Twitter sentiment around the Earnings Announcement events

Peter Gabrovšek[☯], **Darko Aleksovski**[☯]*, **Igor Mozetič, Miha Grčar**

Department of Knowledge Technologies, Jožef Stefan Institute, Ljubljana, Slovenia

☯ These authors contributed equally to this work.
* darko.aleksovski@ijs.si

Abstract

We investigate the relationship between social media, Twitter in particular, and stock market. We provide an in-depth analysis of the Twitter volume and sentiment about the 30 companies in the Dow Jones Industrial Average index, over a period of three years. We focus on Earnings Announcements and show that there is a considerable difference with respect to when the announcements are made: before the market opens or after the market closes. The two different timings of the Earnings Announcements were already investigated in the financial literature, but not yet in the social media. We analyze the differences in terms of the Twitter volumes, cumulative abnormal returns, trade returns, and earnings surprises. We report mixed results. On the one hand, we show that the Twitter sentiment (the collective opinion of the users) on the day of the announcement very well reflects the stock moves on the same day. We demonstrate this by applying the event study methodology, where the polarity of the Earnings Announcements is computed from the Twitter sentiment. Cumulative abnormal returns are high (2–4%) and statistically significant. On the other hand, we find only weak predictive power of the Twitter sentiment one day in advance. It turns out that it is important how to account for the announcements made after the market closes. These after-hours announcements draw high Twitter activity immediately, but volume and price changes in trading are observed only on the next day. On the day before the announcements, the Twitter volume is low, and the sentiment has very weak predictive power. A useful lesson learned is the importance of the proper alignment between the announcements, trading and Twitter data.

Introduction

It is now accepted that financial markets are not governed solely by rational behavior of investors, as captured by the efficient market hypothesis. Their decisions are also influenced by their subjective beliefs and expectations, and by the information from the Internet. Online news and social media provide large amounts of data, from which potentially useful information can be extracted. We are interested in collective opinion and expectations of investors in relation to financial markets. We analyze social media data from the Twitter micro-blogging

platform in terms of the attention to the most important events, and the collective expectations about the market moves.

Twitter is becoming an increasingly popular platform used to monitor and forecast financial markets. The first to show a clear relation between the Twitter mood indicators and Dow Jones Industrial Average (DJIA) were Bollen et al. [1–3]. In general, related work provides mixed conclusions about the relation between Twitter and stock markets. The results depend on the type of analyses performed and whether the individual stocks or aggregate indices are considered. The work of Preis et al. [4] studies the relation over time between the daily number of search queries for a particular stock and the volume of daily trades with the same stock. The number of search queries is also analyzed as a proxy for the popularity of stocks and stock riskiness [5].

The range of the methodologies for analyzing the relations consists of the Granger causality [1, 3, 6], one-step ahead forecasting analyses [1, 3, 6, 7], information theoretic approaches [8, 9], and event studies [10–12]. On the one hand, Granger causality and the information theoretic approaches analyze time series over a longer time period. They provide results about the existence of a quasi-causal relation between the social media and stock market. They do not identify precise time periods when this relation is stronger, weaker, or non-existent. Event studies, on the other hand, focus on the relations in specific time intervals, thus providing potentially more actionable evidence for trading purposes.

Several papers analyze the relation between Twitter and stock market for the aggregated indices only, e.g., DJIA [1, 3] or S&P 500 [7, 13, 14]. Only a few provide conclusions regarding the relation between the Twitter posts and stocks of individual companies, e.g., [8, 10–12]. The main reason is the typically insufficient number of Twitter posts about individual companies to draw statistically significant results.

We overcome this limitation by focusing on the most interesting time periods of an individual company, the quarterly Earnings Announcements (EA). It turns out that the volume of Twitter posts around most of the EAs is substantially higher and allows to draw statistically significant conclusions. This type of analysis is enabled by the "event study" methodology [15, 16], used in economics and finance. The event study has been often used to verify if the content of EAs conveys useful information for the valuation of companies. It allows to draw conclusions about the price movement of a stock on average, over several different events of the same type. In related work in economics, the event study typically relies on the earnings surprise, i.e., the difference between the expectations of financial analysts and the reported valuation of a company in its earnings report. In our work, however, we test if the aggregate sentiment expressed in financial tweets around the EAs indicates the direction of the stock price movement.

There have been applications of the event study methodology to Twitter data already. We are aware of three recent works which analyze the Twitter sentiment data in relation to the stock price movement. Sprenger et al. [10, 11] analyze known EA events as well as other, unexpected events. They conclude that both the sentiment and the type of the news can explain the market reaction (movement of the stock price). Our previous work by Ranco et al. [12] presents evidence of significant dependence between stock price returns and Twitter sentiment in tweets about the companies. Ranco et al. apply an event detection procedure to detect events from the Twitter data. They report that most of the EA events have a corresponding peak in the Twitter volume. This fact is the main motivation for the current work, where we focus on and perform an in-depth analysis of the EA events.

There are several improvements over our previous work [12]. In this study we analyze data over a longer period of three years. There are over 4.5 million tweets labeled with sentiment, one of the largest datasets available. We provide and analyze Twitter data at hourly resolution,

which enables fine-tuned aggregation of tweets at the daily resolution. Instead of analyzing events detected from the Twitter stream, we focus only on the EA events which are known in advance. We observe important differences between the timings of the EA events, either before the market opens, or after the market closes. It turns out that it is crucial to appropriately aggregate the tweets at daily resolution and align them with the market activities. Finally, we use a different, formally sound, sentiment measure than the one used by Ranco et al. [12].

There are several works in the financial literature, dealing with EAs and their timings, related to our work. Berkman et al. [17] observe that the proportion of EAs reported after the close of the market has increased in recent years. Their main conclusion is that it is important to account for the after-hours announcements when performing event studies. Specifically, in the case of an after-hours announcement, the day 0 prices should be shifted to the next market day. In case that no shifting is performed, abnormal returns could be biased.

Doyle et al. [18] find that typical companies consistently report either after the close of the market, or before the market opens. They conclude that more complex companies tend to announce after the market closes. They also find higher trading volume around the after close announcements in comparison to the before open announcements—our study confirms the same observation. These two facts provide evidence for their hypothesis that reporting after the market closes allows for broader dissemination of the information contained in the announcements.

Schroff et al. [19] analyze the collective actions of individual investors around EAs. They find that individual investors take more risk and tend to overestimate the likelihood of positive events while underestimating the likelihood of negative ones. This intense buying (selling) actions of individual investors prior to EAs are followed by significant positive (negative) abnormal returns after the events [20].

A recent work by Alostad et al. [21] is closely related to the event study applied here. They combine two types of complementary data: volume from Twitter and sentiment from financial news. They conclude that it is useful to predict the direction of a stock price move only when there is an abnormally high Twitter volume. However, in contrast to the other event studies [10, 12], they assign polarity of the events from the financial news instead of the tweets. The work of Tafti et al. [22] relates the peaks of Twitter volume (events detectable from the Twitter time series) to the subsequent increase of trading volume. The authors conclude that it is difficult to make use of the information from Twitter for forecasting purposes.

This work makes several contributions to the analysis of relations between social media and stock market. First, we find significant relation between the Twitter sentiment and EA returns on the days of the announcements, with cumulative abnormal returns around 2–4%. Second, we observe important differences between different timings of the announcements. The announcements before the market opens show lower cumulative abnormal returns in comparison to the announcements after the market closes. Third, based on these results, we test a simple trading strategy with buy/hold/sell at the market close of the day prior to the EA. Fourth, we compare the Twitter sentiment to the earnings surprise, a measure frequently used in event studies.

An important conclusion from these results is the requirement for a proper setup of event studies and other methods which investigate relations between Twitter and stock market. It is important to take into account the exact timing of the events with respect to the market trading hours. The daily aggregation of the Twitter data and its alignment with the market data have an impact on the perceived predictive power of Twitter. When analyzing the data at the daily resolution one needs to attribute the Twitter posts created after the market closes to the next trading day.

Data

In this section we provide details about the data used in the study. The data are about the 30 companies in the DJIA index in the period of three years, from June 1, 2013, to June 3, 2016. The data consist of the Earnings Announcement (EA) events, the stock market data, and the Twitter data. All the data were collected according to the Terms of Use and Service of the source websites, and are available at https://dx.doi.org/10.6084/m9.figshare.4036269. The terminology and abbreviations used throughout the paper are in Table 1.

Earnings announcement data

The data regarding the EAs contains the exact timings of the announcements, as well as the reported and expected price of a share. The earnings surprise is the difference between the reported and the expected earnings of a company. The earnings surprise *ES* is defined as:

$$ES = \frac{p_{rep} - p_{est}}{p_{est}} \tag{1}$$

where p_{rep} is the reported price of a share in the EA report, while p_{est} is the expected price, as estimated by financial analysts. We collected the EA data from the http://www.zacks.com website. The missing values of the timings were filled from the information issued by the companies themselves.

Market data

The market data was collected from http://www.google.com/finance. It consists of the daily trading volume and closing prices of the 30 DJIA companies and the DJIA index. From the data we calculate daily returns and longer term trading returns. The daily return R_d, used in the calculation of Cumulative Abnormal Returns (event study applications), is defined as:

$$R_d = \frac{p_d - p_{d-1}}{p_{d-1}} \tag{2}$$

where p_d denotes the closing price of the stock on day d. Consistent with the original event study [15], we operate with raw-returns, and not the more standard log-returns.

Table 1. Terminology and abbreviations used.

DJIA	Dow Jones Industrial Average index
NYSE	New York Stock Exchange
EA	Earnings Announcement
Day 0	the day of the EA
Day −1	the day before the EA
CAR	Cumulative Abnormal Return
EPS	Earnings Per Share
ES	Earnings Surprise
BeforeOpen	EA before the opening of NYSE (9:30 a.m. US/Eastern)
AfterClose	EA after the closing of NYSE (4:00 p.m. US/Eastern)
Twitter volume	number of tweets at a given resolution
Twitter sentiment	stance or leaning w.r.t. stock price move
Sent(0)	Twitter sentiment on the day of the EA
Sent(−1)	Twitter sentiment on the day before the EA

doi:10.1371/journal.pone.0173151.t001

The longer term trading return, on the other hand, compares prices over several days, and is used in the evaluation of trading strategies. We take as a basis the closing price of a stock on the day before the EA (day −1) and compare it to the closing price after the EA. The trading return RT_d is defined as:

$$RT_d = \frac{p_d - p_{-1}}{p_{-1}} \tag{3}$$

where p_{-1} is the closing price on the day prior to the EA (day −1), and p_d is the closing price on the trading day d after the EA. Note that the trading return is computed as the relative difference in prices over $d + 1$ days.

Twitter data

The Twitter data used in this study is summarized in Table 2 and contains approximately 4.5 million tweets for 30 companies, during a period of three years. The data were collected by the Twitter Search API, where a query is specified by the stock cash-tag (e.g., "$MSFT" for Microsoft).

Each tweet is then labeled with a 'sentiment' with three possible values: negative, neutral, or positive. The label denotes the future stock price move, as anticipated by the author of the tweet: down (negative sentiment), unchanged (neutral), or up (positive). The term 'Twitter sentiment' used here is misleading and used for historical reasons. What is actually meant is stance [23] or leaning of a Twitter user w.r.t. the future stock price move. The sentiment vocabulary alone, positive or negative, used in a tweet does not necessarily reflect the user expectations about the stock price move, therefore all the relevant vocabulary is explored. The tweets were labeled for sentiment automatically, by a supervised learning method, described in more detail in the "Sentiment classification" subsection in "Methods".

The tweets about each company are aggregated at hourly and daily resolution. The close of the market is used to delimit the daily aggregation of tweets. The sentiment of a set of tweets at day d is defined by the sentiment score $Sent_d$:

$$Sent_d = \frac{N_d(pos) - N_d(neg)}{N_d(pos) + N_d(neut) + N_d(neg) + 3} \tag{4}$$

where $N_d(neg)$, $N_d(neut)$ and $N_d(pos)$ denote the daily number of negative, neutral and positive tweets, respectively. The sentiment score has the range $-1 < Sent < +1$. Formally, the sentiment score is the mean of a discrete probability distribution with values of −1, 0 and +1 for negative, neutral and positive sentiment, respectively [24]. The probabilities of each label are estimated from their relative frequencies, but when dealing with small samples (e.g., only a few tweets about a stock per day) it is recommended to estimate probabilities with *Laplace estimate*. This is the reason for the constant 3, the number of discrete labels, in the denominator of Eq (4).

Each company in Table 2 is identified by its ticker symbol according to the NYSE. The table also reports the number and sentiment distribution of tweets, the market capitalization, and the timing used by the company to report the EAs. Most of the companies time their reports consistently, either always AfterClose or BeforeOpen. There are only a few exceptions which switch between the two options [25]. In summary, out of a total of 359 EAs during the three years there are 253 BeforeOpen announcements, and 106 AfterClose announcements.

Table 2. The data about the 30 DJIA companies. The collected tweets and Earnings Announcements (EA) cover the period of three years, from June 1, 2013 to June 3, 2016. Companies are ordered by the total number of tweets collected. For each company, there is the sentiment distribution, market capitalization, and the prevailing timing of EAs with respect to the NYSE trading hours. Each company issues four EAs per year, therefore there is a total of 360 EAs (30 companies, three years, four EAs per year)[1].

Ticker	Company	Number of tweets				Market cap [10^9 US$]	Earnings Announcements
		Negative	Neutral	Positive	Total		
MSFT	Microsoft	31,626	328,336	72,961	432,923	449.39	AfterClose
IBM	Intl. Business Machines	26,318	204,219	38,685	269,222	152.50	AfterClose[2]
GS	Goldman Sachs Group	24,708	205,860	34,005	264,573	72.14	BeforeOpen
JPM	JPMorgan Chase	35,263	183,407	32,395	251,065	243.74	BeforeOpen[1,3]
DIS	Walt Disney	15,060	166,657	43,968	225,685	151.74	AfterClose
INTC	Intel	16,222	156,301	37,267	209,790	170.69	AfterClose
T	AT&T	10,039	156,935	28,113	195,087	251.92	AfterClose
GE	General Electric	9,285	157,059	27,477	193,821	280.40	BeforeOpen
WMT	Wal-Mart Stores	21,774	141,010	25,767	188,551	224.26	BeforeOpen
XOM	Exxon Mobil	17,864	140,413	24,406	182,683	362.50	BeforeOpen
CSCO	Cisco Systems	11,822	125,233	29,763	166,818	160.14	AfterClose
MCD	McDonald's	19,554	121,320	21,612	162,486	98.84	BeforeOpen
PFE	Pfizer	7,541	115,453	24,422	147,416	210.90	BeforeOpen
JNJ	Johnson & Johnson	10,700	108,927	20,888	140,515	326.44	BeforeOpen
KO	Coca-Cola	10,156	105,703	21,851	137,710	188.44	BeforeOpen
MRK	Merck & Co	5,826	101,404	18,375	125,605	174.15	BeforeOpen
CAT	Caterpillar	15,611	91,688	16,480	123,779	47.73	BeforeOpen
V	Visa	7,456	94,786	21,047	123,289	193.52	AfterClose[4]
NKE	Nike	8,431	83,267	31,308	123,006	97.34	AfterClose
CVX	Chevron	11,911	90,240	17,399	119,550	190.41	BeforeOpen
BA	Boeing	11,090	82,097	24,410	117,597	81.82	BeforeOpen
VZ	Verizon Communications	7,200	86,632	20,917	114,749	215.55	BeforeOpen
HD	Home Depot	7,091	74,311	20,701	102,103	166.99	BeforeOpen
AXP	American Express	7,378	64,912	11,665	83,955	60.22	AfterClose
PG	Procter & Gamble	6,393	63,960	12,241	82,594	235.38	BeforeOpen
UNH	UnitedHealth Group	4,596	42,602	9,817	57,015	130.11	BeforeOpen
DD	DuPont	4,400	43,164	7,887	55,451	61.28	BeforeOpen
MMM	3M	4,020	40,262	8,485	52,767	109.28	BeforeOpen
UTX	United Technologies	3,652	31,293	7,725	42,670	89.49	BeforeOpen
TRV	Travelers Companies	2,772	18,649	4,526	25,947	34.26	BeforeOpen
Total		375,759	3,426,100	716,563	4,518,422	5,231.57	359

[1] There are no tweets on the day of one EA—as a consequence, we consider the total of 359 EAs instead of 360.

Exceptions to the prevailing timings of EAs:

[2] all EAs are AfterClose, except one is BeforeOpen,

[3] all EAs are BeforeOpen, except one is AfterClose,

[4] all EAs are AfterClose, except two are BeforeOpen.

doi:10.1371/journal.pone.0173151.t002

Data alignment

We focus on the relations between the stock market and Twitter posts around the EAs. Of particular importance for our analyses is proper alignment of the Twitter and market data.

We focus on the days of the EAs (denoted as day 0), and the days immediately before the EAs (day −1). There is an important distinction when exactly are the EAs made with respect to the NYSE trading hours. Some announcements (denoted BeforeOpen) are made before the
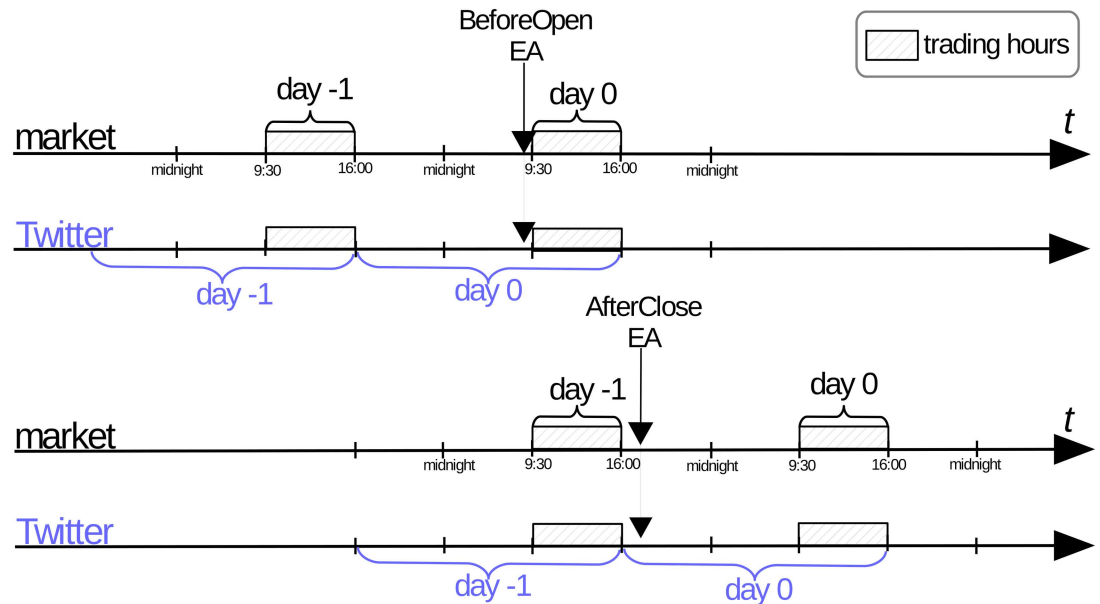
Fig 1. Timings of the Earnings Announcements. Relation between the two different types of EAs, trading hours and daily aggregation of tweets.

doi:10.1371/journal.pone.0173151.g001

market opens (9:30 a.m. US/Eastern), and some (denoted AfterClose) are made after the market closes (4:00 p.m. US/Eastern). Fig 1 depicts the relation between the trading hours and EAs. Note that the days are delimited by the market close hour, and not by the midnight. Consequently, the day 0 trading for the AfterClose announcements occurs on the next calendar day (see the lower part of Fig 1). This is consistent with the treatment of the EAs in the financial literature [17].

Results and discussion

This section presents analyses of interactions between social media (Twitter) and financial market (stock returns). First we compare the volume of tweets to the trading volume and notice very similar patterns in both systems, namely, highly elevated activity around the EA events. We observe a considerably higher trading activity for the AfterClose announcements, and find similar results for the Twitter volume at hourly resolution.

Next, we adapt and apply the event study methodology to our data. Event study, as defined in financial econometrics [15, 16], analyses abnormal stock returns during external events. The external events are first identified and grouped into categories whether the event should have positive, negative, or no effect on the stock returns. The null hypothesis H_0 is that external events have no impact on the returns. Under H_0, abnormal returns are normally distributed [16], therefore one can test whether abnormal returns during external events are statistically significant.

In our study, the EAs are the only external events we consider. We derive the categorization of the EAs (negative, neutral, or positive) from the Twitter sentiment alone, and not from the EA reports, as in the standard approaches. We test the H_0 for the AfterClose and BeforeOpen announcements separately, and find very different results. We are not only interested in the significance of abnormal returns, but also in their magnitude. Further, we test if the Twitter sentiment has any predictive power, i.e., if the EA reports are anticipated in the social media before the actual announcements are made.

We compare Cumulative Abnormal Returns (from the event study) with trading returns of the stocks and the DJIA index, and find very similar results. Based on these, we propose and backtest a simple trading strategy over the period of three and half years.

Finally, we compare the relation between the Twitter sentiment score to the earnings surprise values. We find very weak relation between the two variables, but we observe some difference between the AfterClose and BeforeOpen announcements.

Twitter and trading volumes

The goal of this subsection is to analyze the activities on social media around the Earnings Announcements. If one observes an elevated Twitter activity together with higher trading activity than this indicates that the EA events are reflected in social media. This is a motivation to apply the event study methodology, described in the next subsection, to analyze if there are also abnormal returns corresponding to the sentiment signal from Twitter.

We first compare the activity of Twitter users and stock traders on the days around the EAs. The Twitter activity is estimated by the average number of tweets per day, and the trading activity by the average daily trading volume. The results are in Fig 2.

We consider five days around the day of an EA (day 0) and observe a very similar pattern of elevated activity in both cases. The average number of tweets over the three years is 200 tweets per trading day. The above average activity is observed not only on day 0, but also on days −1 and +1. Cumulatively, the three days around the EAs exhibit 2.4 larger volume than on the average. This indicates that Twitter users are active around the EAs days and post their opinions about the companies and their finances.

The trading activity around the EAs is also higher, since the trading volume increases in the same time period, as shown by the black line in Fig 2B. However, Fig 2B also shows that the trading volume of companies which announce their earning reports AfterClose (blue line) is considerably higher than for the BeforeOpen announcements (red line). This is not due to
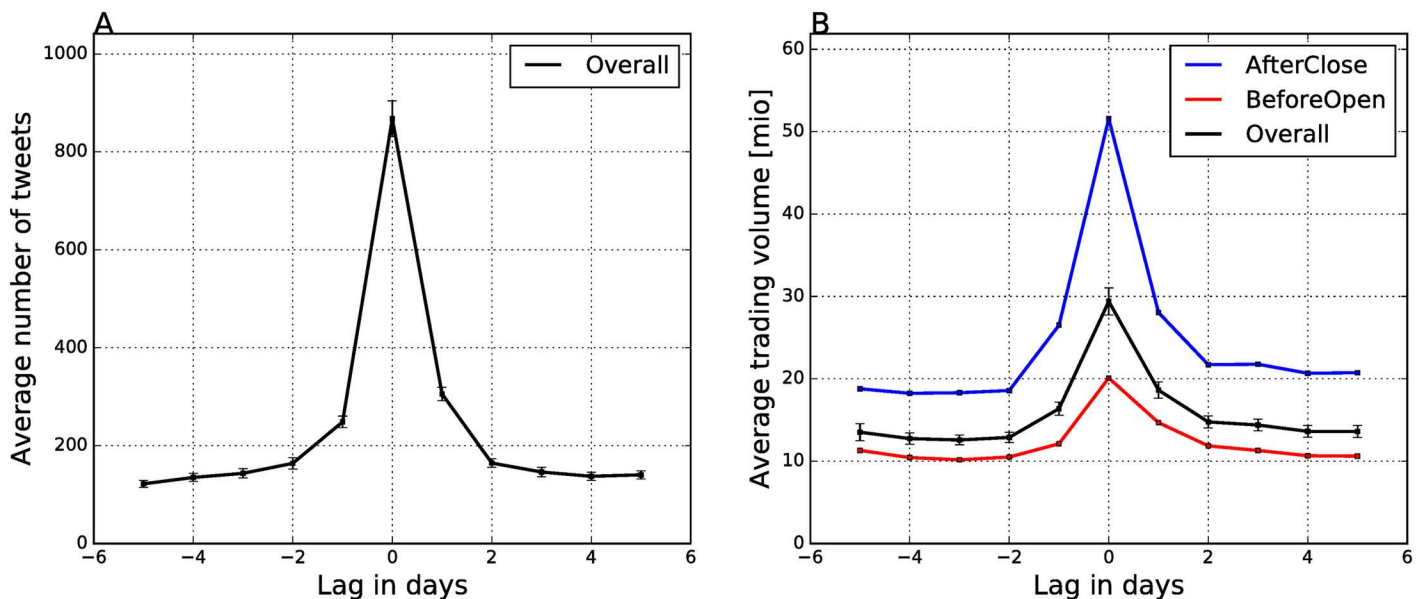

Fig 2. Daily number of tweets (A) and trading volume (B) around the Earnings Announcements. The overall average number of tweets per trading day is 200. The trading volume (B) shows the overall average across all EAs (black line), the average trading for the AfterClose (blue line), and for the BeforeOpen (red line) announcements. Error bars around the black lines denote one standard error.
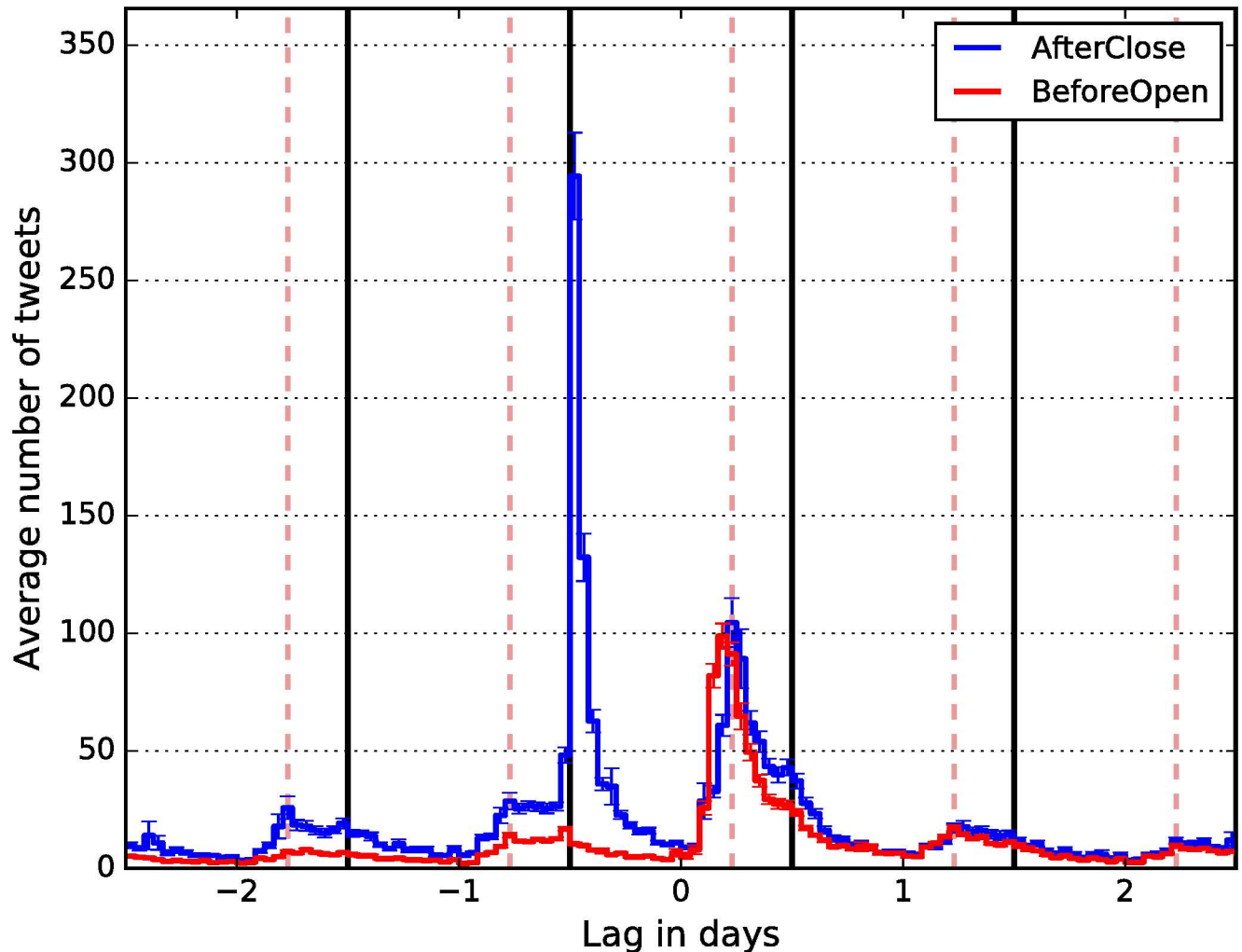
doi:10.1371/journal.pone.0173151.g002

Fig 3. Hourly distribution of tweets around the Earnings Announcements. Day 0 is the day of the EAs. Dashed lines denote market open (9:30 a.m. US/Eastern) and solid lines denote market close (4:00 p.m. US/Eastern). Solid lines also delimit days for aggregation of tweets at the daily resolution. Error bars denote one standard error.

doi:10.1371/journal.pone.0173151.g003

their higher capitalization, which is only slightly above the average (see Table 2). One possible explanation for the increased trades can be the assimilation hypothesis [18]: AfterClose reporting allows the market more time to assimilate the information in the announcement. Companies that announce their earnings AfterClose are typically more technologically oriented, e.g., Microsoft, IBM, Cisco, Intel, and have more complex operations.

Next we compare the Twitter volumes between the companies which make the AfterClose and BeforeOpen announcements. Fig 3 shows the average hourly number of tweets around the EAs (day 0) for both types of companies.

The comparison of the Twitter volumes at day 0 shows a considerably higher average number of tweets for the AfterClose announcements, consistent with the higher trading activity. Hourly distribution of tweets also matches the timing of the announcements: the AfterClose peak is immediately after the market on day −1 closes and the announcement is made. BeforeOpen peaks immediately before the market opens on day 0. In both cases, the Twitter activity is very similar after the market opens on day 0.

Event study applications

The Earnings Announcements are important events which trigger higher trading on stock exchange and also draw attention and comments on social media. Is there also any correspondence between the stance of Twitter users and abnormal returns of the stocks after the EA events? The goal of this subsection is to answer this question by applying the event study methodology.

An event study captures the impact of external events on the stock returns. In an event study, Cumulative Abnormal Returns (CAR) are defined as a measure of returns which are above or below the overall market returns. Details of the event study methodology applied here are in the "Event study methodology" subsection in "Methods".

External events that we consider in this paper are EAs only. Their dates are known in advance, and we compute their polarity from the Twitter sentiment. Details about how the sentiment of the tweets on the day of the EA (or the day before) is used to derive the polarity of the event (negative, neutral, or positive) are in the "Polarity of the EA events" subsection in "Methods".

The event window in this study starts on the day before the EA (day −1) and runs until 10 days after the EA. For each day, we check the correspondence between the polarity of the events and the direction of CARs (profit or loss), significance of CARs, and their magnitude. The null hypothesis H_0 is that the EAs have no impact on the CARs. We test the H_0 for the AfterClose and BeforeOpen announcements separately.

Fig 4 gives the results for the EA events, when we determine their polarity from the Twitter sentiment on the day of the EA, $Sent(0)$. Results show that the null hypothesis H_0 is rejected for all the days after the EA. There is almost a perfect match between the polarity of the EAs, determined from the Twitter sentiment, and the direction of CARs. Neutral announcements (blue lines) yield no returns (CARs are around zero), while positive (green lines) and negative
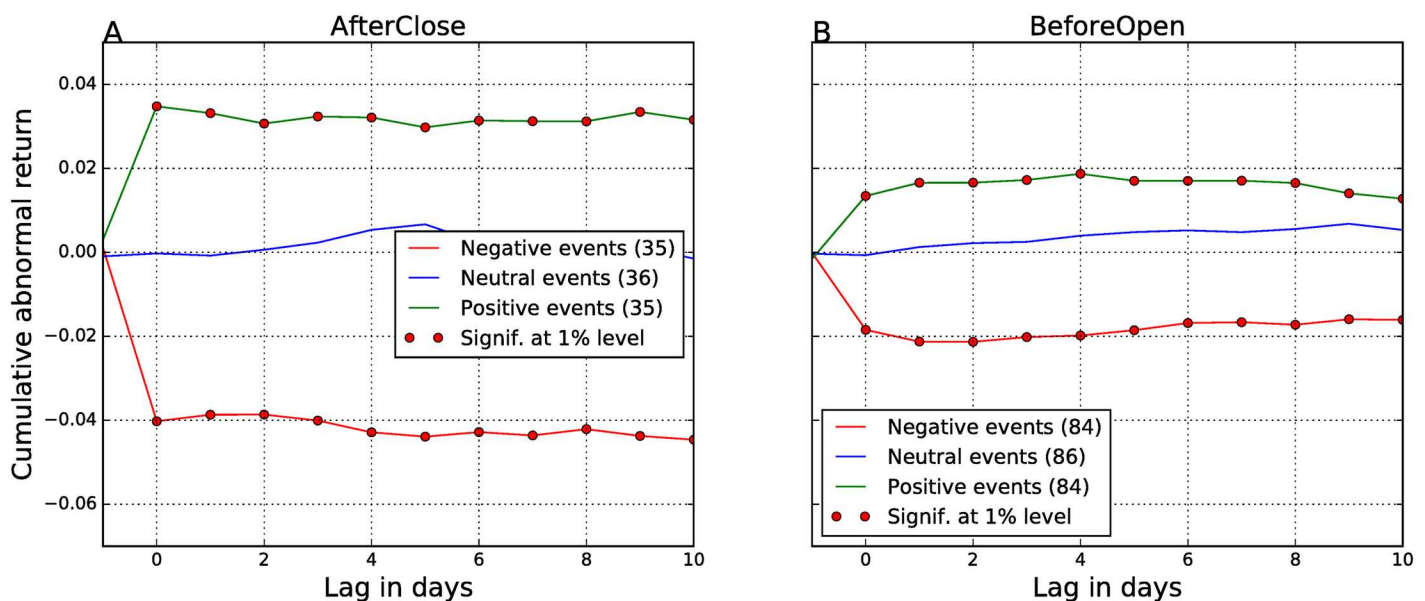

Fig 4. Cumulative abnormal returns—Polarity of the EAs is computed from the sentiment of tweets on day 0. The AfterClose (A) and BeforeOpen (B) events are analyzed separately. Different line colors denote different polarity of the events: green line denotes positive events, blue line neutral events, and red line negative events. In the legends, the numbers in parentheses are the numbers of different types of events. Days when CARs are significant at the 1% level are marked with red dots.

doi:10.1371/journal.pone.0173151.g004

announcements (red lines) are aligned with profits (positive CARs) and losses (negative CARs), respectively. The magnitude of CARs is high (around 2–4%), and all of them are significant at the 1% level (denoted by red dots). These results are consistent with the existing literature on the information contents of the EA reports. In our previous event study [12], where we analyzed all Twitter peaks as events and not just EAs, the CARs were between 1–2%. Here, where we have longer time period and the EA events only, the CARs are between 2–4%. This confirms that the Twitter sentiment correctly captures the contents of the EA reports.

However, the magnitude of CARs is different for the AfterClose (around 4% in Fig 4A) and BeforeOpen events (around 2% in Fig 4B). Also, the CARs for BeforeOpen are declining with time, and the neutral line shows a slight upward trend. This suggests that tweets convey a weaker signal for the BeforeOpen announcements, in addition or due to their lower volume, as compared to the AfterClose announcements.

Next, we investigate if there is any anticipation of information about the upcoming EAs in the social media. We determine the polarity of the EA events from tweets on the day before the announcement (day −1). All other parameters of the events study remain the same. The results are in Fig 5.

In Fig 5B we see that the returns are practically zero, for all types of EAs. We can conclude that there is no information about the BeforeOpen announcements in the Twitter posts on the day before the EA.

The returns in Fig 5A are small, but nonzero. However, the polarity of the neutral and positive events from the tweets does not match the sign of the corresponding CARs (green and blue lines in Fig 5A are misplaced). There is a weak signal for the negative AfterClose events (red line in Fig 5A). The negative CARs for the first three days after the EAs are small (about 1%), but statistically significant (marked by red dots). We exploit this result in the next subsection where we design a trading strategy.
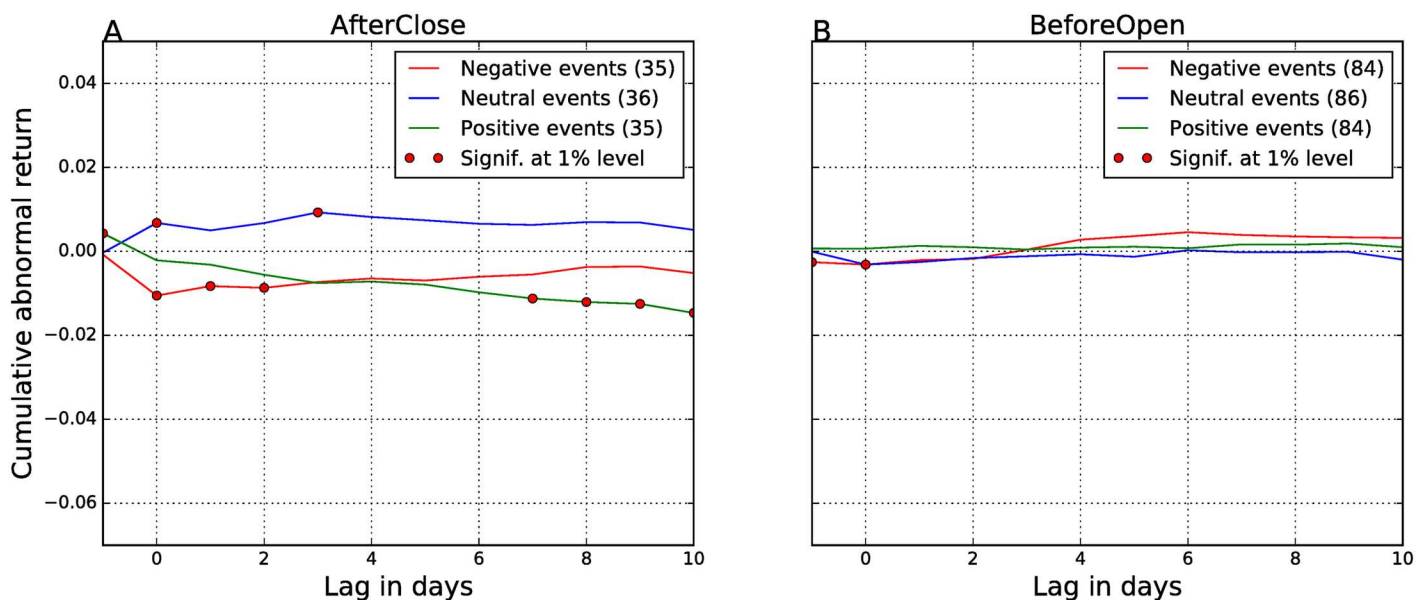

Fig 5. Cumulative abnormal returns—Polarity of the EAs is computed from the sentiment of tweets on day −1. The AfterClose (A) and BeforeOpen (B) events are analyzed separately. Different line colors denote different polarity of the events: green line denotes positive events, blue line neutral events, and red line negative events. In the legends, the numbers in parentheses are the numbers of different types of events. Days when CARs are significant at the 1% level are marked with red dots.

doi:10.1371/journal.pone.0173151.g005

It is important to note the impact of different alignments between the Twitter data and the EAs on the predictive power of the tweets. If the tweets are delimited at calendar days, one might observe a spurious predictive power of the Twitter sentiment. For the AfterClose announcements, there is a peak of Twitter activity immediately after the market closes, but before midnight (see Fig 3). If this is aligned with trading on day −1, and not on day 0, one might well observe the results similar to Fig 4A. Then one can draw a misleading conclusion that the Twitter sentiment on day −1 anticipates significant CARs on day 0 and subsequent days. This problem was already identified in the financial literature [17], and here we reiterate its proper treatment in the social media context.

Exploring trade returns

The goal of this subsection is to develop an actionable trading strategy based on the Twitter sentiment. The results of the event study, in terms of the CARs, cannot be directly exploited for trading. They show that our results, obtained with automated Twitter sentiment classification, are consistent with the existing financial literature. For trading, however, they provide just some hints on the timings and polarity of the EAs worth exploring. A trading strategy has to specify which stocks to select and when to buy/sell them. The aim of this subsection is to modify the event study to identify the stocks (from the type and polarity of the EAs), the actions (buy or sell, from the computed returns), and exact timings of the trades (from the time line of the returns).

Here we analyze trade returns, as defined in Eq (3), instead of CARs. We assume that one buys/sells a stock at a closing price of the day before the EA (day −1), and then sells/buys the same stock d days after the EA. For comparison, we also show the results when one buys/sells the DJIA index, instead of the individual stock. This should yield results very similar to the event study, which already incorporates a market model in the CARs.

Our starting point are the results of the event study. We first make an unrealistic assumption that at the trade on day −1 we already foresee the Twitter sentiment on the next day, *Sent* (0). We therefore sell/hold/buy a stock on day −1 if *Sent*(0) is negative/neutral/positive, respectively. The results are in Fig 6. The returns are high, as expected, and very similar to CARs in Fig 4.

Next, we make a realistic assumptions, and trade on day −1, based on the tweets and sentiment of the same day, *Sent*(−1). The results are in Fig 7, again very similar to CARs in Fig 5. They show that the polarity of the BeforeOpen announcements cannot be predicted one day in advance from the tweets alone (Fig 7B). For the AfterClose announcements, some low return can be expected only for the negative events, and is already diminishing after the announcement day (red line in Fig 7A). A possible explanation is that companies leak positive news already several days in advance, but they hold negative news for as long as they can [10].

The above results provide the guidelines on how to devise a trading strategy. We can only trade based on the Twitter sentiment before the EAs, therefore the returns in Fig 7 are relevant. The magnitude of returns is around 1% only for the AfterClose announcements (Fig 7A) and the polarity of the Twitter sentiment is aligned only with the negative returns (red line in Fig 7A). Based on these insights we can devise a simple trading strategy:

- consider only the AfterClose announcements,

- trade only on negative events, i.e., polarity of *Sent*(−1) is negative,

- sell (short) a stock at day −1, and buy it back at day 0.

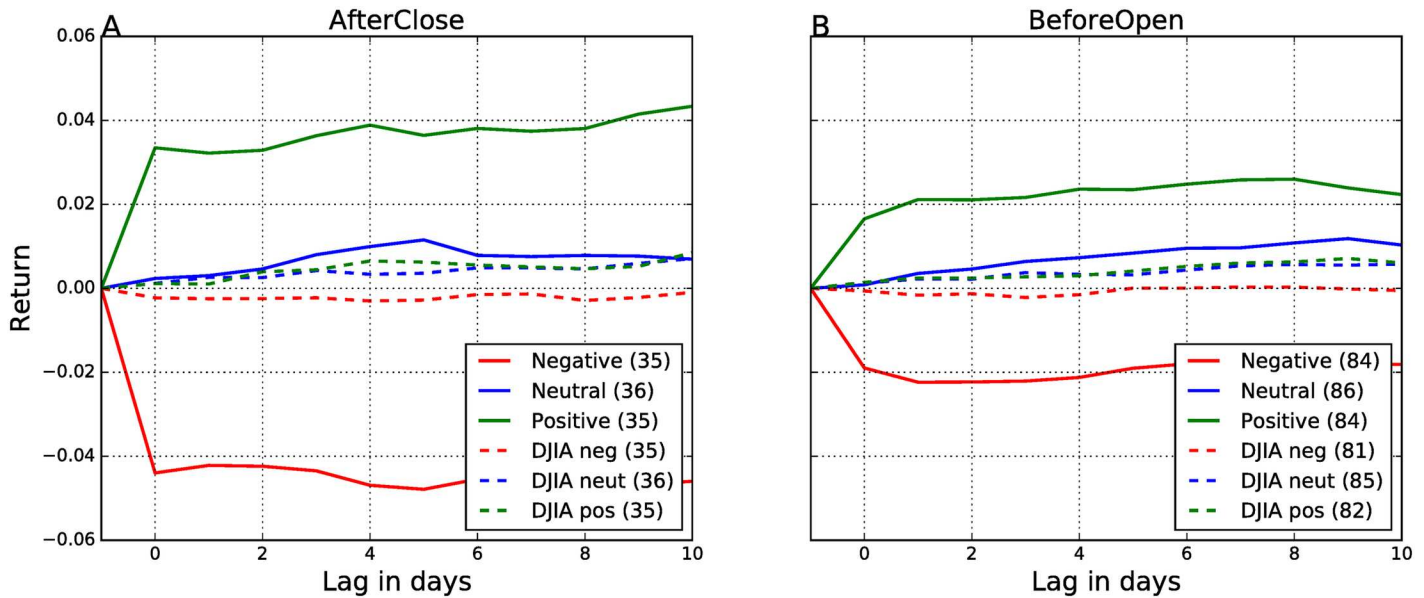Note that short selling is a common practice of selling a stock that is not currently owned.

Fig 6. Trade returns—Polarity of the EAs is computed from tweets on day 0. The AfterClose (A) and BeforeOpen (B) events are analyzed separately. Solid lines denote trades with individual stocks, and dashed lines denote the corresponding trades with the DJIA index. Line colors denote different polarity of events as determined from the sentiment of tweets.

We evaluate this simple trading strategy by backtesting it on three and half years worth of historical data, from June 1, 2013 until December 31, 2016. We assume that all the trades are executed at the closing price, and that all returns are reinvested. We also take into account spread, chosen conservatively at 0.05$ per share. In practice, spread is usually around one cent or less [26].
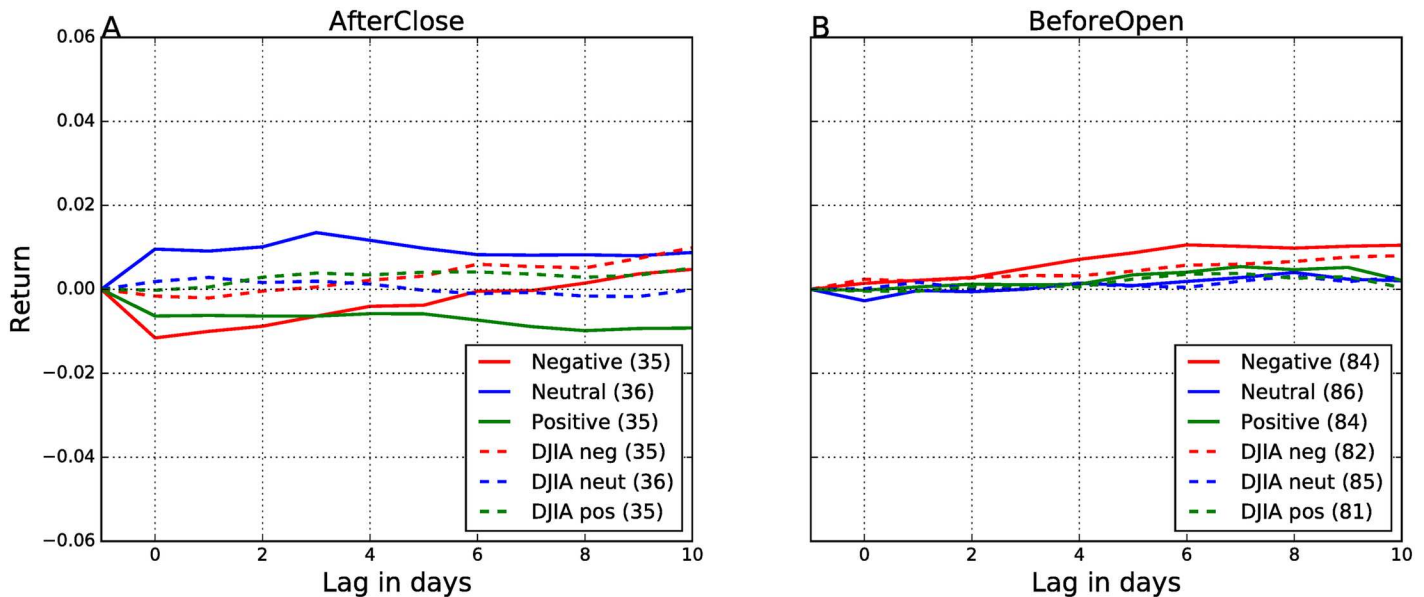

Fig 7. Trade returns—Polarity of the EAs is computed from tweets on day −1. The AfterClose (A) and BeforeOpen (B) events are analyzed separately. Solid lines denote trades with individual stocks, and dashed lines denote the corresponding trades with the DJIA index. Line colors denote different polarity of events as determined from the sentiment of tweets.
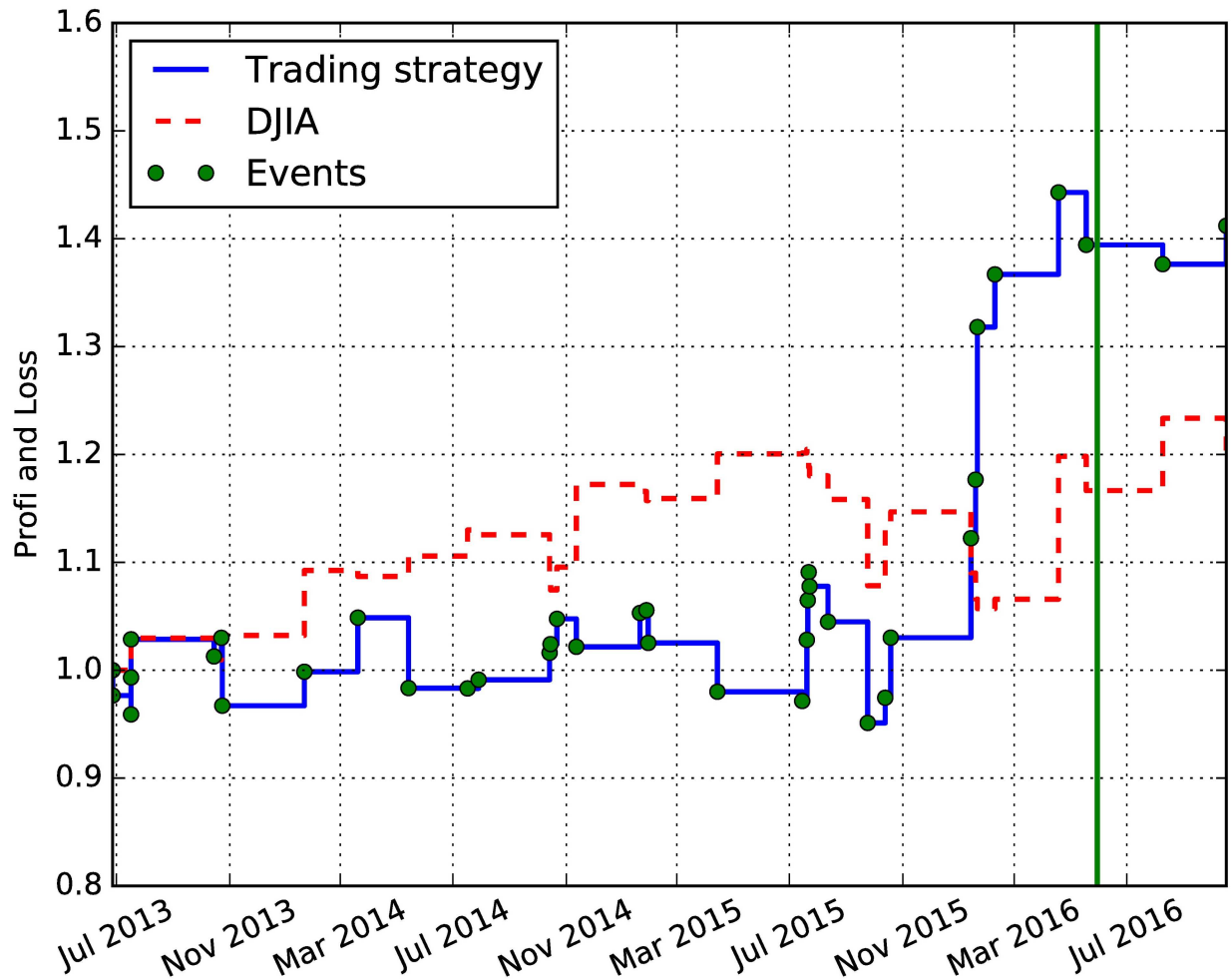
Fig 8. Trading simulation based on the simple trading strategy. Blue line shows the trade returns, and green dots denote the 37 negative EA events that triggered the trades. For comparison, the red dashed line shows the value of the DJIA index. The green vertical line delimits the first three years of data from the last half year of new data.

doi:10.1371/journal.pone.0173151.g008

The result of the trading simulation are in Fig 8. The green dots represent the negative EA events (i.e., $Sent(-1)$ was negative) during which our strategy executed a trade. Solid blue line represents a cumulative return of our strategy, assuming an initial investment of 1.0. Dashed red line shows the return of the DJIA index, considered as benchmark. The green vertical line delimits the first three years of data, on which the event study was applied, from the last half year of new data.

The simple trading strategy executes 37 trades (short sells and repurchases), and yields a 42% return in the tree and half years. For comparison, the DJIA index gained about 21% in the same period. While this simple strategy considerably outperforms the benchmark, most of the difference in the returns was realized in a half a year, from January to June 2016. The six EAs in this period, classified as negative and yielding most of the profits, are from the following companies: IBM (twice), INTC, AXP, DIS and CSCO. The above trading strategy was derived from the three years of data. We have tested the same strategy also on the new data, from July to December 2016. In this period, there are only two trades (with DIS and IBM) and the profits are negligible.

From these results we cannot draw any reliable conclusion about the performance of the proposed trading strategy. We do not claim that the relatively large returns are significant, nor that the strategy would yield similar results in the future. However, it is interesting to note that this trading strategy exhibits low profits and losses during the first two and a half years, and that it does not follow the index.

Relation between the Twitter sentiment and earnings surprise

The goal of this section is to compare the information about the Earnings Announcements extracted from social media to financial expectations. Financial analysts estimate earnings per share of a company a few weeks in advance of its EA (see e.g., http://www.zacks.com/earnings/). This estimate is more or less accurate, but raises some expectations. When the actual, reported earnings are different, the result is an earnings surprise, negative or positive. Earnings surprise (ES) is defined as a normalized difference between the reported and estimated earnings of a company, see Eq (1). Earnings surprise is often used in event studies to categorize the EA events. For example, in the original event study [15], MacKinlay proposes to categorize the EA event as positive if the actual earnings exceed the expected by more than 2.5% (and the opposite for the negative events). In our study we use the Twitter sentiment to categorize the EA events.

We compare the information contents of the Twitter sentiment to the earnings surprise. We apply the ordinary least squares estimate to determine the linear regression between the sentiment score and ES. The results are shown in Fig 9. The regression lines have the following form:

$$\text{AfterClose (day 0)}: \quad ES = 0.13 \cdot Sent(0) + 0.04 \, (R^2 = 0.17),$$
$$\text{BeforeOpen (day 0)}: \quad ES = 0.15 \cdot Sent(0) + 0.05 \, (R^2 = 0.09),$$
$$\text{AfterClose (day } -1): \quad ES = 0.08 \cdot Sent(-1) + 0.05 \, (R^2 = 0.007),$$
$$\text{BeforeOpen (day } -1): \quad ES = 0.02 \cdot Sent(-1) + 0.06 \, (R^2 = 0.0003).$$
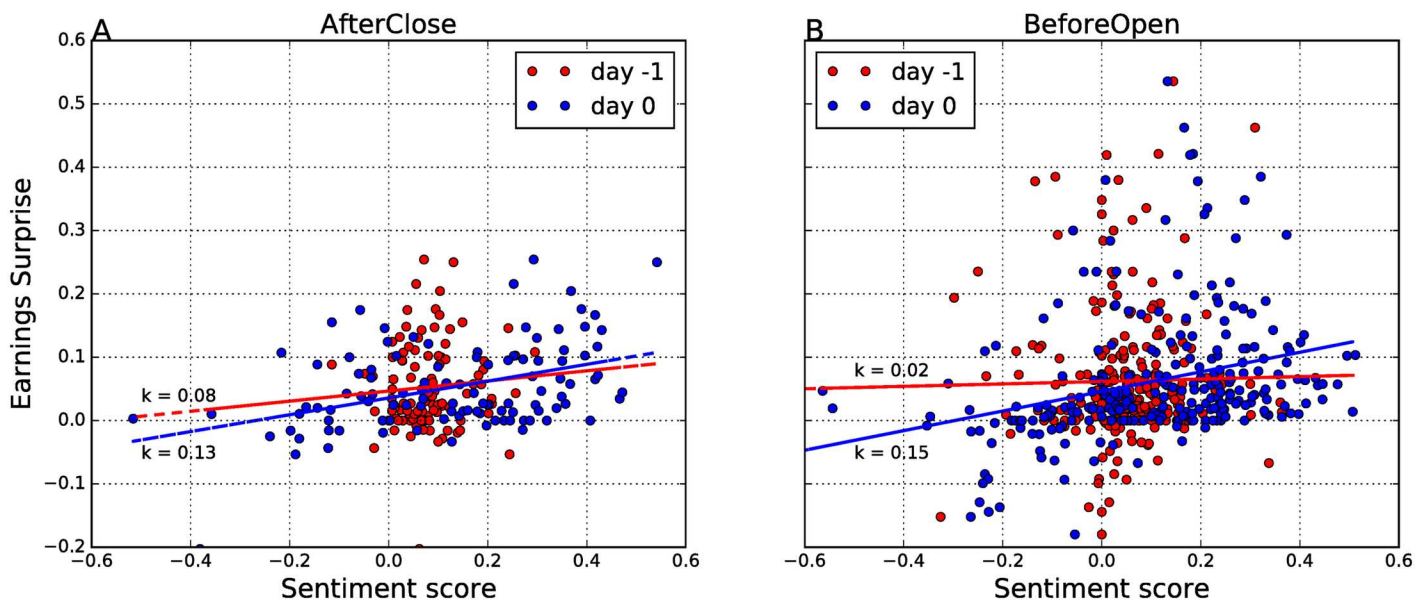

Fig 9. Relation between the sentiment score and earnings surprise. The AfterClose (A) and BeforeOpen (B) events are analyzed separately. Blue dots denote the polarity of the events on day −1, and red dots on day 0. The corresponding regressions are represented by solid lines.

The results of the linear regression suggest that the sentiment score of day 0 and earnings surprise are related, but very weakly. However, no evidence of relation is found between *Sent* (−1) and *ES*, since the R^2 coefficient shows that *Sent*(−1) explains less than 1% of the total variance. In more detail, the linear models which use *Sent*(−1) have very small explanatory power, for AfterClose as well as BeforeOpen EAs.

Conclusions

The present study shows that there is a considerable interplay between the social media and stock market. To some extent the results of the related work are corroborated, but we also present more detailed, in-depth analyses. In particular, we focus only on the Earnings Announcements, the events that draw the highest trading activity and social media attention. We find important differences regarding the timings of the announcements: before the market opens versus after the market closes. These differences have to be taken into account when aggregating the Twitter data at the daily resolution and when aligning the Twitter and market data.

We applied the event study methodology, where the Twitter sentiment determines the polarity of the Earnings Announcement reports. We show that the Twitter sentiment is a very good interpreter of the announcements contents. Cumulative Abnormal Returns are high and statistically significant. However, we did not find evidence that the Twitter sentiment alone can predict the returns one day before they are announced. This negative result might be due to the chosen alignment between the Twitter and market data for the after-hours announcements. If the data are not aligned as recommended in the literature, one might observe spurious predictive impact of the Twitter sentiment on price returns.

We also analyze earnings surprise, which is a measure frequently used in event studies. Our comparison to the Twitter sentiment shows that they have little in common. A possible reason might be that the aggregate measure from social media contains different information than the aggregated anticipations of the financial analysts.

This study is limited to Earnings Announcements only, where we observe considerably elevated trading and tweeting activities. There are other, unexpected events which can be identified with peaks in social media activities. These events can have significant impact on the market, and the Twitter sentiment can play an important role in devising social media-enhanced trading strategies.

Methods

In this section we first outline our Twitter sentiment classification approach. We then show how to determine the polarity of the EA events from the sentiment of tweets on a particular day. The polarity of the events is then used in the event study. The event study methodology is briefly summarized in the last subsection.

Sentiment classification

All the collected financial tweets are labeled with sentiment. The sentiment captures the leaning or stance of a Twitter user with respect to the anticipated future move of the stock. A stock mentioned in the tweet is identified by a cash-tag (e.g., "$IBM"). The anticipated change of its price is approximated by three sentiment values: negative (stock price will go down), neutral (price will remain unchanged), or positive (stock price will go up). The labeling of tweets is automatic, by applying a sentiment classification model.

Our approach to automatic sentiment classification [27] is based on supervised machine learning. The procedure consists of the following steps: (i) a large sample of tweets (about 100,000) is first manually annotated with stance by financial experts, (ii) the labeled set is used

to train and tune a classifier, (iii) the classifier is evaluated by cross-validation and compared to the inter-annotator agreement, and (iv) the classifier is applied to the whole set of collected tweets.

There are many supervised machine learning algorithms suitable for training a sentiment classifier. Often, variants of Support Vector Machine (SVM) [28] are used, because they are well suited for large scale text categorization tasks, are robust, and perform well. For this study, a two plane SVM classifier was constructed [27]. The two plane SVM assumes the ordering of sentiment values and implements ordinal classification. It consists of two SVM classifiers: One classifier is trained to separate the negative tweets from the neutral-or-positives; the other separates the negative-or-neutrals from the positives. The result is a classifier with two hyperplanes that partitions the vector space into three subspaces: negative, neutral, and positive. During classification, the distances from both hyperplanes determine the predicted sentiment value.

The labeled tweets for each stock are aggregated on a daily basis, and the sentiment score, defined in Eq (4), is computed. Note that in our previous event study research [12], we operated with sentiment polarity instead of the sentiment score. Sentiment polarity ignores the neutral tweets, and is defined as $\frac{N_d(pos) - N_d(neg)}{N_d(pos) + N_d(neg)}$.

Polarity of the EA events

The event study methodology requires that external events, EAs in our case, are categorized whether they should have negative, positive, or no effect on stock returns. We determine the polarity of the EA events from the sentiment scores, aggregated on a particular day (day 0 or −1). Distributions of the sentiment scores, for all the EAs, for the two relevant days, are in Fig 10.

Note that the number of the AfterClose events (Fig 10A) is 106, and the number of the BeforeOpen events (Fig 10B) is 253. The sentiment scores, Sent(0) (red bars) and Sent(−1)
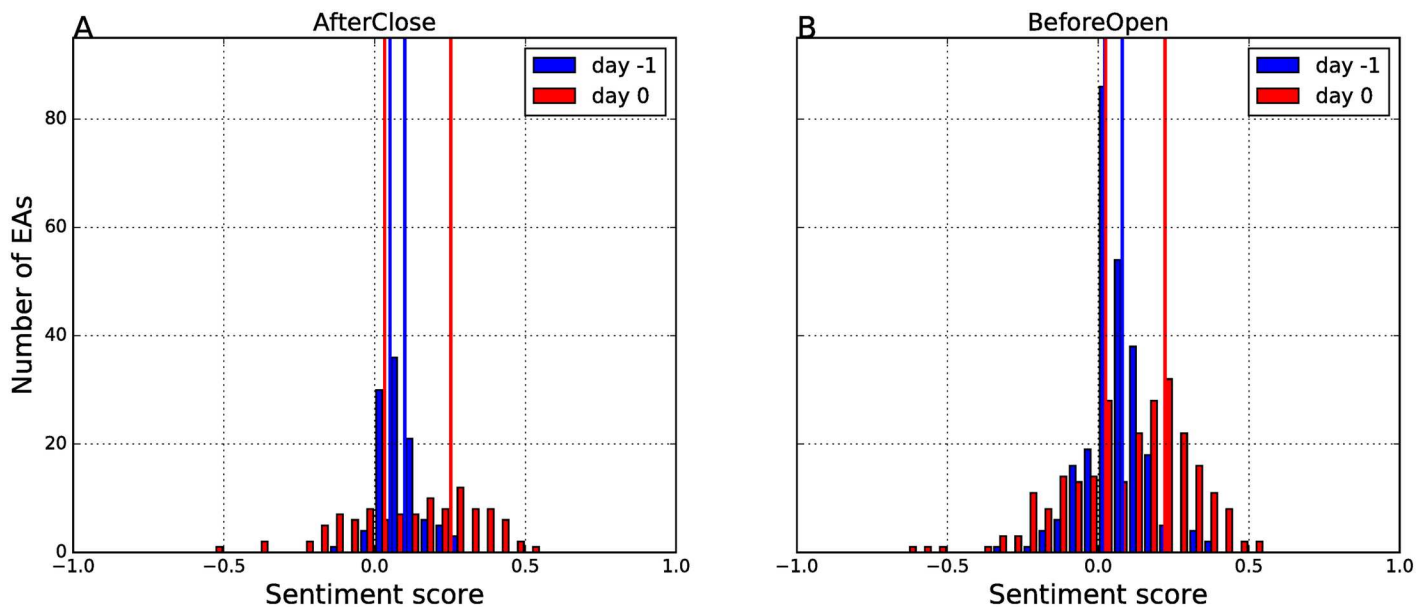

Fig 10. Sentiment distribution of all the Earnings Announcements. Sentiment score is computed from the tweets on day −1 (blue) and day 0 (red), separately for the AfterClose (A) and BeforeOpen (B) events. The vertical lines mark the thresholds used to discriminate between the negative, neutral, and positive event polarity.

doi:10.1371/journal.pone.0173151.g010

Table 3. Categorization of the EA events from the sentiment scores on days 0 and −1.

EA event polarity	AfterClose		BeforeOpen	
	day 0	day −1	day 0	day −1
Negative	$Sent(0) \in (-1, 0.03]$	$Sent(-1) \in (-1, 0.05]$	$Sent(0) \in (-1, 0.02]$	$Sent(-1) \in (-1, 0.02]$
Neutral	$Sent(0) \in (0.03, 0.25]$	$Sent(-1) \in (0.05, 0.10]$	$Sent(0) \in (0.02, 0.22]$	$Sent(-1) \in (0.02, 0.08]$
Positive	$Sent(0) \in (0.25, 1)$	$Sent(-1) \in (0.10, 1)$	$Sent(0) \in (0.22, 1)$	$Sent(-1) \in (0.08, 1)$

doi:10.1371/journal.pone.0173151.t003

(blue bars) are roughly normally distributed with slightly positive means. Note also that the strength of the Twitter sentiment signal on day −1 is much weaker than on day 0. This is indicated by the large number of events with values of $Sent(-1)$ close to 0. In other words, the tweets of day −1 contain less information about the upcoming event than the tweets of day 0, as expected.

We determine the polarity of the EAs from the distribution of $Sent(0)$ and $Sent(-1)$. We define thresholds in such a way, that the three categories are distributed uniformly. The thresholds are reported in Table 3, and are also shown in Fig 10, as red and blue vertical lines.

Putting a threshold on a signal is always somehow arbitrary, and there is no systematic treatment of this issue in the event study [15]. The justification for our approach, already used in [12], is that sentiment should be regarded in relative terms, in the context of related events. Sentiment score has no absolute meaning, but provides just an ordering of events on the scale from −1 (negative) to +1 (positive). The most straightforward choice is to distribute all the events uniformly between the three classes. In the closely related work by Sprenger et al. [10], the authors use the percentage of positive tweets for a given day d, to determine the event polarity. Since they also report an excess of positive tweets, they use the median share of positive tweets as a threshold between the positive and negative events.

Event study methodology

The event study methodology was originaly defined in financial econometrics [15, 16]. The first adaptations and applications to social media data were reported by Sprenger et al. [10] and Ranco et al. [12]. In the current study, there are two differences with respect to our previous work [12]: here we focus just on the events anticipated in advance (i.e., EAs), and we use a shorter event window, compatible with the devised trading strategy.

In summary, in the current event study we use an event window of 12 trading days, i.e., one day before the EA event, and up to 10 days afterwards. We use an estimation window of 120 trading days, and a market model as the normal performance model, estimated with an ordinary least squares regression of the DJIA returns.

Cumulative abnormal returns. An event study is based on the premise that in order to correctly capture the impact of an event, a measure of abnormal price return must be defined. This measure is the actual price return minus the normal return of the stock during the event window. For company i and event date d the abnormal return is:

$$AR_{i,d} = R_{i,d} - E[R_{i,d}] \tag{5}$$

where $AR_{i,d}$, $R_{i,d}$, $E[R_{i,d}]$ are the abnormal, actual, and expected normal returns, respectively. The normal performance model used in this work is the market model: it assumes a linear relation between the overall market return and the return of the stock. More details are given in [12].

In order to draw overall conclusions for the set of events being analyzed, the abnormal return observations must be first aggregated. The aggregation is performed through time and

across stocks. By aggregating across all the stocks, we obtain:

$$\overline{AR}_\tau = (1/N) \sum_{i=1}^{N} AR_{i,\tau} .$$ (6)

The cumulative abnormal return (*CAR*) from time τ_1 to τ_2 is the sum of the abnormal returns:

$$CAR(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} \overline{AR}_\tau .$$ (7)

For the calculation of the *CAR* variance, we assume that $\sigma_{AR}^2 = \sigma_{\epsilon_{i,t}}^2$ (shown in [15]):

$$var(CAR(\tau_1, \tau_2)) = (1/N^2) \sum_{i=1}^{N} (\tau_2 - \tau_1 + 1)\sigma_{\epsilon_i}^2$$ (8)

where *N* is the total number of events. Finally, we introduce the test statistic $\hat{\theta}$. This quantity is used to assess whether the impact of the external event on the cumulative abnormal returns is significant. The test statistic is defined as:

$$\frac{CAR(\tau_1, \tau_2)}{\sqrt[2]{var(CAR(\tau_1, \tau_2))}} = \hat{\theta} \sim \mathcal{N}(0, 1)$$ (9)

where τ is the time index inside the event window, and $|\tau_2 - \tau_1|$ is the total length of the event window.

Acknowledgments

Author Contributions

Conceptualization: IM.

Data curation: MG PG DA.

Formal analysis: PG DA.

Funding acquisition: IM.

Investigation: PG DA IM MG.

Methodology: PG DA IM MG.

Project administration: IM.

Resources: MG PG DA.

Software: PG DA.

Supervision: IM.

Validation: PG DA.

Visualization: PG DA.

Writing – original draft: IM PG DA.

Writing – review & editing: IM PG DA.

References

1. Bollen J, Mao H, Zeng X. Twitter mood predicts the stock market. Journal of Computational Science. 2011; 2(1):1–8. doi: 10.1016/j.jocs.2010.12.007

2. Bollen J, Mao H, Pepe A. Modeling public mood and emotion: Twitter sentiment and socio-economic phenomena. In: Proc. 5th Intl. AAAI Conf. on Weblogs and Social Media. vol. 11. AAAI; 2011. p. 450–453.

3. Mao H, Counts S, Bollen J. Predicting financial markets: Comparing survey, news, Twitter and search engine data. arXiv preprint. 2011;Available from: http://arxiv.org/abs/1112.1051.

4. Preis T, Reith D, Stanley HE. Complex dynamics of our economic life on different scales: insights from search engine query data. Philosophical Transactions of the Royal Society of London A: Mathematical, Physical and Engineering Sciences. 2010; 368(1933):5707–5719. doi: 10.1098/rsta.2010.0284 PMID: 21078644

5. Kristoufek L. Can Google trends search queries contribute to risk diversification? Scientific reports. 2013; 3 (2713). doi: 10.1038/srep02713 PMID: 24048448

6. Souza TTP, Kolchyna O, Treleaven PC, Aste T. Twitter sentiment analysis applied to finance: A case study in the retail industry. arXiv preprint. 2015;Available from: http://arxiv.org/abs/1507.00784.

7. Wang G, Wang T, Wang B, Sambasivan D, Zhang Z, Zheng H, et al. Crowds on Wall Street: Extracting value from social investing platforms. arXiv preprint. 2014;Available from: http://arxiv.org/abs/1406.1137.

8. Zheludev I, Smith R, Aste T. When can social media lead financial markets? Scientific Reports. 2014; 4:4213. doi: 10.1038/srep04213 PMID: 24572909

9. Souza TTP, Aste T. A nonlinear impact: evidences of causal effects of social media on market prices. arXiv preprint. 2016;Available from: http://arxiv.org/abs/1601.04535.

10. Sprenger TO, Sandner PG, Tumasjan A, Welpe IM. News or noise? Using Twitter to identify and understand company-specific news flow. Journal of Business Finance & Accounting. 2014; 41(7–8):791–830. doi: 10.1111/jbfa.12086

11. Sprenger TO, Tumasjan A, Sandner PG, Welpe IM. Tweets and trades: The information content of stock microblogs. European Financial Management. 2014; 20(5):926–957. doi: 10.1111/j.1468-036X.2013.12007.x

12. Ranco G, Aleksovski D, Caldarelli G, Grčar M, Mozetič I. The effects of Twitter sentiment on stock price returns. PLoS ONE. 2015; 10(9):e0138441. Available from: http://dx.doi.org/10.1371/journal.pone.0138441. PMID: 26390434

13. Mao Y, Wei W, Wang B, Liu B. Correlating S&P 500 stocks with Twitter data. In: Proc. 1st ACM Intl. Workshop on Hot Topics on Interdisciplinary Social Networks Research. ACM; 2012. p. 69–72.

14. Makrehchi M, Shah S, Liao W. Stock prediction using event-based sentiment analysis. In: Proc. Intl. Conf. on Web Intelligence and Intelligent Agent Technologies. vol. 1. IEEE; 2013. p. 337–342.

15. MacKinlay AC. Event studies in economics and finance. Journal of economic literature. 1997;p. 13–39.

16. Campbell JY, Lo AWC, MacKinlay AC. The econometrics of financial markets. Princeton University Press; 1997.

17. Berkman H, Truong C. Event day 0? After-hours earnings announcements. Journal of Accounting Research. 2009; 47(1):71–103. doi: 10.1111/j.1475-679X.2008.00312.x

18. Doyle JT, Magilke MJ. The timing of earnings announcements: An examination of the strategic disclosure hypothesis. The Accounting Review. 2009; 84(1):157–182. doi: 10.2308/accr.2009.84.1.157

19. Schroff S, Meyer S, Burghof HP. Individual investor trading in leverage products-risk appetite and positioning around Earnings Announcements. SSRN. 2013;Available from: https://ssrn.com/abstract=2223957.

20. Kaniel R, Liu S, Saar G, Titman S. Investor trading and return patterns around earnings announcements. Journal of Business. 2007;p. 1–49.

21. Alostad H, Davulcu H. Directional prediction of stock prices using breaking news on Twitter. In: Proc. Intl. Conf. on Web Intelligence and Intelligent Agent Technologies. vol. 1. IEEE; 2015. p. 523–530.

22. Tafti A, Zotti R, Jank W. Real-time diffusion of information on Twitter and the financial markets. PLoS ONE. 2016; 11(8):e0159226. Available from: http://dx.doi.org/10.1371/journal.pone.0159226. PMID: 27504639

23. Mohammad S, Kiritchenko S, Sobhani P, Zhu X, Cherry C. A dataset for detecting stance in tweets. In: Proc. 10th Intl. Conf. on Language Resources and Evaluation; 2016. p. 3945–3952.

24. Kralj Novak P, Smailović J, Sluban B, Mozetič I. Sentiment of emojis. PLoS ONE. 2015; 10(12): e0144296. Available from: http://dx.doi.org/10.1371/journal.pone.0144296. PMID: 26641093

25. Truong C. Strategic timing of earnings announcements? Accounting & Finance. 2010; 50(3):719–738.

26. NYSEData.com Factbook;. Accessed: 2016-10-10. http://www.nyxdata.com/nysedata/asp/factbook/viewer_edition.asp?mode=table&key=252&category=3.

27. Mozetič I, Grčar M, Smailović J. Multilingual Twitter sentiment classification: The role of human annotators. PLoS ONE. 2016; 11(5):e0155036. Available from: http://dx.doi.org/10.1371/journal.pone.0155036. PMID: 27149621

28. Vapnik VN. The Nature of Statistical Learning Theory. Springer; 1995.