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Heroes, just for one day: The impact of Donald Trump's tweets on stock prices

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ABSTRACT

We analyze the effect of Donald Trump's tweets on individual stock returns. We use intraday (minute-by-minute) data in order to uncover causal effects of the tweets on prices and trading activity. We find that the tweets cause increased trading activity but do not have lasting effects on stock prices. We also find evidence of abnormal returns, increased trading volume and increased investor attention *before* the tweets. This finding is consistent with Donald Trump's tweets not providing new information but rather being comments on events that happened, and already attracted investor attention, before the tweet.

1. Introduction

The former US President Donald Trump has revolutionized the way in which top politicians communicate political opinions or decisions. Instead of turning to the public via official press conferences or the intermediary media, he directly communicated with the public via the microblogging platform Twitter throughout his presidency. While most other politicians (like Trump's predecessor Barack Obama) have used social media platforms primarily for representative issues, President Trump used tweets to express concrete personal political views and opinions. The unique combination of the power of his position as a world leader and the very colloquial tone of his posts led to the big "success" of his tweets. The number of his followers approached 80 million by the end of 2020, and he published more than 50,000 tweets[1] before his Twitter account was permanently suspended in January 2021. Even as a President, Trump continued to address individual companies in his tweets. The present paper deals with the question how these tweets affected the stocks of the firms addressed in the tweets.

An extensive number of papers investigate the information content of microblogging messages (mostly based on the social networking platform Twitter) with a direct reference to the stock market, mostly finding strong associations. In an early study Bollen et al. (2011) use 10 million tweets by 2.7 million users to investigate public sentiment and its interrelation with the DJIA. They find that the so-called "Twitter-mood" can be used as a predictor for stock market behavior. Sprenger et al. (2014a,b), Yang et al. (2015), Reed (2016), Broadstock and Zhang (2019), Gholampour (2019), and Saurabh and Dey (2020) are more recent contributions documenting similar results.

Several papers analyze the impact of Donald Trump's tweets on stock prices at the market level (approximated by index levels or ETF prices). These studies focus on tweets with content related to macroeconomic and/or political issues rather than on tweets with company-specific content. Abdi et al. (2021) conclude that Trump's tweets do not convey material new information. Kinyua et al. (2021) document a negative price reaction of the DJIA and the S&P 500 to tweets broadcasted during trading hours. Burggraf et al. (2020) provide evidence that tweets on the US–China trade war affect S&P 500 returns. Klaus and Koser (2021) find that an index quantifying Trump's tweeting activity (the Volfefe Index proposed by Salem et al. (2019)) affects European equity market returns. Nishimura et al. (2021) show that Trump's tweets affect volatility and the jump component of equity returns. Tillmann (2020) focuses on tweets addressing the Fed's monetary policy

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[1] Source: https://www.trackalytics.com/twitter/profile/realdonaldtrump/, accessed 22 June 2021.

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and finds that tweets requesting the Fed to lower interest rates are indeed followed by lower long-term rates.

A more specific strand of the literature covers the impact of Donald Trump's company-specific tweets on stock prices. In contrast to the studies on the general relation between Twitter traffic and stock markets, studies on these Trump tweets provide conflicting results. Born et al. (2017) consider 15 tweets during the period from Trump's election on November 8, 2016 to his swearing in ceremony on January 20, 2017. They find that positive (negative) content tweets elicited positive (negative) abnormal returns on the event day. Moreover, these tweets were associated with increased Google search activity and trading volume. Rayarel (2018) confirms these results with a slightly larger database including 16 negative and eight positive tweets. In contrast, Juma'h and Alnsour (2018) using a sample of 58 Trump tweets on 23 companies find no significant effects, neither at the market level nor at the level of individual stocks.

The most comprehensive study on this subject so far is that of Ge et al. (2019). These authors analyze the effect of Trump's company-specific tweets from November 9, 2016 to December 31, 2017 on daily stock prices, trading volume, volatility and institutional investor attention. Using a sample of 48 events they find abnormal effects that were stronger before the Presidential inauguration on January 20, 2017 than during Trump's presidency. Moreover the authors report that price effects are reversed during the next few trading days after a tweet. Kleczka (2020) confirms these results using an extended sample including tweets relating to social media companies such as Twitter and Facebook, which account for a significant portion of the overall sample. Brans and Scholtens (2020) document that Trump tweets with extreme negative sentiment trigger negative abnormal returns, while positive tweets do not render a significant effect. Their sample includes 100 tweets from November 8, 2016 (President elect) to November 8, 2018 and their analysis exclusively focusses on daily returns of US stocks after tweet publications.

We contribute to the literature on the effects of Donald Trump's company-specific tweets on stock prices in three ways. First, we use an extended sample period comprising all relevant tweets from Trump's personal Twitter account "@realdonaldtrump" between August 11, 2016 and July 31, 2019. Our final sample comprises 99 events for 39 different companies. Second, we analyze two data sets, a daily data set and a high-frequency data set. Because Donald Trump often twittered while markets were closed the high-frequency data set is smaller; it comprises 29 tweets on 25 companies. However, it allows us to gain deeper insights into the speed and duration of market reactions to Trump's tweets and enables us to analyze whether these tweets have a *causal* effect on the market. We are aware of three other papers that use high frequency data in the context of Trump's tweets (Abdi et al., 2021; Kinyua et al., 2021; Nishimura et al., 2021). However, all three papers focus on the impact of Trump's tweets at the market (index or ETF) level while we study individual stock returns. Third, in order to obtain a broader picture of stock market effects preceding and following Trump's tweets, we analyze, besides changes in stock prices, also changes in trading volume and media and investor attention before and after the publication of the tweet.

Our empirical results reveal several important insights. We find Trump's tweets generally to be associated with an increase in absolute returns as well as trading volume on the same trading day. They are also accompanied by increased media and investor attention as measured by the appearance of company news on Refinitiv Eikon and increased Google search volume. When we classify tweets into positive and negative news we find that stock prices increase [decrease] after tweets categorized as positive [negative]. However, we also find (1) that the price effect observed on the event date is subsequently reversed and (2) that there are abnormal returns, increased trading volume and elevated media and investor attention already on the days before the tweet. The first finding suggests that Trump's tweets have no lasting effect on market prices. The second finding implies that Donald Trump's tweets may be a reaction to past news rather than conveying new information to the market. Even if Trump's tweets are a reaction to past events and have no permanent effect on stock prices, they may still trigger a transitory stock market reaction. Indeed, when analyzing our high frequency sample we find significant abnormal returns and trading volume in the minute of the tweet and shortly thereafter.

The remainder of the paper is organized as follows. Section 2 develops our hypotheses. Section 3 presents the methodology. Section 4 describes our data and Section 5 our results. Section 6 concludes.

2. Hypotheses

We build our analysis of the impact of ex-President Donald Trump's messages via Twitter on the following hypotheses.

Hypothesis 1. Trump's tweets affect the prices and the trading volume of the stocks addressed in his tweets. They will also attract attention from investors and the media.

This hypothesis can be based on two opposing considerations. First, and in line with standard finance theory, if a tweet contains new and relevant information we expect that the share price reacts to the tweet, and that trading volume and investor attention increase. Being the former President of the world's largest economy, Donald Trump had a huge number of social media followers, authority, and strong political power. Thus it seems reasonable to assume that his company-specific tweets might predict future political decisions,[2] thereby influencing the public opinion with potential consequences for the future business prospects and cash flows of targeted companies.

Second, and based on insights from behavioral finance, even if a Presidential tweet on a company is entirely uninformative,[3] it may still be the case that the stock addressed in the tweet will receive a great deal of attention, not only from Trump's Twitter followers, but also from the media and investors. In such a situation, well-documented behavioral biases such as the preference for attention-grabbing stocks, emotion-based trading, and herding might lead to an impact on investor attention, on trading volume, and possibly also on share prices. If sophisticated investors predict a transitory price movement in response to a tweet they may trade ahead of the predicted reversal, thereby reinforcing the effect on trading volume.

Hypothesis 2. Tweets that can be classified as positive [negative] trigger positive [negative] abnormal returns.

Given the restriction in the number of characters for a single tweet, together with the simple language Trump typically uses in his tweets, it is often easy to connote the sentiment of these messages as either positive or negative. Provided that there is a price reaction in the first place (as predicted by Hypothesis 1) we expect a positive (negative) company-related tweet to induce an increase (a decrease) in the corresponding stock price.

2 Think, for example, of government contracts, trade tariffs, or government subsidies.

3 For instance, when the tweet simply relates to issues that had already been disclosed before, or when it only includes untenable promises, assertions or threats.

Hypothesis 3a. The effects on returns are only transitory (i.e. they are reversed rather quickly).

Hypothesis 3b. The effects on returns are permanent.

In the context of Hypothesis 1 we have described two channels through which tweets may affect stock prices, a "rational channel" and a "behavioral channel". If a price reaction following a tweet is caused by new information contained in the tweet we expect the price impact of the tweet to be permanent. If, in contrast, the price reaction is caused by behavioral biases we expect it to be transitory. By analyzing the price reaction to the tweet over an extended period of time (up to five days after the event day in our implementation) we can differentiate between these two channels. If the initial price reaction is fully reversed, we can conclude that the tweet did not contain new information.

3. Data

We extract all tweets from Donald Trump's personal Twitter account "@realdonaldtrump"[4] between November 08, 2016 (President elect) and July 31, 2019 from trumptwitterarchive.com, a website that collects Trump's tweets in real time. The election date was chosen as the starting date of the sample period in order to ensure a reasonable expected relevance of the tweets. The data include the exact time of the posting and an indication if the tweet is an original tweet or a retweet.

During the sample period Trump published a total of 9,723 tweets via his personal account. In a first step, we systematically search these tweets for those containing the names of firms that are listed on the US, European, Japanese or Korean stock markets. In a second step, we remove tweets according to the following protocol.

- Tweets that relate to "fake news" topics and, in that context, mention broadcasting or social media firms;
- Retweets;
- Tweets in which the mentioning of the company is only a side information.[5]

In cases in which Trump mentions more than one firm in a single tweet we estimate the effect of the tweet on prices and trading volume of all involved stocks.

We construct two samples, a daily sample and an intraday sample. The intraday sample contains all tweets published during the opening hours of the major stock exchange in the home country of the firm addressed in the tweet. The daily sample additionally contains all tweets published before market opening and those published after market closing. For the latter group of events the event day is the next trading day.

We further match all events in the sample with data on media and investor attention. Here, we use the data from the day of the tweet irrespective of whether the tweet was published before, during or after trading hours.

If there is more than one tweet addressing the same firm on the same day[6] we proceed as follows

- If the tweets are published on the same day but more than one hour apart from each other only the first tweet is included in the daily sample while both are included in the intraday sample.
- If both tweets are published within one hour only the first tweet is included in the daily and the intraday sample.

Our final sample includes 99 events for 39 distinct firms in the daily data set and 29 tweets addressing 25 distinct firms in the intraday data set.

We obtain daily and intraday data on stock prices and trading volume from Refinitiv Eikon. We further obtain return data on the S&P 500, the STOXX Europe 600, the Korea KOSPI 200 and the Nikkei 225. These indices are used as market proxies in our event study.

To obtain a measure of market attention (referred to as the Eikon attention measure) we use the Refinitiv Eikon "news" category to extract news items from 1038 News Wires, 94 Global Press sources and 2563 Web News sources[7] for the firms addressed in a tweet. To derive the Google attention measure we use Google Trends which provides normalized information on Google search volume, with the day having the highest volume in the period under consideration receiving a value of 100. We follow the approach of Buchbinder (2019) and include both the company name and the word "stock" in the search query.[8]

4. Methodology

We measure the effect of President Trump's firm-specific Twitter messages along three dimensions, stock returns, trading volume, and media and investor attention. We use both the daily and the intraday sample to analyze returns and volume. The analysis of media and investor attention is confined to the daily data set because the data needed for this analysis is not available at higher frequencies.

Price Reactions to Presidential Tweets

In order to measure price effects associated with President Trump's tweets we apply standard event study methodology. We define the event day as explained in the previous section. For the daily sample we calculate log returns from daily closing prices. We estimate expected returns using the market model over a 250-day estimation window ending 6 days prior to the event. The event window is the 11-day window centered on the event day.

Abnormal returns AR_{it} for company i on date t are estimated as the difference between the observed event-date return R_{it} and the expected return conditional on the market return R_{mt} on the respective day. Averaging event-date abnormal returns across events yields the average abnormal return AAR_t. Similarly, averaging event-date absolute abnormal returns across events yields the average absolute abnormal return $AAbsAR_t$. To assess the statistical significance of the AAR_t we apply (i) a traditional t-test, (ii) the standardized cross-sectional test proposed by Boehmer et al. (1991) (BMP in the sequel), and (iii) the non-parametric approach by Corrado (1989). The same tests are applied for assessing the statistical significance of the $AAbsAR_t$. In these tests the null hypothesis is that the $AAbsAR_t$ is equal to the average absolute abnormal return in the estimation window.

In our tests based on high-frequency (minute-by-minute) data we assume that the expected return over a one-minute interval is

[4] The official Twitter account of the US President, @POTUS, is only used for official announcements.

[5] For instance: Trump tweeted on August 3, 2018: "Congratulations to Gregg Jarrett on his book "THE RUSSIA HOAX THE ILLICIT SCHEME TO CLEAR HILLARY CLINTON AND FRAME DONALD TRUMP", going to #1 on @nytimes and Amazon. It is indeed a HOAX and WITCH HUNT illegally started by people who have already been disgraced. Great book!". While Amazon is explicitly mentioned in the tweet, the firm is not the main addressee of the tweet.

[6] "Same day" refers to the event day which, for tweets published after market close, is the next trading day. Therefore, two tweets published on the same day according to our timing convention may actually have been published on different calendar days.

[7] This set of sources is summarized in Refinitiv Eikon as "suggested" sources.

[8] Buchbinder (2019) argues that Google search volume for the company name might not be a precise measure of investor interest because customers may also use it for research on products and services or customer support.

0. Therefore, the abnormal return is equal to the observed return. Otherwise, the methodology is as described above.

Volume and Attention Reactions to Presidential Tweets

To measure the impact of Trump's tweets on trading volume we also apply event study methodology. We again define a pre-event window comprising 250 trading days. We use average daily trading volume $\overline{V}_i$ over this period to estimate the normal (or expected) volume and define the abnormal trading volume AV_{it} for event i on day t as the difference between actual trading volume V_{it} and $\overline{V}_i$, normalized by $\overline{V}_i$.

For the intraday analysis the estimation window consists of the 100 min preceding the respective tweet. For tweets which occur soon after market opening, so that less than 100 min of pre-event data from the same trading day are available, the estimation period is shortened accordingly. However, we never include in the estimation window data from the first five minutes after market opening because of extraordinarily high trading activity immediately after market opening.[9]

To analyze abnormal media and investor attention we apply a procedure similar to that used to analyze abnormal trading volume. We define abnormal attention, $AMIA_{it}$, for event i on day t as the difference between the actual media and investor attention and an estimate of expected attention, normalized by the latter. For the Eikon and Google attention measures expected attention is estimated as the mean attention during an estimation window. Attention generally increased during the sample period. Therefore, rather than a 250-day pre-event estimation window we use a 50-day window that comprises 25 days prior to the event window and 25 days after the event window, where the event window is an 11-day window centered on the event day, as before.

Tweet Classification

In order to analyze whether the prices of stocks addressed in Donald Trump's tweets move in the direction implied by the contents of the tweet we obviously need to classify tweets into "good news" and "bad news" events. We use two approaches to do so.

1. Tweets are classified based on professional judgment by the authors.
2. A simple Natural Language Processing (NLP) technique, the Bag-of-Word method, is employed. We first cleanse the data by removing the punctuation and then tokenize the text, meaning that the text is split up into single words. These individual words are then matched with the lexicons "bing" and "afinn" from the R tidytext package. The individual word scores are aggregated for each tweet, resulting in a total sentiment score per tweet and package.

The Bag-of-Word approach is more objective because it does not rely on personal judgment and is easily reproducible. On the other hand, the classification by professional judgment may be more appropriate because the sentiment of Trump's tweets can often not be judged without considering the context. Furthermore, some of the tweets address two or more companies; praising one while threatening the others.[10] Therefore, we focus on the results based on professional judgment and report those obtained with the Bag-of-Word approach as a robustness check in the appendix.[11]

5. Results

In this section we present our empirical results. We proceed in three steps. We first present the results obtained from the daily data, followed by a presentation of the intraday results. The final subsection discusses the results and relates them to the hypotheses developed in Section 2 above.

5.1. Daily returns, trading volume, and media and investor attention

The upper Panel of Table 1 shows the daily average absolute abnormal returns in the event window and corresponding test statistics. It thus addresses the question whether prices change on tweet days, irrespective of whether a tweet is classified as positive or negative. The figures in the Panel indicate that prices indeed change on the day of the tweet. The absolute abnormal return on that day is 1.2%, significant according to the t-test. However, the Table also reveals that prices change already on the day prior to the tweet. In fact, the absolute abnormal return is even higher, at 1.3% (significant according to the t-test and the BMP test), on the pre-tweet day than on the tweet day.

In the middle and lower Panels of Table 1 we consider positive and negative tweets separately and relate them to signed returns. We present the results for the "professional judgment classification" (PJ[12]). Those for the NLP classification are qualitatively similar and are shown in Table 6 in the Appendix.

Positive tweets are associated with a significantly positive abnormal return of 0.7%. There is no indication of a significant abnormal return on the pre-tweet day. On the second and third day after the tweet we observe negative abnormal returns (significant on day 3). The sum of these negative abnormal returns slightly exceeds the positive abnormal return on the tweet day. It thus appears that the abnormal return on the tweet-day is fully reversed subsequently.

We obtain a different picture for the subsample of negative tweets. The abnormal return on the tweet day is significantly negative, at −0.6%. However, this abnormal return follows a string of negative abnormal returns on the pre-tweet days (significant on days −1 and −2). While the abnormal returns turn positive after the tweet day, we do not observe a full reversal.

The results are visualized in Fig. 1. The Figure confirms that there is no persistent effect of positive tweets on stock prices. In contrast, there is a persistent effect after negative tweets. However, this effect is due to the pre-tweet abnormal return.

Table 2 presents the results for trading volume. As before, the upper Panel shows the results for the full sample while the middle and lower Panels show separate results for positive and negative tweets. It is apparent from the upper Panel that there is significant positive abnormal volume on the tweet day as well as on the two days surrounding the tweet. Volume stays at an elevated level on days 2 to 5 after the tweet, though not significantly so. The middle and lower Panels of Table 2 reveal that the pattern – elevated volume not only on the tweet day but also before the tweet day – can be observed for both positive and negative tweets but is more pronounced for negative tweets. Using NLP classification technique yields qualitatively similar results (see Table 7 in the Appendix).

[9] Further analyses have shown that trading volume tends to trend downward during the trading day, although not significantly so. We note that such a downward trend would, if anything, bias our tests *against* finding a significant increase in trading volume following a tweet.

[10] For instance: Trump tweeted on December 22, 2016: "Based on the tremendous cost and cost over-runs of the Lockheed Martin F-35 I have asked Boeing to price-out a comparable F-18 Super Hornet!"

[11] Both classification procedures, "professional judgment" and "Bag-of-Word", result in similar classifications. Comparing the "professional judgment" classification to the "Bag-of-Word" classification based on the "bing" ["afinn"] lexikon yields 84% (83/99) [87% (86/99)] identical classifications (counting tweets classified as "neutral" by the Bag-of-Word approach as consistently classified).

[12] We denote the subset of tweets classified as positive [negative] by the professional judgment classification by PJ+ [PJ-].

Table 1
Daily average absolute abnormal returns (AAbsAR) and daily average abnormal returns (AAR) in the event window and corresponding test statistics. The upper panel shows results for the full sample (99 observations) while the middle and lower panels show results for positive tweets (denoted PJ+, 64 observations) and negative tweets (PJ-, 35 observations), respectively.

Full Sample	**Event window - day t**										
	-5	**-4**	**-3**	**-2**	**-1**	**0**	**1**	**2**	**3**	**4**	**5**
AAbsAR	0.009	0.009	0.010	0.010	0.013	0.012	0.011	0.009	0.011	0.008	0.009
t-test	0.513	0.214	0.771	0.748	3.815**	3.200**	1.885	-0.206	2.370*	-0.790	0.463
BMP test	0.340	0.418	0.895	0.454	2.362*	1.864	1.494	-0.179	1.249	-1.027	0.613
Corrado	0.056	0.592	0.852	0.196	1.962	1.525	0.885	-0.613	0.487	-0.568	1.276

Set A	**Event window - day t**										
PJ+	**-5**	**-4**	**-3**	**-2**	**-1**	**0**	**1**	**2**	**3**	**4**	**5**
AAR	0.002	0.002	0.000	-0.002	0.001	0.007	0.000	-0.002	-0.006	0.001	0.000
t-test	1.090	1.423	-0.258	-1.386	0.735	4.361**	-0.294	-1.455	-3.811**	0.847	-0.160
BMP test	0.945	1.190	-0.426	-2.074*	0.812	2.877**	-0.429	-1.338	-2.205*	0.508	-0.051
Corrado	1.319	0.943	-0.386	-1.451	1.072	2.629**	-0.536	-1.090	-2.503*	0.963	-0.082

Set B	**Event window - day t**										
PJ-	**-5**	**-4**	**-3**	**-2**	**-1**	**0**	**1**	**2**	**3**	**4**	**5**
AAR	-0.003	0.001	-0.001	-0.007	-0.006	-0.006	0.003	0.001	0.004	0.000	0.000
t-test	-1.166	0.615	-0.252	-3.219**	-2.776**	-2.635**	1.255	0.590	1.698	-0.156	-0.179
BMP test	-1.241	0.634	-0.142	-1.990*	-1.628	-2.142*	0.764	0.874	1.142	-0.219	-0.275
Corrado	-1.577	0.359	0.103	-1.935	-1.973*	-3.138**	0.925	1.002	0.730	-0.075	-0.210

*p<0.05 **p<0.01

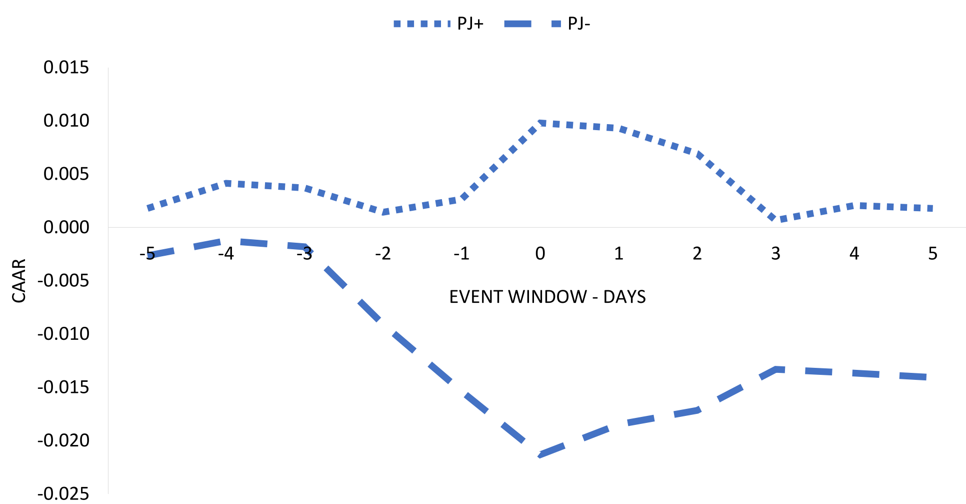

Fig. 1. Cumulative daily average abnormal returns (CAAR) of the positive tweet (PJ+) and negative tweet (PJ-) subsets in the event window.

Fig. 2 visualizes the result. It is clearly visible that volume increases already before the tweet and stays above its pre-tweet level subsequently.

The observation, documented above, of significant abnormal returns (at least for negative news) and elevated volume already on the pre-tweet days suggests that Donald Trump's tweets do not convey new information but rather are comments on news that is already publicly available. To shed further light on this issue we analyze whether there is abnormal media and investor attention around the tweet day. Table 3 shows results for the Eikon and Google attention measures (results for NLP classification technique are shown in Table 8 (Eikon) and Table 9 (Google) in the Appendix).

The results are fully consistent with the previous results. Irrespective of whether we consider the full sample or subsamples of positive and negative tweets, and irrespective of which attention metric we use, we find that media and investor attention is already significantly increased on the pre-tweet day. This pattern is consistent with the notion that Donald Trump's tweets are primarily comments on events that took place (and captured investor attention) already before the tweet.

5.2. Intraday returns and trading volume

The analysis in the previous section has shown that there are abnormal returns and abnormal trading volume on (and before) tweet days. However, the analysis does not reveal whether the effects on the tweet day are *caused* by the tweet or would also have been observed without the tweet. We therefore now turn to an analysis using intraday data with a resolution of one minute. If we find significant abnormal returns or volume in the minute of the tweet we can conclude that the effects are indeed caused by the tweet.

The upper Panel of Table 4 shows the evolution of absolute abnormal returns around the tweet, starting 5 min before the tweet and ending 16 min after the tweet. The highest absolute abnormal return is indeed observed in the minute of the tweet. It amounts to 0.13%, significant based on the t-test and the BMP test. Absolute returns stay at an elevated level in the minutes after the tweet, with several statistically significant values. Thus, it appears that Donald Trump's tweets do have an impact on prices.

In the middle and lower Panel of Table 4 we consider the signed abnormal returns after positive and negative tweets. These

Table 2
Daily average abnormal trading volume (AATV) in the event window and corresponding test statistics. The upper panel shows results for the full sample while the middle and lower panels show results for positive tweets (PJ+) and negative tweets (PJ-), respectively.

Full Sample	Event window - day t										
	-5	-4	-3	-2	-1	0	1	2	3	4	5
AATV	-0.016	-0.002	0.001	0.065	0.242	0.278	0.194	0.044	0.070	0.022	0.099
t-test	-0.234	-0.029	0.013	0.984	3.651**	4.197**	2.935**	0.659	1.054	0.332	1.489
BMP test	-0.601	0.007	0.107	0.614	2.785**	3.073**	2.704**	0.751	1.326	0.654	1.589
Corrado	-0.768	0.029	-0.551	-0.242	2.074*	2.394*	1.984*	0.629	1.252	0.803	1.760

Set A	Event window - day t										
PJ+	-5	-4	-3	-2	-1	0	1	2	3	4	5
AATV	-0.003	0.045	-0.030	-0.065	0.160	0.253	0.208	0.048	0.048	0.054	0.092
t-test	-0.042	0.570	-0.389	-0.829	2.044*	3.241**	2.667**	0.614	0.613	0.685	1.181
BMP test	-0.353	0.723	-0.409	-1.432	2.303*	2.437*	2.055*	0.512	0.828	1.006	1.823
Corrado	-0.857	0.606	-0.440	-0.420	2.109*	2.129*	1.144	0.213	0.993	0.956	1.985*

Set B	Event window - day t										
PJ-	-5	-4	-3	-2	-1	0	1	2	3	4	5
AATV	-0.038	-0.087	0.058	0.303	0.391	0.322	0.168	0.036	0.110	-0.036	0.110
t-test	-0.358	-0.823	0.550	2.865**	3.703**	3.053**	1.592	0.337	1.038	-0.338	1.041
BMP test	-0.636	-1.082	0.546	1.202	1.803	1.856	1.912	0.602	1.066	-0.608	0.866
Corrado	-0.161	-1.067	-0.444	0.230	0.816	1.516	2.416*	1.047	1.018	0.055	0.326

*p<0.05 **p<0.01

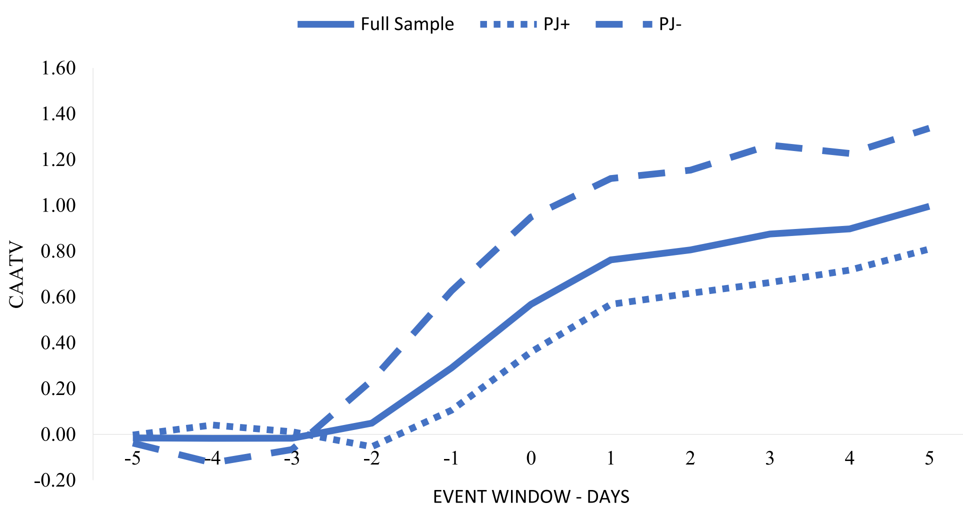

Fig. 2. Cumulative daily average abnormal trading volume (CAATV) of the full sample as well as of the positive tweet (PJ+) and negative tweet (PJ-) subsets in the event window.

results are based on a sample of 18 [11] tweets classified as positive [negative]. There is no discernible price reaction after positive tweets. The abnormal return in the minute of the tweet is very small and insignificant. While there are four significant abnormal returns in the subsequent minutes (minutes 2, 4, 6 and 13), these are as often negative as they are positive. The picture is different for negative tweets. The abnormal return in the minute of the tweet is -0.21% and is statistically significant. Abnormal returns in the minutes after the event are much smaller and are mostly insignificant. It thus appears that prices react almost instantaneously to negative tweets while positive tweets have no effect on prices. The results are visualized in Fig. 3. The Figure confirms the result that there is an immediate price reaction after negative, but not after positive tweets.

Table 5 shows the results for trading volume. The upper Panel considers all tweets jointly while the middle and lower Panels show separate results for positive and negative tweets. What we see is essentially a mirror image of the results for returns presented above. There is no abnormal volume prior to the tweet. In the minute of the tweet trading volume increases sharply and stays at significantly elevated levels for more than ten minutes. However, this result is almost entirely driven by the subsample of negative tweets. These findings are confirmed by Fig. 4.

5.3. Discussion of results

We have hypothesized that Donald Trump's tweets cause price changes and trigger abnormal trading volume. With data at the daily frequency (the data frequency used in all prior studies of the effect of Trump's tweets on individual stock returns) this question cannot be answered in a satisfactory way. There are already significant absolute returns, increased trading activity and investor attention on the days before the tweets. Therefore, it is not possible to determine whether the effects on the tweet day are (fully or partially) caused by the tweet or whether they would also have occurred without the tweet.

The analysis of intraday data helps to overcome this problem. Prices change, accompanied by significantly increased trading volume, in the very minute of the tweet. Thus, and consistent with Hypothesis 1, Donald Trump's tweets do affect prices and trading volume. If we consider positive and negative tweets separately, we find that the prices of the firms addressed in the tweets drop instantaneously after a negative tweet while there is

Table 3
Daily average abnormal media and investor attention (AAMIA) in the event window and corresponding test statistics. The first two panels show results for the full sample (Eikon attention and Google search volume) while the two middle and the two lower panels show results for positive tweets (PJ+) and negative tweets (PJ-), respectively.

Full Sample	Event window - day t										
	-5	-4	-3	-2	-1	0	1	2	3	4	5
AAMIA Eikon	-0.058	-0.181	0.156	0.457	1.208	3.048	2.632	0.949	0.542	0.620	0.407
t-test	-0.353	-1.111	0.957	2.804**	7.403**	18.69**	16.13**	5.818**	3.322**	3.802**	2.494*
BMP test	-0.572	-2.114*	0.643	1.798	4.332**	7.623**	6.504**	3.471**	2.704**	2.434*	2.820**
Corrado	-0.446	-0.732	-0.279	0.426	2.917**	5.620**	4.375**	1.855	1.186	0.728	1.527

Full Sample	Event window - day t										
	-5	-4	-3	-2	-1	0	1	2	3	4	5
AAMIA Google	-0.070	-0.083	0.327	0.564	0.888	2.370	2.162	1.092	0.812	0.732	0.384
t-test	-0.626	-0.743	2.940**	5.072**	7.987**	21.32**	19.45**	9.828**	7.308**	6.584**	3.455**
BMP test	-1.204	-2.248*	1.012	1.180	2.324*	4.649**	4.298**	3.323**	3.221**	2.274*	3.059**
Corrado	0.137	-0.169	0.912	0.910	2.473*	5.170**	4.443**	2.233*	2.035*	1.171	2.009*

Set A	Event window - day t										
PJ+	-5	-4	-3	-2	-1	0	1	2	3	4	5
AAMIA Eikon	-0.053	-0.296	-0.232	0.166	1.017	2.873	2.064	0.664	0.390	0.755	0.406
t-test	-0.252	-1.418	-1.109	0.794	4.868**	13.75**	9.880**	3.181**	1.866	3.615**	1.944
BMP test	-0.183	-3.495**	-2.272*	0.964	4.622**	5.607**	5.086**	1.917	1.466	1.855	2.062*
Corrado	-0.506	-0.837	-0.687	0.465	2.775**	4.522**	3.389**	0.887	0.430	0.317	1.222

Set B	Event window - day t										
PJ-	-5	-4	-3	-2	-1	0	1	2	3	4	5
AAMIA Eikon	-0.067	0.029	0.866	0.991	1.556	3.369	3.671	1.469	0.820	0.373	0.408
t-test	-0.387	0.169	5.031**	5.759**	9.047**	19.58**	21.34**	8.541**	4.768**	2.170*	2.373*
BMP test	-0.887	-0.119	1.589	1.543	2.257*	5.291**	4.196**	3.539**	2.696**	1.773	1.909
Corrado	-0.139	-0.211	0.884	0.181	2.311*	6.611**	5.492**	3.782**	2.770**	1.554	1.808

Set A	Event window - day t										
PJ+	-5	-4	-3	-2	-1	0	1	2	3	4	5
AAMIA Google	-0.105	-0.088	-0.050	0.017	0.221	0.994	1.105	0.379	0.546	0.611	0.402
t-test	-0.837	-0.702	-0.400	0.131	1.756	7.907**	8.790**	3.010**	4.343**	4.862**	3.199**
BMP test	-1.528	-1.415	-0.481	0.444	2.899**	5.166**	3.605**	1.796	1.890	1.256	2.458*
Corrado	-0.428	-0.206	0.496	0.613	1.997*	3.758**	3.274**	0.609	0.921	-0.187	1.471

Set B	Event window - day t										
PJ-	-5	-4	-3	-2	-1	0	1	2	3	4	5
AAMIA Google	-0.004	-0.072	1.016	1.564	2.107	4.884	4.095	2.397	1.299	0.952	0.351
t-test	-0.024	-0.383	5.404**	8.319**	11.21**	25.98**	21.78**	12.75**	6.907**	5.062**	1.864
BMP test	-0.103	-1.916	1.117	1.142	1.888	3.475**	3.087**	2.925**	2.971**	3.488**	1.796
Corrado	1.658	0.000	1.711	1.368	2.819**	7.050**	5.914**	5.873**	4.313**	4.475**	2.704**

*p<0.05 **p<0.01

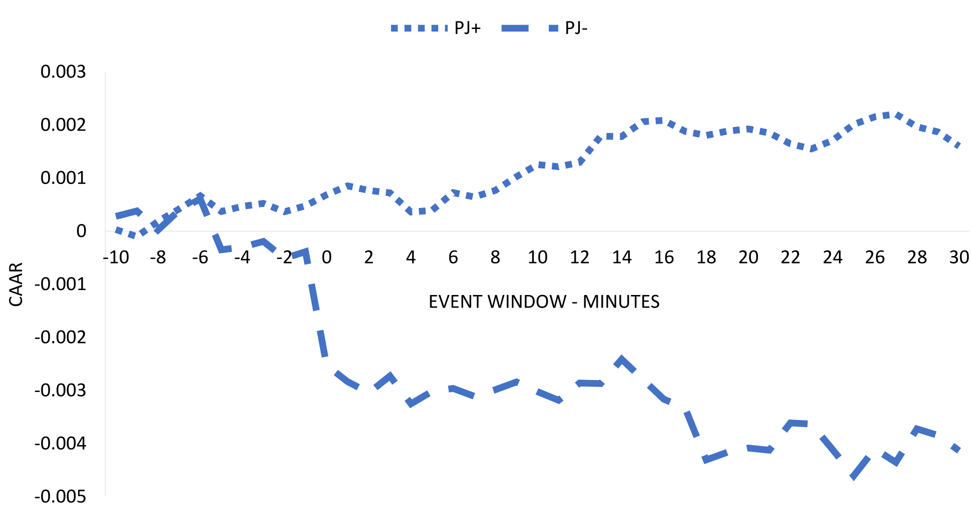

Fig. 3. Cumulative intraday average abnormal returns (CAAR) of the positive tweet (PJ+) and negative tweet (PJ-) subsets in the event window.

no such effect after positive tweets. Thus, Hypothesis 2 can only be accepted for negative tweets.

With respect to the persistence of the effect on stock prices of Trump's tweets, the analysis of daily data yields results consistent with Hypothesis 3a. Price effects are reversed within three days, implying that the tweets have no lasting impact on prices. The intraday data analysis results in a more differentiated picture. After positive tweets there is no price reaction to begin with. After

Table 4
Intraday (minute-by-minute) average absolute abnormal returns (AAbsAR) and daily average abnormal returns (AAR) around the event minute and corresponding test statistics. The upper panel shows results for the full sample while the middle and lower panels show results for positive tweets (PJ+) and negative tweets (PJ-), respectively.

Full Sample	Event window - minute t										
Intra	-5	-4	-3	-2	-1	0	1	2	3	4	5
AAbsAR	0.0009	0.0004	0.0005	0.0007	0.0006	0.0013	0.0010	0.0010	0.0005	0.0010	0.0007
t-test	2.7910**	-1.0337	-0.0656	1.5285	0.3043	6.5198**	4.3029**	3.7776**	0.1363	4.0343**	1.4450
BMP test	0.5734	-0.9540	-2.2199*	1.0730	1.0450	2.0808*	1.9437	1.7902	0.8432	1.9327	1.9223
Corrado	-0.1149	-1.3457	-1.1087	-0.0338	-1.0337	1.3587	1.8117	1.3195	-2.2422*	1.0775	1.1908
	6	7	8	9	10	11	12	13	14	15	16
AAbsAR	0.0006	0.0006	0.0008	0.0009	0.0010	0.0007	0.0007	0.0007	0.0006	0.0007	0.0007
t-test	0.7639	0.6582	2.4314*	3.5640**	3.8258**	1.4176	1.3511	1.4158	1.0075	1.1855	1.7954
BMP test	0.8941	1.0276	1.7750	2.4573*	2.4157*	0.9452	1.3662	1.1170	1.1334	0.8736	1.0333
Corrado	-0.2704	0.1417	1.8517	2.1784*	2.8665**	-0.1139	-0.0755	-0.2996	-0.4314	-0.3608	-0.3347

Set A Intra	Event window - minute t										
PJ+	-5	-4	-3	-2	-1	0	1	2	3	4	5
AAR	-0.0003	0.0001	0.0001	-0.0002	0.0001	0.0002	0.0002	-0.0001	0.0000	-0.0004	0.0000
t-test	-1.3763	0.4461	0.2554	-0.7415	0.5400	0.9769	0.7863	-0.3892	-0.2133	-1.7200	0.1446
BMP test	-1.4544	0.6610	-0.2879	-0.0173	0.3231	0.5273	0.9906	-1.7304	-0.1167	-3.0533**	-0.6673
Corrado	-1.5076	0.6324	-0.3872	0.2685	0.5594	-0.7354	-0.5062	-2.2121*	-0.6325	-2.9486**	-0.7488
	6	7	8	9	10	11	12	13	14	15	16
AAR	0.0003	-0.0001	0.0001	0.0003	0.0002	0.0000	0.0001	0.0005	0.0000	0.0003	0.0000
t-test	1.5968	-0.4042	0.5824	1.2175	1.0802	-0.1892	0.3872	2.3355*	-0.0330	1.3373	0.1063
BMP test	3.3283**	-0.6226	1.5473	1.2627	1.4708	0.3287	0.5373	2.1353*	-0.8345	0.8029	0.3599
Corrado	2.7989**	-1.4163	1.5084	1.1123	1.3636	-0.6636	0.8661	2.5622*	-0.0572	0.9239	-0.4564

Set B Intra	Event window - minute t										
PJ-	-5	-4	-3	-2	-1	0	1	2	3	4	5
AAR	-0.0010	0.0000	0.0001	-0.0003	0.0001	-0.0021	-0.0003	-0.0002	0.0003	-0.0005	0.0002
t-test	-3.4194**	0.1722	0.3942	-1.1485	0.4564	-7.6526**	-1.1004	-0.7571	1.1248	-1.8638	0.8319
BMP test	-1.8175	0.7112	-0.0309	-0.9874	0.9629	-2.4353*	-0.9036	-1.2196	0.9096	-0.5372	1.2753
Corrado	-2.1589*	0.4223	0.4141	-1.4267	1.2142	-3.9690**	1.7471	-0.8736	0.7107	-0.4965	1.6626
	6	7	8	9	10	11	12	13	14	15	16
AAR	0.0001	-0.0001	0.0001	0.0001	-0.0002	-0.0002	0.0003	0.0000	0.0005	-0.0004	-0.0004
t-test	0.2036	-0.5179	0.4376	0.5197	-0.6618	-0.5728	1.1675	-0.0486	1.6422	-1.3509	-1.3385
BMP test	-0.1638	0.0367	1.1975	0.0823	0.8011	0.9586	1.4688	-0.8719	0.1070	-0.6094	-1.7616
Corrado	-1.0989	-0.3029	2.0135*	-0.3503	0.0656	1.4568	2.6277**	0.0781	0.6750	-0.7201	-1.5098

*p<0.05 **p<0.01

Table 5
Intraday (minute-by-minute) average abnormal trading volume (AATV) around the event minute and corresponding test statistics. The upper panel shows results for the full sample while the middle and lower panels show results for positive tweets (PJ+) and negative tweets (PJ-), respectively.

Full Sample	Event window - minute t										
Intra	-5	-4	-3	-2	-1	0	1	2	3	4	5
AATV	-0.102	0.172	-0.110	0.150	-0.032	3.786	4.614	3.436	1.504	1.296	1.265
t-test	-0.505	0.852	-0.543	0.742	-0.158	18.77**	22.88**	17.04**	7.455**	6.425**	6.271**
BMP test	-0.465	0.597	-1.561	0.373	-0.386	2.651**	2.503*	2.363*	2.213*	1.670	1.343
Corrado	-0.193	-0.066	-1.027	-0.503	-0.887	3.193**	4.855**	3.346**	1.299	0.757	0.840
	6	7	8	9	10	11	12	13	14	15	16
AATV	0.806	0.750	0.806	0.898	0.662	0.688	0.290	0.867	0.374	0.163	0.276
t-test	3.998**	3.719**	3.995**	4.453**	3.284**	3.410**	1.436	4.297**	1.854	0.806	1.371
BMP test	1.142	1.619	1.562	1.858	1.649	1.920	1.070	2.410*	1.698	0.745	1.018
Corrado	-0.444	1.405	-0.015	1.532	0.015	2.233*	0.251	1.370	1.718	-0.391	-0.463

Set A Intra	Event window - minute t										
PJ+	-5	-4	-3	-2	-1	0	1	2	3	4	5
AATV	-0.118	0.070	-0.055	0.393	0.090	0.810	1.464	0.914	0.047	-0.222	-0.032
t-test	-0.464	0.273	-0.216	1.542	0.355	3.180**	5.751**	3.587**	0.184	-0.872	-0.125
BMP test	-0.378	0.094	-0.669	0.826	0.331	1.253	2.548*	1.630	-0.068	-1.747	-0.549
Corrado	-0.659	-0.508	0.058	0.538	0.543	0.710	3.973**	2.348*	-0.902	-1.024	-0.294
	6	7	8	9	10	11	12	13	14	15	16
AATV	-0.337	-0.003	0.215	-0.111	-0.147	0.199	-0.122	0.757	-0.146	0.024	0.033
t-test	-1.323	-0.013	0.843	-0.434	-0.577	0.781	-0.479	2.974**	-0.573	0.094	0.128
BMP test	-4.086**	-0.181	0.626	-0.136	-0.966	0.464	-1.081	0.962	-0.763	0.039	-0.060
Corrado	-2.054*	0.427	-0.480	-0.814	-0.940	0.273	-1.185	-0.658	0.049	-1.175	-1.692

Set B Intra	Event window - minute t										
PJ-	-5	-4	-3	-2	-1	0	1	2	3	4	5
AATV	-0.076	0.321	-0.194	-0.248	-0.232	8.656	9.768	7.106	3.755	3.642	3.269
t-test	-0.258	1.096	-0.662	-0.848	-0.794	29.59**	33.39**	24.29**	12.83**	12.45**	11.17**
BMP test	-0.300	0.710	-1.734	-1.172	-1.290	2.872**	2.342*	2.270*	2.562*	1.932	1.418
Corrado	0.393	0.433	-1.696	-1.376	-1.982*	4.276**	3.579**	2.851**	2.976**	2.325*	1.654
	6	7	8	9	10	11	12	13	14	15	16
AATV	2.573	1.914	1.719	2.457	1.913	1.443	0.926	1.036	1.130	0.364	0.631
t-test	8.795**	6.543**	5.876**	8.399**	6.538**	4.934**	3.165**	3.539**	3.863**	1.244	2.157*
BMP test	1.475	1.753	1.432	2.088*	2.006*	2.052*	1.719	2.632**	1.946	1.104	1.183
Corrado	1.494	1.786	0.489	3.286**	1.026	3.235**	1.653	2.867**	2.640**	0.636	1.077

*p<0.05 **p<0.01

negative tweets we observe a price decline that is not reversed within the subsequent 30 min (see Fig. 3), thereby providing some support for Hypothesis 3b at the intraday level. This result should be interpreted with care, though. First, the intraday price effects are rather small. Fig. 3 reveals that the cumulative abnormal return after negative tweets amounts to approximately 0.4%. Second, the analysis of the daily data has revealed that the event day abnormal returns are subsequently reversed, implying

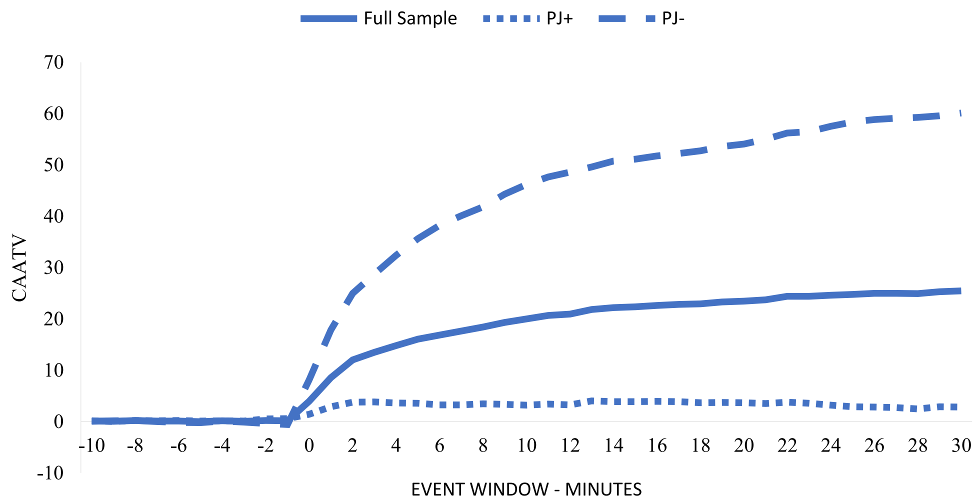

Fig. 4. Cumulative intraday average abnormal trading volume (CAATV) of the full sample as well as of the positive tweet (PJ+) and negative tweet (PJ-) subsets in the event window.

Table 6
Daily average abnormal returns (AAR) in the event window and corresponding test statistics of positively and negatively classified tweets using the lexicons "bing" (upper panels) and "afinn" (lower panels) from the R tidytext package.

Set C	**Event window - day t**										
bing+	**-5**	**-4**	**-3**	**-2**	**-1**	**0**	**1**	**2**	**3**	**4**	**5**
AAR	0.002	0.002	0.000	-0.005	0.000	0.005	-0.001	-0.001	-0.003	0.000	-0.002
t-test	1.266	1.388	-0.271	-2.662**	-0.253	3.022**	-0.450	-0.664	-1.829	0.175	-0.874
BMP test	0.900	0.968	-0.197	-1.902	0.210	1.144	-0.289	-0.281	-1.107	-0.109	-0.716
Corrado	1.269	1.189	-0.233	-2.516*	0.237	1.505	-0.713	-0.254	-2.199*	0.087	-0.786

Set D	**Event window - day t**										
bing-	**-5**	**-4**	**-3**	**-2**	**-1**	**0**	**1**	**2**	**3**	**4**	**5**
AAR	-0.003	0.003	0.002	-0.005	-0.010	-0.010	-0.001	0.000	0.007	0.002	0.003
t-test	-1.231	1.055	0.578	-1.793	-3.789**	-3.639**	-0.467	-0.069	2.545*	0.846	1.185
BMP test	-1.429	0.667	0.495	-1.367	-2.299*	-3.781**	-0.414	0.135	2.093*	1.487	1.153
Corrado	-1.699	0.278	0.997	-0.583	-2.245*	-3.706**	-0.553	0.222	1.929	1.383	0.675

Set E	**Event window - day t**										
afinn+	**-5**	**-4**	**-3**	**-2**	**-1**	**0**	**1**	**2**	**3**	**4**	**5**
AAR	0.001	0.002	0.000	-0.005	0.001	0.004	0.001	-0.002	-0.003	0.000	-0.001
t-test	0.714	1.281	-0.252	-2.570*	0.648	2.401*	0.353	-1.094	-1.895	-0.055	-0.789
BMP test	0.451	0.944	-0.245	-1.784	0.552	0.760	0.008	-0.584	-1.289	-0.216	-0.634
Corrado	1.046	1.116	-0.735	-2.204*	0.979	0.971	-0.296	-0.828	-2.128*	-0.014	-0.608

Set F	**Event window - day t**										
afinn-	**-5**	**-4**	**-3**	**-2**	**-1**	**0**	**1**	**2**	**3**	**4**	**5**
AAR	-0.004	0.001	0.002	-0.006	-0.012	-0.007	-0.002	0.003	0.007	0.000	-0.001
t-test	-1.351	0.506	0.865	-2.165*	-4.247**	-2.651**	-0.658	1.105	2.733**	-0.004	-0.388
BMP test	-1.254	0.473	0.906	-1.699	-2.836**	-2.367*	-0.578	1.402	1.910	0.206	-0.667
Corrado	-1.690	-0.178	0.988	-1.201	-2.562*	-3.033**	-0.746	1.482	1.652	0.417	-0.597

*p<0.05 **p<0.01

that negative tweets have no lasting effect on prices. Overall we therefore consider our results to be consistent with Hypothesis 3a and inconsistent with Hypothesis 3b, suggesting that behavioral biases are the main drivers of the observed effects.

6. Conclusion

In this paper we analyze the effect of Donald Trump's tweets on stock returns. We focus on tweets that explicitly mention individual firms and classify them into positive and negative tweets. We then analyze how the tweets affect stock prices and trading volume. Unlike previous papers we use intraday (minute-by-minute) data in addition to daily data. The intraday data allows a better identification of causal effects of the tweets on prices and trading activity.

We find that Donald Trump's tweets cause increased trading activity but do not have lasting effects on stock prices. We also find evidence of abnormal returns, increased trading volume and increased investor attention *before* the tweet. This finding is consistent with Donald Trump's tweets being comments on events that happened, and attracted investor attention and trading interest, already before the tweet.

CRediT authorship contribution statement

Tobias Machus: Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Visualization. **Roland Mestel:** Conceptualization, Methodology, Writing – review & editing, Project administration. **Erik Theissen:** Conceptualization, Methodology, Validation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

We gratefully acknowledge financial support from the University of Graz.

Table 7
Daily average abnormal trading volume (AATV) in the event window and corresponding test statistics of positively and negatively classified tweets using the lexicons "bing" (upper panels) and "afinn" (lower panels) from the R tidytext package.

Set C	Event window - day t										
bing+	-5	-4	-3	-2	-1	0	1	2	3	4	5
AATV	-0.048	-0.036	0.010	0.009	0.145	0.142	0.129	0.018	0.018	-0.049	0.175
t-test	-0.543	-0.413	0.117	0.102	1.652	1.613	1.467	0.206	0.207	-0.560	1.990*
BMP test	-1.173	-0.391	0.164	0.172	2.013*	1.573	1.579	0.419	0.692	-0.760	1.668
Corrado	-0.416	-0.297	-0.351	0.079	1.794	1.293	1.046	0.186	0.930	0.245	1.943

Set D	Event window - day t										
bing-	-5	-4	-3	-2	-1	0	1	2	3	4	5
AATV	-0.009	0.135	0.051	0.463	0.764	0.526	0.286	0.132	0.175	-0.010	0.006
t-test	-0.086	1.255	0.474	4.290**	7.084**	4.879**	2.648**	1.224	1.619	-0.092	0.052
BMP test	0.049	1.158	0.525	1.145	2.123*	2.172*	1.894	0.776	0.973	-0.200	0.259
Corrado	-0.441	1.699	0.427	0.700	2.619**	2.355*	2.455*	1.002	1.472	-0.030	0.202

Set E	Event window - day t										
afinn+	-5	-4	-3	-2	-1	0	1	2	3	4	5
AATV	0.001	-0.065	-0.022	-0.030	0.145	0.209	0.162	-0.009	-0.017	-0.040	0.085
t-test	0.016	-0.728	-0.252	-0.340	1.636	2.361*	1.828	-0.099	-0.188	-0.454	0.964
BMP test	-0.392	-0.964	-0.277	-0.604	2.122*	1.975*	1.603	-0.100	-0.138	-0.553	1.594
Corrado	-0.287	-0.662	-0.536	-0.072	2.003*	1.733	1.036	-0.364	0.629	0.442	1.770

Set F	Event window - day t										
afinn-	-5	-4	-3	-2	-1	0	1	2	3	4	5
AATV	0.008	0.048	-0.041	0.392	0.589	0.363	0.196	0.077	0.191	-0.066	-0.057
t-test	0.082	0.471	-0.404	3.846**	5.782**	3.564**	1.921	0.759	1.874	-0.652	-0.554
BMP test	0.162	0.441	-0.391	0.998	1.769	1.630	1.437	0.593	1.076	-0.934	-0.581
Corrado	-0.659	0.695	-0.518	0.043	1.597	1.303	1.376	0.778	0.731	-0.911	-0.309

*p<0.05 **p<0.01

Table 8
Daily average abnormal Eikon attention (AAMIA Eikon) in the event window and corresponding test statistics of positively and negatively classified tweets using the lexicons "bing" (upper panels) and "afinn" (lower panels) from the R tidytext package.

Set C	Event window - day t										
bing+	-5	-4	-3	-2	-1	0	1	2	3	4	5
AAMIA Eikon	0.000	-0.243	0.011	0.636	1.571	2.662	1.743	0.534	0.118	0.511	0.409
t-test	0.000	-1.109	0.052	2.897**	7.158**	12.13**	7.940**	2.433*	0.536	2.326*	1.864
BMP test	0.132	-2.604**	-0.074	1.882	4.002**	5.169**	4.625**	2.442*	0.584	1.463	2.509*
Corrado	-0.230	-0.582	-0.517	0.860	3.144**	4.173**	3.338**	1.305	0.226	0.245	1.578

Set D	Event window - day t										
bing-	-5	-4	-3	-2	-1	0	1	2	3	4	5
AAMIA Eikon	-0.097	0.005	0.389	0.223	1.000	4.325	3.306	1.484	0.527	0.072	0.091
t-test	-0.413	0.023	1.664	0.954	4.283**	18.52**	14.16**	6.354**	2.256*	0.307	0.388
BMP test	-0.930	-0.243	0.697	0.374	1.296	3.414**	2.903**	2.595*	1.182	0.152	0.632
Corrado	-0.511	-1.210	0.214	0.016	0.561	5.223**	4.386**	3.070**	1.179	-0.049	0.000

Set E	Event window - day t										
afinn+	-5	-4	-3	-2	-1	0	1	2	3	4	5
AAMIA Eikon	-0.056	-0.268	-0.051	0.517	1.562	2.840	2.065	0.532	0.018	0.386	0.234
t-test	-0.251	-1.210	-0.228	2.332*	7.048**	12.82**	9.319**	2.401*	0.083	1.744	1.057
BMP test	-0.238	-2.856**	-0.396	1.497	3.680**	5.411**	4.920**	2.435*	-0.094	1.067	1.543
Corrado	-0.483	-0.695	-0.675	0.295	2.635**	4.125**	3.338**	1.221	0.034	-0.017	0.986

Set F	Event window - day t										
afinn-	-5	-4	-3	-2	-1	0	1	2	3	4	5
AAMIA Eikon	-0.365	-0.053	0.476	0.285	0.529	3.600	3.070	1.079	0.395	0.248	0.377
t-test	-0.251	-1.210	-0.228	2.332*	7.048**	12.82**	9.319**	2.401*	0.083	1.744	1.057
BMP test	-3.837**	-0.377	1.261	0.703	1.057	3.394**	2.908**	1.915	1.219	1.124	1.497
Corrado	-1.452	-1.716	1.279	1.076	1.212	5.926**	4.278**	2.036*	1.168	0.773	1.211

*p<0.05 **p<0.01

Table 9
Daily average abnormal Google attention (AAMIA Google) in the event window and corresponding test statistics of positively and negatively classified tweets using the lexicons "bing" (upper panels) and "afinn" (lower panels) from the R tidytext package.

Set C	Event window - day t										
bing+	-5	-4	-3	-2	-1	0	1	2	3	4	5
AAMIA Google	-0.084	-0.085	0.015	0.127	0.319	0.855	0.852	0.421	0.264	0.385	0.254
t-test	-0.718	-0.725	0.128	1.077	2.714**	7.276**	7.253**	3.580**	2.248*	3.274**	2.163*
BMP test	-1.117	-1.587	0.412	1.097	2.604**	4.474**	3.268**	1.812	1.687	1.101	1.806
Corrado	-0.676	-0.395	0.312	0.609	2.280*	3.397**	3.157**	0.905	0.748	0.154	0.985

Set D	Event window - day t										
bing-	-5	-4	-3	-2	-1	0	1	2	3	4	5
AAMIA Google	-0.056	-0.384	-0.103	-0.188	2.122	4.473	2.519	1.809	1.010	0.847	0.310
t-test	-0.235	-1.617	-0.434	-0.792	8.929**	18.82**	10.60**	7.612**	4.250**	3.564**	1.305
BMP test	-0.157	-2.501*	-0.096	-0.532	1.392	1.910	1.967	1.822	1.472	1.917	1.364
Corrado	2.736**	-0.300	1.705	0.672	3.433**	6.083**	5.642**	4.428**	2.110*	3.475**	3.120**

Set E	Event window - day t										
afinn+	-5	-4	-3	-2	-1	0	1	2	3	4	5
AAMIA Google	-0.123	-0.120	-0.012	0.046	0.314	1.226	1.310	0.498	0.229	0.317	0.257
t-test	-0.987	-0.959	-0.098	0.366	2.512*	9.824**	10.49**	3.990**	1.832	2.543*	2.061*
BMP test	-1.789	-1.855	0.301	0.728	2.303*	4.430**	3.647**	2.150*	1.382	0.889	1.792
Corrado	-0.675	-0.348	0.300	0.293	1.894	3.563**	3.400**	1.210	0.708	0.102	0.952

Set F	Event window - day t										
afinn-	-5	-4	-3	-2	-1	0	1	2	3	4	5
AAMIA Google	-0.221	-0.031	-0.117	-0.107	1.621	4.376	2.823	1.742	1.036	0.844	0.251
t-test	-0.961	-0.136	-0.508	-0.466	7.049**	19.03**	12.28**	7.574**	4.507**	3.672**	1.091
BMP test	-1.485	-1.036	0.271	0.251	1.036	2.161*	2.212*	1.974*	2.080*	2.660**	1.493
Corrado	0.841	0.230	2.077*	1.664	1.940	5.604**	3.999**	3.457**	3.065**	3.925**	3.079**

*p<0.05 **p<0.01

Appendix

See Tables 6–9.

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