet levels through the constant, and the figures plot changes relative to the pre-tweet average. Any bias from ongoing market sentiment would therefore require systematic trends in the variables. For example, if spreads were already rising before a tweet, they might have continued to rise absent the tweet. Given the post-tweet patterns in volatility, spreads, and depth in Figures 3 and 4, such trends are unlikely to explain the results. Also note that my analysis is at substantially higher frequencies compared to the aforementioned studies and uses relatively short windows, making it less likely that my documented effects are solely due to ongoing market trends.

However, to further empirically address this concern, I repeat the analyses by first running a regression of the dependent variable on a linear time trend and a constant for each tweet individually, using the observations from the 60 seconds before the tweet.[7] I then compute predicted values for the time after the tweet, again separately for each tweet, and obtain the residuals as the difference between the realized and the predicted values. This approach not only controls for the pre-tweet level of the dependent variables as before, but also their tweet-specific linear time trend. The results can be found in Table A2 in the Appendix. Overall, most results are very similar to the results without this pre-trend filtering. Trading liquidity appears to react more strongly and, in the case of effective spreads, faster when employing the filtering.

Similarly, there are well documented intraday patterns in volatility and liquidity in many markets (McInish & Wood, 1992; Wood et al., 1985). Since the event windows in my study are very short, these are unlikely to meaningfully impact my results. Additionally, the regressions above already include intraday fixed effects. Moreover, the documented patterns above are inconsistent with these alternative explanations. However, to address any remaining concerns, I use a higher degree polynomial filtering procedure. First, I estimate the regression equation

$$V_{dt} = \alpha_0 + \alpha_1 H_{t,\text{Pre}} + \alpha_2 H_{\text{After},t} + \sum_{k=1}^{K} \beta_k t^k + \sum_{k=1}^{K} \gamma_k t^k H_{\text{Pre},t} + \sum_{k=1}^{K} \delta_k t^k H_{\text{After},t} + \varepsilon_{dt}, \tag{7}$$

where V_{dt} is the value of the variable with potential intraday patterns during the 1-second interval t on day d. H_{Pre} and H_{After} are binary variables indicating the extended hours before and after the core trading session, respectively. $K = \{1, \ldots, 10\}$ is the maximum number of polynomials included and is selected for each variable according to the Bayesian information criterion. Then, letting $\widehat{V_{dt}}$ be the fitted value based on the selected model, the filtered variable is given by

$$V_{dt}^{f} = V_{dt} - \widehat{V_{dt}} \tag{8}$$

Intuitively, the procedure provides another estimate of "abnormal" values for the variables. Using the filtered measures as the dependent variables in the same analyses does not meaningfully impact the conclusions. The differences are minuscule and thus untabulated.

4.4.2 | Macroeconomic announcements, days of travel, and futures trading

While Donald Trump's tweets are unscheduled and occur throughout the day, some tweets might be published around important macroeconomic announcements. To control for potential confounding effects, I repeat the analysis without tweets occurring within ±10 minutes of an important announcement. Following Brogaard et al. (2014), I collect scheduled announcements on Construction Spending, Consumer Confidence, Existing Home Sales, Factory Orders, the Institute of Supply Management (ISM) Manufacturing Index, ISM Services, Leading Indicators, and Wholesale Inventories from Bloomberg.[8] Omitting the 51 tweets surrounding these announcements does not impact the results. All estimates stay at virtually identical levels and significances.

While Twitter operates multiple data centers on both coasts of the United States, it is unknown where exactly Twitter's infrastructure processes a given tweet and how quickly it is disseminated to the public. As long as any lag is constant and there is no information leakage, this does not pose a problem for the analyses above. However, one reason the lag might change is travel by Donald Trump, leading to the tweets being processed in a different data

[7] I require at least 60 observations in the pre-tweet period. This is only relevant for the trading liquidity measures, as these can only be computed if there is at least one trade in a given 100-milliseconds interval.

[8] See https://www.bloomberg.com/markets/economic-calendar.

center from where the information might take longer to reach the exchange. To account for this, I drop all tweets during presidential trips to other time zones.[9] The results do not materially change.

In a similar vein, another concern might be that it is well documented that price discovery occurs mostly in futures and not in ETF markets (see e.g., Shkilko & Sokolov, 2020). However, it is unclear exactly how the delayed price discovery in the ETF market would impact the results beyond a slightly delayed reaction in the investigated measures. If the ETF market simply reacts to the futures market, then the reaction times of algorithmic traders monitoring social media channels (and then trading in the futures market) would be even faster than what I measure when looking at the ETF reaction. However, to investigate this issue further, I consider the Chicago Mercantile Exchange with its electronic trading platform, CME Globex, which is the most relevant market for futures on the S&P500 (see also, Dungey et al., 2009). Trading there is open almost around the clock from Sunday evening to Friday afternoon with the exception of a trading halt from 4:15 p.m. to 4:30 p.m. and a maintenance period from 5:00 p.m. to 6:00 p.m. (all in Central Time). Since the exceptions fall into the after-hours market at NYSE Arca, I exclude these times to verify that any differences between the core and extended trading sessions are not driven by differences between trading hours overlap with the futures market. Again, the results are not materially affected.

4.4.3 | Placebo tests

Finally, I conduct placebo tests to further establish the robustness of my findings. I repeat the same regression analysis as before but randomly set the timestamps of the tweets by drawing from a uniform distribution covering the entire sample period. The results can be found in Table A3 in the Appendix. Almost all coefficients are statistically insignificant. Moreover, there does not appear to be any clear pattern as the sign of the coefficients usually varies across the different window lengths. Overall, the placebo tests thus confirm the robustness of the main findings. In an untabulated variation of these placebo tests, I randomly change the date of the tweets, but keep the time of day the same. This approach ensures that each tweet falls into the same trading session as before. The results resemble those found for the previous placebo test as most coefficients are statistically insignificant.

5 | THE INFORMATIONAL CONTENT OF TWEETS

So far, the analysis has treated all presidential tweets as homogenous shocks. Yet an important question raised in the literature (e.g., Abdi et al., 2023; Born et al., 2017) is whether markets interpret such messages as genuine information or merely as noise. However, given the strong reaction of volatility and liquidity documented above, it appears as if traders at least expect that some tweets contain relevant information and subsequently adjust their quotes until this uncertainty has been resolved.

To investigate this issue further, I now examine whether the reaction of liquidity providers and traders depends on the content of tweets. I consider three approaches to capture their informational content: expressed sentiment, a tweet's ex-post reach as measured by retweets, and topic modeling.

5.1 | Sentiment and economic keywords

I first repeat the analysis of the effects on prices by multiplying the returns by their sentiment, as classified by the pre-trained natural language processing model Twitter-roBERTa-base. This step effectively signs the observations

[9]An aggregated schedule of Trump's travel can be accessed at https://factba.se/topic/calendar, but can also be reconstructed based on official releases available on the White House website at https://www.whitehouse.gov/news/.

by their sentiment. However, note that a positive sentiment in Donald Trump's tweets is not necessarily perceived as good news by the average market participant.[10] Instead, signing the tweets by their sentiment facilitates an analysis of how much investors in aggregate agree with Donald Trump's sentiment.

Table 5 shows the results for returns that are multiplied by their sentiment score, first for all tweets and then only for economic tweets as identified by the dictionary of Baker et al. (2026). Since most coefficients are insignificant, I conclude that the sentiment of the tweet does not appear to matter much at high frequencies when considering the aggregate stock market. In additional to the high frequencies, one explanation for these findings could be that I consider a broad market index where evaluating the sentiment is overall more difficult than when considering the impact of company-specific tweets on individual stocks. For example, the two trading bots mentioned in the institutional background trade individual stocks. This would explain why my results differ from those of Born et al. (2017), who consider Donald Trump's communicated sentiment regarding specific companies and the reaction of their respective stock prices. Nonetheless, my results are similar in the sense that any effects are rather short-lived and overall tend to agree with Abdi et al. (2023) and Machus et al. (2022).[11]

5.2 | Reach of individual tweets

Next, I turn to the reach of individual tweets as measured by subsequent retweets. Note that this information is not available to traders reacting immediately after a tweet, as no users, or only very few, will have retweeted it shortly after its first publication. Instead, I consider the future number of retweets as an indirect measure of the impact of the content of the tweet. I hence split the sample based on terciles of the distribution of the number of retweets. If widely shared tweets are more informative, then tweets that gain this kind of traction should elicit stronger market reactions.

Table 6 confirms this notion: Messages that are retweeted heavily are associated with stronger increases in volatility and wider spreads, particularly during the extended trading hours. In contrast, tweets with few retweets generate more muted responses as can be seen in Table A1 in the Appendix. The intensity of the market reaction thus appears to be correlated with the perceived relevance of the message. Since this information is not initially available to the fastest traders, I consider this indirect evidence that some traders quickly analyze the tweets' contents and trade based on their estimated impact.

5.3 | Topic modeling

Finally, I use topic modeling to differentiate between the themes of presidential communication. The procedure is based on the pre-trained BERTopic model by Grootendorst (2022). I include only tweets during exchange trading hours and pre-process them by removing hyperlinks, “@mentions”, and numbers; lowercasing and lemmatizing words; and filtering out stopwords. I ignore words that appear in fewer than 5 tweets and allow for frequent two-word combinations (bigrams). The cleaned texts are then embedded and clustered into semantically coherent groups using a density-based clustering algorithm combined with dimensionality reduction where I set the minimum cluster size to 15. This procedure yields 44 distinct clusters of topics plus a residual category. I focus on the 10 most frequent topics, which coincides with topics that have at least 50 tweets.

[10]For example, on June 11, 2020, Donald Trump tweeted: “*The Federal Reserve is wrong so often. I see the numbers also, and do MUCH better than they do. We will have a very good Third Quarter, a great Fourth Quarter, and one of our best ever years in 2021. We will also soon have a Vaccine & Therapeutics/Cure. That's my opinion. WATCH!*”. This economic tweet has a very positive sentiment score of 0.9115, although not everyone might have agreed with that outlook.

[11]I obtain very similar results when using the Valence Aware Dictionary for Sentiment Reasoning (VADER) by Hutto and Gilbert (2014) (see also Yaqub, 2020).

TABLE 5 Sentiment and economic topics.

	Return × Sentiment			Return × Sent. × Econ. Tweet		
	±1s	±10s	±60s	±1s	±10s	±60s
Panel A: Full trading day						
Post	−0.005	0.018	0.022	0.187	0.232	0.044
	(−0.03)	(0.36)	(1.06)	(0.47)	(1.64)	(0.71)
Panel B: Extended trading hours						
Post × CoreTrading	0.079	0.056	0.014	0.066	0.363	−0.014
	(0.26)	(0.55)	(0.35)	(0.09)	(1.30)	(−0.12)
Post × ExtHours	−0.071	−0.012	0.028	0.293	0.117	0.096*
	(−0.49)	(−0.29)	(1.58)	(0.70)	(1.14)	(1.85)
Panel C: Pre-market and after hours						
Post × CoreTrading	0.079	0.055	0.014	0.066	0.363	−0.014
	(0.26)	(0.55)	(0.34)	(0.09)	(1.30)	(−0.12)
Post × PreMarket	−0.143	−0.056	0.057**	0.228	0.145	0.125*
	(−0.68)	(−0.93)	(2.20)	(0.36)	(0.98)	(1.83)
Post × AfterHours	0.021	0.073	0.023	0.371	0.083	0.058
	(0.11)	(1.40)	(0.98)	(0.69)	(0.60)	(0.74)

Note: This table shows the reactions of quote midpoint returns as given by the average 1 millisecond logarithmic quote midpoint return in 0.0001 bps. In the left columns, returns are signed by their sentiment as estimated by Twitter-roBERTa. In the rightmost columns, only tweets containing economic keywords from the dictionary of Baker et al. (2026) are considered and then signed by their sentiment. Panel A shows the results for the full trading day where the observations are taken from a window of ±1, ±10, and ±60 seconds around each tweet, respectively. *Post* is a binary variable set to 1 for observations after a tweet. Panel B shows the effect split by the core and extended trading hours, indicated by the binary variables *CoreTrading* and *ExtHours*. In panel C, this effect is further separated by the binary variables *PreMarket* and *AfterHours*, which are set to 1 for the trading sessions before and after the core trading session, respectively. All models include day fixed and intraday fixed effects for every 15-minute interval of the day. The standard errors are clustered by tweet and the resulting t statistics are given in parentheses. ***, **, * denotes significance at the 1%, 5%, 10% level, respectively.

Figure 5 illustrates representative keywords for these clusters of topics. The algorithm appears to perform well at identifying different themes across tweets. The sample period contains the first impeachment trial of Donald Trump and subsequent acquittal, the outbreak of the COVID-19 pandemic, as well as the 2020 presidential election and preceding campaign, which are also reflected in the identified topic clusters. Topics 4 and 7 are particularly related to economic content. While the former covers the stock market and the economy, the latter is mostly on infrastructure investments.

I then re-estimate the previous regressions separately for each of the 10 topics. Figure 6 summarizes the estimates for returns, volatility, and quoted spreads in the ±1-second window, split between the core and extended sessions. In addition to the 10 most frequent topics, I also show the residual category as topic 0, containing all tweets that were not assigned a topic. Note that statistical power is necessarily reduced as the first 10 topics contain on average about 90 tweets each.

The results show that while the magnitude of effects varies across topics, the common pattern of increases in volatility and deterioration in liquidity is visible across most clusters. This confirms that the results of the main analyses are not driven by very specific tweets. However, the coefficient estimate for the impact of tweets on the stock market and the economy (topic 4) is smaller than for the other topics and close to zero. This is consistent with some content

TABLE 6 Tweets with many retweets.

	Return			Return × Sent. × Econ. Tweet		
	±1s	±10s	±60s	±1s	±10s	±60s
Post × CoreTrading	−0.749	−0.022	−0.073	0.722	0.395	0.133
	(−1.54)	(−0.13)	(−0.99)	(0.67)	(0.97)	(0.70)
Post × Extended Hours	−0.397	0.035	0.009	0.382	0.249*	0.136
	(−1.25)	(0.44)	(0.25)	(0.53)	(1.70)	(1.61)
	Volatility			**Volume**		
Post × CoreTrading	0.033	0.083***	0.009	−2.492**	0.946	0.268
	(0.72)	(3.24)	(0.37)	(−2.00)	(1.48)	(0.61)
Post × Extended Hours	0.225***	0.134***	0.058***	−0.654	0.449**	0.369***
	(5.34)	(5.35)	(4.09)	(−1.21)	(2.29)	(2.59)
	Quoted Spreads			**Depth**		
Post × CoreTrading	0.003	0.001	−0.002	−88.141	−65.630	19.694
	(0.51)	(0.14)	(−0.79)	(−0.95)	(−0.87)	(0.38)
Post × Extended Hours	0.294***	0.309***	0.098***	−408.88***	−308.99*	−12.024
	(9.64)	(8.48)	(3.49)	(−3.19)	(−1.77)	(−0.07)
	Effective Spreads			**Price Impact$_{1s}$**		
Post × CoreTrading	0.029	0.013*	0.002	−0.022	0.038	0.028
	(1.49)	(1.88)	(0.68)	(−0.15)	(0.90)	(1.23)
Post × Extended Hours	0.257*	0.160***	0.064*	0.114	0.322**	0.131**
	(1.66)	(2.83)	(1.78)	(0.22)	(2.00)	(2.46)

Note: This table shows the reaction to tweets with many retweets (i.e., to tweets where the number of retweets is in the top tercile of the distribution of tweets). The regression approach and variable definitions are identical to those of Tables 2 to 4. All models include day fixed and intraday fixed effects for every 15-minute interval of the day. The standard errors are clustered by tweet and the resulting *t* statistics are given in parentheses. ***, **, * denotes significance at the 1%, 5%, 10% level, respectively.

processing by market makers, who then do not withdraw liquidity following these tweets, perhaps because they are more reactive to market conditions than other tweets (as in Abdi et al., 2023). These patterns are very similar when using the ±1-second window, indicating that the results are driven by algorithms rather than human traders.

5.4 | Summary of the informational content of tweets

Overall, the three approaches point to a limited informational value of presidential tweets for short-horizon market returns. The sentiment analysis indicates that the tone of messages does not translate into systematic price changes, and even for economic tweets, the effects are very weak. Instead, the main driver of market reactions appears to be whether a message attracts broader attention, which I use as a proxy for the informational content. Tweets that are heavily retweeted show stronger increases in volatility and wider spreads than tweets that have fewer retweets. The topic analysis leads to a similar conclusion: Although the magnitude of effects differs across topics, the recurring pattern shows brief but noticeable spikes in volatility and liquidity deterioration, rather than

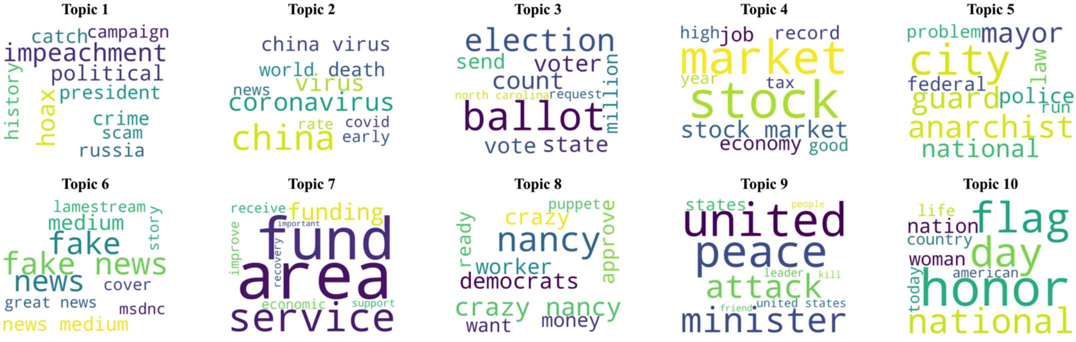

FIGURE 5 Topic modeling. *Note:* This figure shows representative words of the ten most frequent topic clusters as estimated by the BERTopic model of Grootendorst (2022). Only tweets during exchange trading hours are included. The size and color of the individual words have no meaning. [Color figure can be viewed at wileyonlinelibrary.com]

persistent return movements. A possible exception to this pattern is that tweets regarding the stock market and overall economy are not followed by a decrease in liquidity.

Taken together, these results suggest that, at very high frequencies, some market participants trade based on the content of the tweet, but most activity is related to the brief uncertainty they create before the content is fully processed. The effects on liquidity and volatility fade quickly, yet are widespread across topics and amplified when tweets resonate more broadly. Traders and algorithms therefore seem to treat such messages as potentially relevant signals, even if not all tweets contain lasting informational content.

6 | TWEETS BY MEMBERS OF CONGRESS

A natural concern is whether the high-frequency market reactions documented above are specific to tweets by President Donald Trump or whether they reflect a broader phenomenon of how markets and algorithms respond to influential voices on social media. The President's unique position as head of state and his unconventional use of Twitter arguably make his account an extreme case. To assess the generalizability of my results, I complement the analysis with tweets by members of Congress. Legislators also command sizable audiences on social media and often comment on economic, financial, and political issues with potential market relevance (Bianchi et al., 2024). By extending the sample in this way, I can test whether the observed patterns of sharp but short-lived spikes in volatility and dry-ups of liquidity are unique to presidential communications or indicative of a broader class of market responses to prominent political figures on social media.

For this analysis, I rely on the Twitter Parliamentarian Database by van Vliet (2020), which provides tweets from legislators around the world. The dataset contains the Snowflake ID which can be translated to the precise timestamp of each tweet, the identity of the user, and their party affiliation. However, the data does not contain the actual text of the tweet. I restrict the sample to members of the U.S. Congress, use the same time period as in the main analysis, and consider only tweets during trading hours. The regression setup is also the same as in the main analysis.

The resulting dataset is naturally much larger. It contains 396,967 tweets by 529 individuals, of which 281 are Democrats, 246 are Republicans, and 2 are independent. The regression results can be found in Table 7. Overall, the results suggest that the market's high-frequency reactions are not unique to Donald Trump's account. Tweets from members of Congress also lead to short-lived liquidity dry-ups and, during the core trading session, noticeable increases in volatility. At the same time, the pattern is not identical: unlike Donald Trump's tweets, congressional messages do not raise volatility in the extended hours, and the overall effects are smaller. The liquidity response is also mixed. Quoted spreads widen and depth falls almost immediately after a tweet, pointing to liquidity providers stepping back in the face of higher

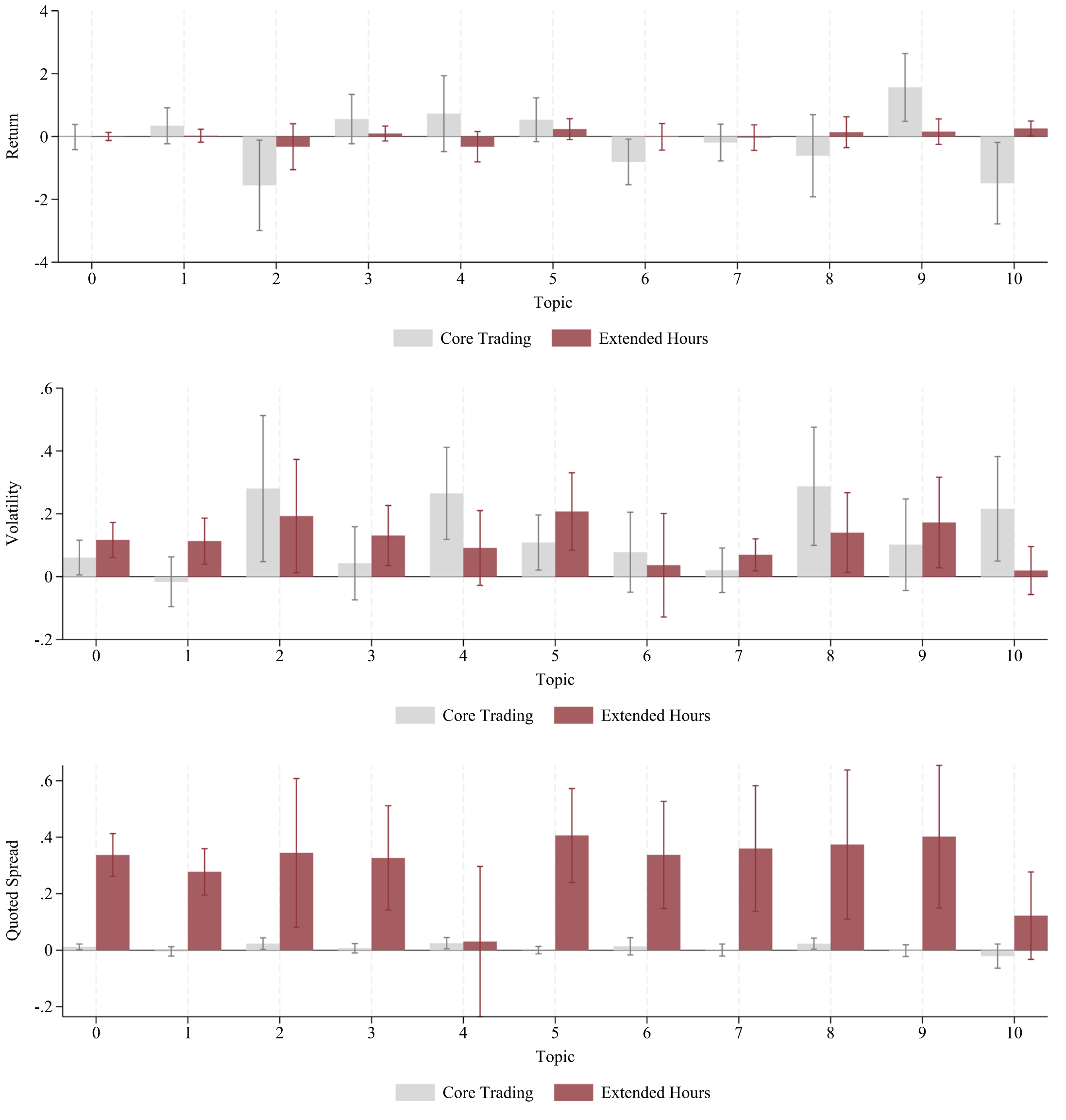

FIGURE 6 Returns, volatility, and spreads by topic 10s. *Note:* These graphs show results for the effect of the topic of a tweet on returns, volatility, and quoted spreads. The bars show the coefficient estimate of a regression of the dependent variable on indicator variables for the time after a tweet during the core trading session and the extended trading hours, respectively. The observations are taken from a window of ±10 seconds around each tweet All models include day fixed and intraday fixed effects for every 15-minute interval of the day. *Return* is the the average 1 millisecond logarithmic quote midpoint return in 0.0001 bps. *Volatility* is the average standard deviation of 1 millisecond returns in 0.01 bps. *Quoted Spread* is the average relative quoted bid-ask spread in bps. 90% confidence intervals are shown with each bar. [Color figure can be viewed at wileyonlinelibrary.com]

uncertainty. By contrast, effective spreads show a brief narrowing in the ±1-second window before widening at longer horizons. This suggests that some trades initially benefit from price improvements or fast liquidity provision, but that these opportunities vanish quickly as market makers adjust, leaving trading costs higher once the uncertainty is incorporated. Taken together, the evidence points to the President's exceptional influence, yet also shows that the broader pattern of fast, algorithmic reactions to political communication via social media generalizes to other prominent figures.

TABLE 7 Tweets by Members of Congress.

	Return			Volatility		
	±1s	±10s	±60s	±1s	±10s	±60s
Post × CoreTrading	0.016	0.005	−0.004	0.006***	0.013***	0.010***
	(0.78)	(0.70)	(−1.44)	(3.05)	(11.90)	(12.17)
Post × ExtHours	−0.038***	−0.003	0.000	−0.001	−0.001	−0.010***
	(−2.80)	(−0.58)	(0.27)	(−0.67)	(−1.03)	(−11.52)
	Quoted Spreads			**Depth**		
Post × CoreTrading	0.000	0.000*	−0.001***	−7.146	−2.540	8.218***
	(0.04)	(1.84)	(−4.31)	(−1.60)	(−0.68)	(3.25)
Post × ExtHours	0.004***	0.007***	0.012***	−24.745***	−23.189***	−27.793***
	(4.04)	(4.00)	(6.53)	(−4.34)	(−2.63)	(−2.91)
	Effective Spreads			**Price Impact$_{1s}$**		
Post × CoreTrading	0.001	0.001***	0.000	0.005	0.001	−0.000
	(1.38)	(4.16)	(1.06)	(0.88)	(0.30)	(−0.42)
Post × ExtHours	−0.040***	0.023***	0.047***	−0.014	0.021***	0.018***
	(−6.06)	(7.28)	(21.02)	(−0.69)	(3.01)	(6.14)

Note: This table shows the market reaction to tweets by members of Congress. The regression approach and variable definitions are identical to those of Tables 2 to 4. All models include day fixed and intraday fixed effects for every 15-minute interval of the day. The standard errors are clustered by tweet and the resulting *t* statistics are given in parentheses. ***, **, * denotes significance at the 1%, 5%, 10% level, respectively.

I furthermore repeat this analysis for Democratic and Republican members of Congress separately. The results can be found in Table A4 in the Appendix. Overall, the findings from the joint analysis do not appear to be driven by a single party only. Instead, the results are qualitatively similar for both parties. While the decrease in liquidity and the initial negative returns appear to be stronger after tweets by Republicans, the changes in volatility arise faster after those by Democrats. The results thus suggest that while the strength of the response may differ slightly across parties, the pattern of short-lived reactions is neither unique to presidential tweets nor limited to one party.

7 | CONCLUSION

In this article, I analyze the high-frequency reactions of equity markets to potentially market-stirring social media news. Using presidential tweets as such events, I document an almost instantaneous increase in return volatility, even though on average tweets do not appear to move prices beyond a very short time frame of 2 to 3 seconds. Similarly, there is a short-term liquidity dry-up following presidential tweets that lasts for about 10 seconds. The speed of quote updates indicates that algorithmic and high-frequency traders monitor social media and quickly change their orders when faced with increased uncertainty due to new information. Compared to the core trading session, the reduction in market quality is especially severe during the extended trading hours, when liquidity is lower and the participation of designated market makers is optional. Furthermore, there is some evidence that market participants respond to the informational content of tweets, as those that subsequently attract more retweets are associated with stronger market reactions.

While the reductions in market quality and liquidity are rather short-lived, it is important to note that the results show the average market reaction to presidential tweets. During the sample, there are, on average, about 11 such tweets during each trading day, making the market quality deteriorations and liquidity dry-ups a short-lived but frequent phenomenon. Moreover, beyond the presidential account, I also find that tweets by members of Congress trigger noticeable high-frequency reactions. The effects are smaller than for the President, but similar patterns of temporary liquidity withdrawals and short spikes in volatility are clearly visible. This suggests that the results are not driven by one exceptional account alone, but reflect a broader tendency of traders and the algorithms they employ to treat political tweets as brief uncertainty shocks. While each of these shocks fades within seconds, their sheer frequency means that they can matter in the aggregate as there are on average about 1,890 tweets by members of Congress per trading day. Even if each shock only lasts for a few seconds, this creates a background of recurring disturbances that need to be considered in trading strategies and risk management, particularly in times of frequent political communication.

The results have important implications. I confirm reservations that traders might have regarding trading in the extended trading hours, as liquidity and prices can change more severely when faced with new information than during the core trading hours. This finding is likely partially the result of the absence of designated market makers that commit to continuously providing liquidity. Previous studies have documented that designated market makers can indeed stabilize prices during times of heightened volatility (Theissen & Westheide, 2020; Venkataraman & Waisburd, 2007), even if their formal obligations are relatively mild (Clark-Joseph et al., 2017). Hence, implementing such a program during the extended hours might substantially enhance market quality. Moreover, my findings show that fast, algorithmic traders are active throughout all trading sessions, monitoring and trading upon alternative data sources, such as social media news. Recent evidence that retail traders increasingly trade after hours (Cui & Gozluklu, 2025) makes stabilizing this segment of trading all the more important.

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REFERENCES

Abdi, F., Kormanyos, E., Pelizzon, L., Getmansky Sherman, M., & Simon, Z. (2023). The President Reacts to News Channel of Government Communication. *Working Paper*. https://doi.org/10.2139/ssrn.3840203

Agrawal, S., Azar, P. D., Lo, A. W., & Singh, T. (2018). Momentum, mean-reversion, and social media: evidence from StockTwits and twitter. *The Journal of Portfolio Management*, *44*(7), 85–95. https://doi.org/10.3905/jpm.2018.44.7.085

Almond, D., & Du, X. (2020). Later bedtimes predict president trump's performance. *Economics Letters*, *197*, 109590. https://doi.org/10.1016/j.econlet.2020.109590

Anand, A., Tanggaard, C., & Weaver, D. G. (2009). Paying for market quality. *Journal of Financial and Quantitative Analysis*, *44*(6), 1427–1457. https://doi.org/10.1017/S0022109009990421

Anand, A., & Venkataraman, K. (2016). Market conditions, fragility, and the economics of market making. *Journal of Financial Economics*, *121*(2), 327–349. https://doi.org/10.1016/j.jfineco.2016.03.006

Baker, S. R., Bloom, N., Davis, S. J., & Kost, K. (2026). Policy news and stock market volatility. *Journal of Financial Economics*, *175*, 104187. https://doi.org/10.1016/j.jfineco.2025.104187

Barbieri, F., Camacho-Collados, J., Espinosa Anke, L., & Neves, L. (2020). TweetEval: Unified benchmark and comparative evaluation for tweet classification. In *Findings of the Association for Computational Linguistics*: EMNLP 2020 (pp. 1644–1650). Association for Computational Linguistics. https://doi.org/10.18653/v1/2020.findings-emnlp.148

Barclay, M. J., & Hendershott, T. (2003). Price discovery and trading after hours. *Review of Financial Studies*, *16*(4), 1041–1073. https://doi.org/10.1093/rfs/hhg030

Barclay, M. J., & Hendershott, T. (2004). Liquidity externalities and adverse selection: evidence from trading after hours. *The Journal of Finance*, *59*(2), 681–710. https://doi.org/10.1111/j.1540-6261.2004.00646.x

Behrendt, S., & Schmidt, A. (2018). The twitter myth revisited: intraday investor sentiment, twitter activity and individual-level stock return volatility. *Journal of Banking & Finance*, *96*, 355–367. https://doi.org/10.1016/j.jbankfin.2018.09.016

Benton, A. L., & Philips, A. Q. (2020). Does the @realDonaldTrump really matter to financial markets? *American Journal of Political Science*, *64*(1), 169–190. https://doi.org/10.1111/ajps.12491

Bessembinder, H., Hao, J., & Zheng, K. (2020). Liquidity provision contracts and market quality: evidence from the new york stock exchange. *Review of Financial Studies*, *33*(1), 44–74. https://doi.org/10.1093/rfs/hhz040

Bianchi, F., Gómez-Cram, R., Kind, T., & Kung, H. (2023). Threats to central bank independence: high-frequency identification with twitter. *Journal of Monetary Economics*, *135*(9), 37–54. https://doi.org/10.1016/j.jmoneco.2023.01.001

Bianchi, F., Gómez-Cram, R., & Kung, H. (2024). Using social media to identify the effects of congressional viewpoints on asset prices. *Review of Financial Studies*, *37*(7), 2244–2272. https://doi.org/10.1093/rfs/hhae001

Born, J. A., Myers, D. H., & Clark, W. J. (2017). Trump tweets and the efficient market hypothesis. *Algorithmic Finance*, *6*(3–4), 103–109. https://doi.org/10.3233/AF-170211

Brogaard, J., Hendershott, T., & Riordan, R. (2014). High-Frequency trading and price discovery. *Review of Financial Studies*, *27*(8), 2267–2306. https://doi.org/10.1093/rfs/hhu032

Burggraf, T., Fendel, R., & Huynh, T. L. D. (2020). Political news and stock prices: evidence from trump's trade war. *Applied Economics Letters*, *27*(18), 1485–1488. https://doi.org/10.1080/13504851.2019.1690626

Camacho-Collados, J., Rezaee, K., Riahi, T., Ushio, A., Loureiro, D., Antypas, D., Boisson, J., Espinosa Anke, L., Liu, F., & Martínez Cámara, E. (2022). TweetNLP: Cutting-edge natural language processing for social media. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing: System Demonstrations* (pp. 38–49). Association for Computational Linguistics. https://doi.org/10.18653/v1/2022.emnlp-demos.5

Chung, K. H., Chuwonganant, C., & Kim, Y. (2022). Preopening price indications and market quality: evidence from NYSE rule 48. *Journal of Financial Research*, *45*(2), 205–228. https://doi.org/10.1111/jfir.12272

Clark-Joseph, A. D., Ye, M., & Zi, C. (2017). Designated market makers still matter: evidence from two natural experiments. *Journal of Financial Economics*, *126*(3), 652–667. https://doi.org/10.1016/j.jfineco.2017.09.001

Cole, B., Daigle, J., Van Ness, B. F., & Van Ness, R. A. (2015). Do high frequency traders care about earnings announcements? An analysis of trading activity before, during, and after regular trading hours. In *Handbook of High Frequency Trading*, (pp. 255–270). Elsevier Inc. https://doi.org/10.1016/B978-0-12-802205-4.00015-4

Cui, B., & Gozluklu, A. E. (2025). A pond for small fish? News and retail trading after-hours. *Working Paper*. https://doi.org/10.2139/ssrn.3796812

Dredze, M., Kambadur, P., Kazantsev, G., Mann, G., & Osborne, M. (2016). How Twitter is changing the nature of financial news discovery. In *Proceedings of the ACM SIGMOD International Conference on Management of Data*. https://doi.org/10.1145/2951894.2951903

Dungey, M., Fakhrutdinova, L., & Goodhart, C. (2009). After-hours trading in equity futures markets. *Journal of Futures Markets*, *29*(2), 114–136. https://doi.org/10.1002/fut.20354

Filippou, I., Gozluklu, A. E., Nguyen, M. T., & Viswanath-Natraj, G. (2025). Signal in the noise: trump tweets and the currency market. *Journal of International Money and Finance*, *156*, 103343. https://doi.org/10.1016/j.jimonfin.2025.103343

FINRA. (2009). Rule 2265: Extended Hours Trading Risk Disclosure. https://www.finra.org/rules-guidance/rulebooks/finra-rules/2265

Forbes. (2017). A 'Trump And Dump' Stock Bot Is Cashing In On POTUS' Tweets – For Animals. https://www.forbes.com/sites/janetwburns/2017/02/10/a-trump-and-dump-stock-bot-is-cashing-in-on-potus-tweets-for-animals/

Gan, B., Alexeev, V., & Yeung, D. (2024). Tweets versus broadsheets: sentiment impact on stock markets around the world. *Journal of Financial Research*, *47*(3), 601–633. https://doi.org/10.1111/jfir.12380

Ge, Q., Kurov, A., & Wolfe, M. H. (2019). Do investors care about presidential company-specific tweets? *Journal of Financial Research*, *42*(2), 213–242. https://doi.org/10.1111/jfir.12177

Giannetti, A., Larson, S. J., Lee, C. I., & Madura, J. (2006). Price movements, information, and liquidity in the night trading market. *Financial Review*, *41*(1), 119–137. https://doi.org/10.1111/j.1540-6288.2006.00136.x

Gjerstad, P., Meyn, P. F., Molnár, P., & Næss, T. D. (2021). Do president trump's tweets affect financial markets? *Decision Support Systems*, *147*, 113577. https://doi.org/10.1016/j.dss.2021.113577

Goldstein, M. A., Kumar, P., & Graves, F. C. (2014). Computerized and high-frequency trading. *Financial Review*, *49*(2), 177–202. https://doi.org/10.1111/fire.12031

Grootendorst, M. (2022). BERTopic: Neural topic modeling with a class-based TF-IDF procedure. *arXiv*. https://doi.org/10.48550/arXiv.2203.05794

Hagströmer, B. (2021). Bias in the effective bid-ask spread. *Journal of Financial Economics*, *142*(1), 314–337. https://doi.org/10.1016/j.jfineco.2021.04.018

Hagströmer, B., & Nordén, L. (2013). The diversity of high-frequency traders. *Journal of Financial Markets*, *16*(4), 741–770. https://doi.org/10.1016/j.finmar.2013.05.009

Hutto, C., & Gilbert, E. (2014). VADER: A parsimonious rule-based model for sentiment analysis of social media text. In *Proceedings of the International AAAI Conference on Web and Social Media*.

Huynh, T. L. D. (2021). Does bitcoin react to trump's tweets? *Journal of Behavioral and Experimental Finance*, *31*, 100546. https://doi.org/10.1016/j.jbef.2021.100546

Jain, A., Jain, C., & Jiang, C. X. (2019). Early movers advantage? Evidence from short selling during after-hours on earnings announcement days. *Financial Review*, *54*(2), 235–264. https://doi.org/10.1111/fire.12174

Jiang, C. X., Likitapiwat, T., & McInish, T. H. (2012). Information content of earnings announcements: evidence from after-hours trading. *Journal of Financial and Quantitative Analysis*, *47*(6), 1303–1330. https://doi.org/10.1017/S002210901200049X

Klaus, J., & Koser, C. (2020). Measuring trump: the volfefe index and its impact on european financial markets. *Finance Research Letters*, *37*, 101447. https://doi.org/10.1016/j.frl.2020.101447

Lee, C. M., & Ready, M. J. (1991). Inferring trade direction from intraday data. *The Journal of Finance*, *46*(2), 733–746. https://doi.org/10.1111/j.1540-6261.1991.tb02683.x

Loureiro, D., Barbieri, F., Neves, L., Espinosa Anke, L., & Camacho-collados, J. (2022). TimeLMs: Diachronic language models from Twitter. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics: System Demonstrations* (pp. 251–260). Association for Computational Linguistics. https://doi.org/10.18653/v1/2022.acl-demo.25

Machus, T., Mestel, R., & Theissen, E. (2022). Heroes, just for one day: the impact of donald trump's tweets on stock prices. *Journal of Behavioral and Experimental Finance*, *33*, 100594. https://doi.org/10.1016/j.jbef.2021.100594

McGill, A. (2017, March 28). A Bot That Can Tell When It's Really Donald Trump Who's Tweeting. The Atlantic. https://www.theatlantic.com/politics/archive/2017/03/a-bot-that-detects-when-donald-trump-is-tweeting/521127/

McInish, T. H., Van Ness, B. F., & Van Ness, R. A. (2002). After-hours trading of NYSE stocks on the regional stock exchanges. *Review of Financial Economics*, *11*(4), 287–297. https://doi.org/10.1016/S1058-3300(02)00060-5

McInish, T. H., & Wood, R. A. (1992). An analysis of intraday patterns in bid/ask spreads for NYSE stocks. *The Journal of Finance*, *47*(2), 753. https://doi.org/10.2307/2329122

Menkveld, A. J. (2016). The economics of high-frequency trading: taking stock. *Annual Review of Financial Economics*, *8*(1), 1–24. https://doi.org/10.1146/annurev-financial-121415-033010

Menkveld, A. J., & Wang, T. (2013). How do designated market makers create value for small-caps? *Journal of Financial Markets*, *16*(3), 571–603. https://doi.org/10.1016/j.finmar.2012.12.003

Nishimura, Y., Dong, X., & Sun, B. (2021). Trump's tweets: sentiment, stock market volatility, and jumps. *Journal of Financial Research*, *44*(3), 497–512. https://doi.org/10.1111/jfir.12248

NPR. (2017). Trading bot BOTUS will buy and sell stock based On Trump's tweets. https://www.npr.org/2017/04/14/523890750/twitter-bot-botus-will-buy-and-sell-stock-based-on-trumps-tweets

NYSE Arca. (2019). Rule 7.23-E. obligations of market makers. *NYSE Arca Bylaws and Rules*.

Pham, D. P. T., Huynh, N. Q. A., & Duong, D. (2022). The impact of US presidents on market returns: evidence from trump's tweets. *Research in International Business and Finance*, *62*, 101681. https://doi.org/10.1016/j.ribaf.2022.101681

Salem, M., Younger, J., & St. John, H. (2019). Introducing the Volfefe index. Report published by JP Morgan, *North American Fixed Income Strategy*.

Scholtus, M., Van Dijk, D., & Frijns, B. (2014). Speed, algorithmic trading, and market quality around macroeconomic news announcements. *Journal of Banking & Finance*, *38*(1), 89–105. https://doi.org/10.1016/j.jbankfin.2013.09.016

Shkilko, A., & Sokolov, K. (2020). Every cloud has a silver lining: fast trading, microwave connectivity, and trading costs. *The Journal of Finance*, *75*(6), 2899–2927. https://doi.org/10.1111/jofi.12969

Theissen, E., & Westheide, C. (2020). Call of duty: designated market maker participation in call auctions. *Journal of Financial Markets*, *49*, 100530. https://doi.org/10.1016/j.finmar.2019.100530

Twitter Inc. (2010, June 1). Announcing Snowflake. https://blog.twitter.com/engineering/en_us/a/2010/announcing-snowflake.html

van Vliet, L. (2020). The Twitter Parliamentarian Database. https://doi.org/10.6084/m9.figshare.10120685.v3

Venkataraman, K., & Waisburd, A. C. (2007). The value of the designated market maker. *Journal of Financial and Quantitative Analysis*, *42*(3), 735–758. https://doi.org/10.1017/S0022109000004166

Wood, R. A., McInish, T. H., & Ord, J. K. (1985). An investigation of transactions data for NYSE stocks. *The Journal of Finance*, *40*(3), 723–739. https://doi.org/10.2307/2327796

Yaqub, U. (2020). Tweeting during the Covid-19 pandemic. *Digital Government: Research and Practice*, *2*(1), 1–7. https://doi.org/10.1145/3428090

Zhang, Q., Frömmel, M., & Baidoo, E. (2024). Donald trump's tweets, political value judgment, and the renminbi exchange rate. *International Review of Financial Analysis*, *93*, 103159. https://doi.org/10.1016/j.irfa.2024.103159

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APPENDIX A

This appendix shows results of additional analyses and robustness tests as discussed in the main part of the article. Firstly, Table A1 shows the results for tweets with relatively few retweets. Only tweets where the number of

TABLE A1 Tweets with few retweets.

	Return			Return × Sent. × Econ. Tweet		
	±1s	±10s	±60s	±1s	±10s	±60s
Post × CoreTrading	0.270	0.029	0.095	0.380	−0.497	−0.223
	(0.43)	(0.14)	(1.15)	(0.26)	(−0.60)	(−0.91)
Post × Extended Hours	−0.078	−0.031	0.011	0.160	−0.083	0.026
	(−0.33)	(−0.43)	(0.37)	(0.24)	(−0.33)	(0.33)
	Volatility			**Volume**		
Post × CoreTrading	−0.019	0.003	−0.030	0.791	−0.561	−0.534
	(−0.35)	(0.09)	(−1.17)	(0.56)	(−0.85)	(−1.17)
Post × Extended Hours	0.171***	0.086***	0.032*	0.536	−0.023	0.236***
	(4.70)	(3.75)	(1.80)	(1.60)	(−0.19)	(2.64)
	Quoted Spreads			**Depth**		
Post × CoreTrading	0.008	0.004	−0.005	−12.327	−140.82*	25.416
	(1.20)	(0.73)	(−1.12)	(−0.12)	(−1.68)	(0.48)
Post × Extended Hours	0.211***	0.291***	0.077***	−191.05*	−180.50	24.749
	(8.32)	(8.28)	(2.66)	(−1.70)	(−1.18)	(0.23)
	Effective Spreads			**Price Impact$_{1s}$**		
Post × CoreTrading	−0.023	0.002	−0.007	0.038	0.038	0.007
	(−1.14)	(0.26)	(−1.16)	(0.20)	(0.82)	(0.35)
Post × Extended Hours	0.094	0.033	0.004	−0.291	0.215	0.008
	(0.68)	(0.61)	(0.14)	(−0.85)	(1.49)	(0.20)

Note: This table shows the reaction to tweets with few retweets (i.e., to tweets where the number of retweets is in the bottom tercile of the distribution of tweets). The regression approach and variable definitions are identical to those of Tables 2 to 4. All models include day fixed and intraday fixed effects for every 15-minute interval of the day. The standard errors are clustered by tweet and the resulting *t* statistics are given in parentheses. ***, **, * denotes significance at the 1%, 5%, 10% level, respectively.

retweets is in the bottom tercile are included. Otherwise, the analysis is identical to Table 6 in the main part, which shows the results for tweets with relatively many retweets.

Secondly, returns, trading volume, and liquidity are adjusted for pre-trends. This is done by first running a tweet-by-tweet regression using the 60 seconds interval before a tweet to estimate a linear time trend and then subtracting the predicted values of this regression for the period after the tweet from the realized values. The results in Table A2 then show results of regressions identical to those in the main part except that here these residuals are used as dependent variables.

Thirdly, Table A3 shows the results of placebo tests where the timestamp of each tweet has been randomly changed by drawing from a uniform distribution of the entire sample period.

Finally, the effects of tweets by members of Congress when split by party affiliation can be found in Table A4.

TABLE A2 Pre-trend adjusted results.

	Return			Return × Sent. × Econ. Tweet		
	±1s	±10s	±60s	±1s	±10s	±60s
Post × CoreTrading	−0.428	−0.033	0.003	−0.606	−0.152	−0.064
	(−1.29)	(−0.28)	(0.03)	(−1.27)	(−0.72)	(−0.28)
Post × Extended Hours	−0.277*	0.021	0.043	0.461	0.109	0.176
	(−1.75)	(0.43)	(0.86)	(1.43)	(1.18)	(1.64)
	Volatility			**Volume**		
Post × CoreTrading	0.013	0.061***	−0.024	−0.108	0.526	0.169
	(0.47)	(3.42)	(−0.99)	(−0.13)	(1.25)	(0.32)
Post × Extended Hours	0.200***	0.106***	0.041**	−0.013	0.196	0.342***
	(8.42)	(7.05)	(2.50)	(−0.05)	(1.37)	(2.63)
	Quoted Spreads			**Depth**		
Post × CoreTrading	0.009**	0.008**	0.008**	−100.13	−109.75**	36.090
	(2.17)	(2.58)	(2.04)	(−1.58)	(−2.11)	(0.51)
Post × Extended Hours	0.251***	0.298***	0.063**	−250.16***	−216.63**	−44.101
	(14.75)	(12.84)	(2.09)	(−3.39)	(−2.07)	(−0.26)
	Effective Spreads			**Price Impact$_{1s}$**		
Post × CoreTrading	0.016	0.016***	0.015*	0.061	0.041	0.018
	(1.34)	(2.63)	(1.70)	(0.63)	(1.14)	(0.52)
Post × Extended Hours	0.383**	−0.237	0.064	−0.459	0.429**	0.528*
	(2.17)	(−0.84)	(0.30)	(−0.78)	(2.19)	(1.88)

Note: This table shows results for pre-trend adjusted dependent variables. In a fist step, the dependent variables are regressed on a linear time trend and a constant using pre-tweet observations. The residuals of predictions for the post-tweet period are then used for this analysis. Other than the first stage regression, the approach and variable definitions are identical to those of Tables 2 to 4. All models include day fixed and intraday fixed effects for every 15-minute interval of the day. The standard errors are clustered by tweet and the resulting t statistics are given in parentheses. ***, **, * denotes significance at the 1%, 5%, 10% level, respectively.

TABLE A3 Placebo tests.

	Return			Return × Sent. × Econ. Tweet		
	±1s	±10s	±60s	±1s	±10s	±60s
Post × CoreTrading	0.741	−0.083	0.082	−0.386	−0.220	0.070
	(1.42)	(−0.48)	(1.00)	(−0.26)	(−0.53)	(0.44)
Post × Extended Hours	−0.311	0.028	0.011	−0.231	−0.053	−0.036
	(−1.46)	(0.40)	(0.37)	(−1.13)	(−0.58)	(−0.64)
	Volatility			**Volume**		
Post × CoreTrading	0.024	−0.004	0.035	−1.527	0.215	0.536
	(0.46)	(−0.15)	(1.44)	(−1.14)	(0.39)	(1.24)
Post × Extended Hours	0.005	−0.012	−0.009	0.295	−0.075	−0.196
	(0.21)	(−0.92)	(−0.95)	(0.92)	(−0.54)	(−1.08)
	Quoted Spreads			**Depth**		
Post × CoreTrading	−0.015*	0.004	−0.005	−154.71	21.053	−47.635
	(−1.71)	(0.58)	(−0.86)	(−1.52)	(0.26)	(−0.88)
Post × Extended Hours	−0.002	−0.008	0.018	27.168	−57.314	46.640
	(−0.14)	(−0.45)	(0.93)	(0.42)	(−0.64)	(0.47)
	Effective Spreads			**Price Impact$_{1s}$**		
Post × CoreTrading	0.003	−0.008	−0.010*	−0.089	−0.051	−0.013
	(0.15)	(−0.76)	(−1.84)	(−0.59)	(−1.11)	(−0.71)
Post × Extended Hours	0.134	−0.009	0.026	−0.299	−0.105	−0.040
	(0.91)	(−0.18)	(0.77)	(−0.84)	(−1.16)	(−0.77)

Note: This table shows results of placebo tests where the timestamps of the tweets have been randomly selected from a uniform distribution covering the entire sample period. The regression approach and variable definitions are identical to those of Tables 2 to 4. All models include day fixed and intraday fixed effects for every 15-minute interval of the day. The standard errors are clustered by tweet and the resulting *t* statistics are given in parentheses. ***, **, * denotes significance at the 1%, 5%, 10% level, respectively.

TABLE A4 Tweets by members of Congress by party.

	±1s	±10s	±60s	±1s	±10s	±60s
Panel A: Democratic members of Congress						
	Return			**Volatility**		
Post × CoreTrading	−0.005	−0.003	−0.006	0.008***	0.012***	0.010***
	(−0.18)	(−0.32)	(−1.58)	(3.13)	(9.35)	(9.83)
Post × ExtHours	−0.030*	0.004	0.001	−0.003	−0.003**	−0.013***
	(−1.81)	(0.69)	(0.60)	(−1.55)	(−2.26)	(−12.55)
	Quoted Spreads			**Depth**		
Post × CoreTrading	0.000	0.000	−0.001***	−4.141	−2.079	3.801
	(0.67)	(0.97)	(−3.50)	(−0.73)	(−0.44)	(1.19)
Post × ExtHours	0.004***	0.005**	0.010***	−17.251**	−22.321**	−30.815**
	(3.49)	(2.31)	(4.46)	(−2.43)	(−2.04)	(−2.56)
	Effective Spreads			**Price Impact$_{1s}$**		
Post × CoreTrading	0.001	0.001*	0.000	−0.002	−0.004*	−0.002*
	(1.43)	(1.69)	(0.13)	(−0.34)	(−1.93)	(−1.86)
Post × ExtHours	−0.035***	0.023***	0.047***	−0.018	0.020**	0.017***
	(−4.29)	(6.14)	(17.66)	(−0.72)	(2.25)	(4.61)
Panel B: Republican members of Congress						
	Return			**Volatility**		
Post × CoreTrading	0.050	0.018	−0.001	0.003	0.013***	0.010***
	(1.46)	(1.56)	(−0.27)	(0.89)	(7.26)	(7.16)
Post × ExtHours	−0.049**	−0.013*	−0.001	0.003	0.002	−0.004***
	(−2.10)	(−1.76)	(−0.38)	(0.92)	(1.02)	(−2.86)
	Quoted Spreads			**Depth**		
Post × CoreTrading	−0.000	0.001*	−0.001**	−11.284	−2.987	15.778***
	(−0.79)	(1.72)	(−2.46)	(−1.53)	(−0.49)	(3.79)
Post × ExtHours	0.004**	0.010***	0.015***	−36.972***	−27.404*	−26.911*
	(2.06)	(3.52)	(4.93)	(−3.85)	(−1.84)	(−1.72)
	Effective Spreads			**Price Impact$_{1s}$**		
Post × CoreTrading	0.001	0.003***	0.001	0.017*	0.009***	0.002
	(0.56)	(4.30)	(1.30)	(1.90)	(2.73)	(1.60)
Post × ExtHours	−0.049***	0.022***	0.047***	−0.001	0.024**	0.020***
	(−4.26)	(3.99)	(11.65)	(−0.04)	(1.96)	(4.05)

Note: This table shows the market reaction to tweets by members of Congress split by party affiliation. Panel A includes only Democrats while panel B includes only Republicans. The regression approach and variable definitions are identical to those of Tables 2 to 4. All models include day fixed and intraday fixed effects for every 15-minute interval of the day. The standard errors are clustered by tweet and the resulting t statistics are given in parentheses. ***, **, * denotes significance at the 1%, 5%, 10% level, respectively.