IJAAF; Vol. 6, No. 4, Autumn 2022, Serial 21

Ferdowsi University of Mashhad

Iranian Journal of
Accounting, Auditing & Finance

Quarterly

RESEARCH ARTICLE

# The Tone of Market Participants' Opinions via Social Media and Capital Market Reaction

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**How to cite this article:**
Amirinasab, M., Mehrazeen, A., & Masih Abadi, A. (2022). The Tone of Market Participants' Opinions via Social Media and Capital Market Reaction. Iranian Journal of Accounting, Auditing and Finance, 6(4), 45-60. doi: 10.22067/ijaaf.2022.42155
https://ijaaf.um.ac.ir/article_42155.html

ARTICLE INFO

Article History
Received: 2022-04-14
Accepted: 2022-09-17
Published online: 2022-10-07

**Keywords:**
Capital Market, Content Analysis, Earnings News, Social Media, Twitter

## Abstract

The present study intends to test and analyze the tone of market participants' opinions via social media and capital market reaction. We use a sample of 345 firm data from the list of S&P 500 firms and analyze it using *Stata* software. The results showed no significant relationship between the tone of earnings tweets and market variables. However, the results of separating the tweets into the original earnings tweets and existing earnings tweets indicated a significant relationship between the tone of the initial earnings tweets and abnormal share turnover. Findings also suggest a significant relationship exists between the tone of existing earnings tweets and bid-ask spreads. Further analysis based on separating tweets into positive and negative demonstrated a meaningful relationship between the tone of positive and negative tweets and abnormal stock turnover and spreads. The results confirm that Twitter can provide complementary awareness in capital markets.

https://doi.org/10.22067/ijaaf.2022.42155



NUMBER OF REFERENCES
16

NUMBER OF FIGURES
-

NUMBER OF TABLES
11

Homepage: https://ijaaf.um.ac.ir
E-Issn: 2588-6142
P-Issn: 2717-4131

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## 1. Introduction

Following the efficient market theory, the securities prices represent the information available. However, the information gap between investors causes information asymmetry and affects capital market efficiency. Many studies find that public disclosure reduces information asymmetry (Beyer et al., 2010). However, to the extent these disclosures are not disseminated to a broad set of investors, information asymmetry may still exist among investors (Blankespoor, Miller and White, 2014). To disseminate information, firms have generally relied on information intermediaries, such as the press. However, the press is biased coverage of high visibility firms because they tend to draw the largest readership base (Miller 2006). Investors also have long relied on information intermediaries (e.g., financial analysts, financial advisors, the business press, credit rating agencies, short sellers, and auditors) to acquire timely and value-relevant information regarding the prospects of stocks. Investors have limited time and resources and tend to rely on only a few sources for their information (Beyer et al., 2010). The past decade has witnessed an explosion in new sources of information that are easily accessible to capital market participants. However, the biggest revolution in disseminating information on the Internet has been the advent of social media platforms such as Twitter, which allow users to post their views instantaneously about stocks to a wide audience (Bartov, Faurel and Mohanram, 2019). In April 2013, the Securities and Exchanges Commission (SEC) issued a new regulation permitting firms to use social media to communicate financial information to investors (SEC, 2013). This new regulation by the SEC was in response to the rise of corporate use of social media to communicate financial information. Because of the rise of Twitter discussions about the stock market, Twitter introduced the "*cashtag*" symbol ($) in 2012. The *cashtag* is used to identify those tweets that specifically discuss a firm's stock and is thus how I identify tweets that pertain to the stocks of specific firms. In other words, market participants can express their opinions about a firm's stock through the symbol of *cashtag* ($).Accordingly, Twitter allows investors to access information in two ways. First, they can follow information directly from firms in which they are interested. Second, the aggregation of Twitter financial discussions about stocks captures the crowd's wisdom and is thus a useful source of financial information (Al Guindy, 2017). Twitter allows users to tap into the Wisdom of Crowds, where the aggregation of information provided by many (non-expert) individuals often predicts outcomes more precisely than experts. Further, Twitter users, who come from diverse backgrounds, are less likely to herd, a phenomenon that plagues traditional information intermediaries (e.g., financial analysts), as well as social media platforms (e.g., blogs, investing portals) where a central piece of information is posted and the users, comment on it. Also, Twitter's short format (up to 140 characters) and ease of information search (e.g., the use of cashtags) make it an ideal medium to share opinions and information in a timely fashion, in contrast to the longer format and potentially reduced timeliness of research reports or articles (Bartov, Faurel and Mohanram, 2019). Finally, most tweeting originating from firms is positive in tone – as expected by theories of selective disclosure in Verrecchia (1983) and Jung and Kwon (1988). On the other hand, Tweeting from market participants exhibits a more varied tone since it carries the crowd's opinions, not those of the firm. Accordingly, the question is whether the unique features of Twitter can improve the information content of firms and affect capital market variables. The academic literature has begun studying the role Twitter plays in the capital market only recently, perhaps because Twitter was created in March 2006 and launched in July 2006. One strand of this literature examines how companies exploit this new channel to communicate with the investors; another investigates whether information from Twitter predicts the overall stock market, and a third one analyzes the relationship between Twitter activity and the investor response to earnings news. A recent study analyzing the market participants' tweets by Bartov, Faurel and Mohanram (2019) examined the relationship between individuals' tweets and their impact on the company's returns. In this paper, we specifically look at earnings news so that we can fill the research gap in the existing literature by examining whether there is a significant relationship between the tone of earnings tweets disseminated by market participants and proxies of abnormal share return as well as with abnormal share turnover and abnormal share bid-ask spreads?

## 2. Literature Review

Complementary information in the capital market leads to improving the market information environment and, ultimately, improving stakeholder decision-making (Warren, Moffitt and Byrnes 2015). The Wisdom of Crowds resulting from the opinions of market participants via Twitter can be related to the increase of information in the capital market because this social media has the most user diversity among social media. Wisdom of Crowds as a concept dates back over a century. It refers to the phenomenon that the aggregation of information by individuals with diverse and independent views and opinions will lead to better predictions than the predictions of any single member of a group or even an individual expert. Tweeting market participants is both a source of new information and a tool for disseminating market information (Bartov, Faurel and Mohanram, 2019). Thus, market participants' tweets and other information can improve or modify the information environment and overshadow market variables. Bollen, Mao and Zeng (2011) indicate that the aggregate mood inferred from textual analysis of daily Twitter feeds can help predict changes in the Dow Jones Index. Mao et al. (2012) found that the daily number of tweets that mention S&P 500 shares is significantly associated with the levels, changes, and absolute changes in the S&P 500 Index. Curtis, Richardson and Schmardebeck (2014), who focus on the overall social media (Twitter and Stock Twits) activity over 30-day rolling windows, found that high levels of activity are associated with greater sensitivity of earnings announcement returns to earnings surprises, while low levels of social media activity are associated with significant post-earnings-announcement drift. Azar and Lo (2016) show that the content of tweets can be used to predict future returns around the Federal Open Market Committee (FOMC) meetings. Al Guindy (2017) considers the role of Twitter in improving the information environment by increasing the wisdom of crowds among investors. The results showed that if Twitter news caused a positive feeling in investors, share returns would be higher; otherwise, share returns would be lower; this effect is especially pronounced when there is no consensus among financial analysts. Jung et al. (2018) found that firms strategically disseminate news via Twitter, especially when more people follow it. In this study, users' opinions about news are also examined, and the results illustrate that news followers' opinions neutralize the effects of disseminating firms' news through Twitter. Bartov, Faurel and Mohanram (2019) examined the opinions of people who follow corporate tweets and found that aggregating those who follow corporate tweets effectively predicts future quarterly earnings and corporate earnings returns. The present study considers the negative tone of market participants' earnings tweets and their relationship with returns, turnover and spreads in the form of the first to third hypotheses. It should be noted that considering the method of analyzing the tone of tweets based on the negative words of the tweets, the negative tone of the tweets has also been considered in the hypotheses.

***H1:*** The negative tone of earnings news disseminated by market participants via Twitter is related to abnormal share returns.

***H2:*** The negative tone of earnings news disseminated by market participants via Twitter is related to abnormal share turnover.

***H3:*** The negative tone of earnings news disseminated by market participants via Twitter is related to the abnormal share bid-ask spreads.

In analysing the tweet's tone, the tweets of market participants play a dual role in the capital market in terms of information. The opinions of market participants, on the one hand, are active in new news and information, and on the other hand, in providing information and news that has already been disseminated from other sources. Re-tweets and tweets containing hyperlinks, disseminated by market participants, can be considered tweets containing duplicate news and no new news for the capital market. These tweets are disseminated for purposes such as re-influencing the reader, providing more explanation about the news and reminding the reader of the news. Re-tweets are tweets received and reposted by market participants from the company's Twitter page or accounts. Tweets containing hyperlinks direct the newsreader to other sources of information to provide further explanations of the news. Bartov, Faurel and Mohanram (2019), in examining the effect of Twitter news on earnings and return forecasting, divided Twitter news into two categories of original news and existing news and found that both types of news are effective in predicting firms' earnings and return. In the present study, the relationship between the tone of disseminated earnings news containing original and existing information by the market participants via Twitter and market variables has been investigated in the form of the fourth to sixth hypotheses:

***H4:*** The negative tone of disseminated earnings news containing the original and existing news via Twitter is related to abnormal share returns.

***H5:*** The negative tone of disseminated earnings news containing the original and existing news via Twitter is related to abnormal share turnover.

***H6:*** The negative tone of disseminated earnings news containing the original and existing news via Twitter is related to abnormal share bid-ask spreads.

## 3. Research Methodology

### 3.1. Methods

The purpose of this study is to investigate the relationship between the disseminated news related to the accounting earnings by market participants on Twitter social media and the reaction of the capital market by collecting past information of the firms, post-event research plan with correlation analysis and applied in terms of purpose. The statistical model used in this research is a multivariate regression model, Excel software is used to collect and classify data, and Stata software is used for multivariate regression analysis. To set the theoretical framework of the research and its background, articles published on the website of the American Accounting Association (AAA) between 2014 and 2019 have been used. Statistical parameters include descriptive statistics to describe and present statistical characteristics of variables and parameters, and inferential statistics consists of estimating coefficients.

### 3.2. Data Collection Instrument

Data on market participants' opinions about each company on Twitter is extracted by adding the slash symbol ($) to the beginning of the firm's Twitter ID. This data includes the text of the participants' tweets and the number of participants' followers at the tweet date; re-tweets were also extracted using Python. In the first phase, the total market participant tweets of the sample firms from the beginning of October 2015 to March 2020 included 450,000 tweets. The tweets disseminated in the research estimation period were selected in the second stage. The estimated period is 58 days before the earnings announcement, so it begins 60 calendar days before the earnings announcement date and ends 2 days before that date (-60 to -2) (Jung et al., 2018). At this stage, the number of tweets was 130 905. In the last step, the tweets containing the news of earnings announcements were separated. At this stage, the number of tweets was 20,037. The identification of tweets containing earnings announcement news is based on the content analysis of the tweets and using the word list introduced by Bartov, Faurel and Mohanram (2019). The necessary condition is the presence of at least one of the words representing the earnings announcement news in the desired tweet. Market data, including share price, maximum and minimum share price, share exchange volume and share returns, are extracted from the https://www.investing.com website. In order to collect market data by referring to the mentioned site, first identify the earnings announcement date of each company and separately for each financial period and then the market data has been extracted for the estimation period as well as the event period (three-day period earnings announcement). The estimation period is based on a calendar because the basis for extracting Twitter data is also the estimation period. The basis for tweeting firms and other Twitter users is not based on the working days on the share market. On the other hand, the three days around the earnings announcement are considered the working days of the share exchange. To measure the abnormal share returns as a variable, we needed to adjust returns based on the firm's size, determined by “the Center for Research Securities Price”. For this purpose, the data related to the portfolio index based on the share market value of the firms were extracted from the https://www.crsp.org website. It should be noted that this index determines the relationship between the market value and share returns. It sorts out the firms into 5 categories and determines the adjusted-based returns. The control variables are extracted from corporate financial statements and through numerous websites.

### 3.3. Population and Sample Size

The statistical population consists of S&P 500 firms from 2016 to 2019. In the first step, the firms listed at least once in the S&P 500 list during the research period (from November 2015 to March 31,

2019) were selected to specify the sample. At this stage, the number of firms was 642. The next step was to pick a statistical sample; the following items were considered in selecting the statistical sample:
Firms that have an official Twitter account.

Firms that joined Twitter in early November 2015 or earlier.

Firms that are listed on the NewYork Share

Exchange and the Nasdaq Share Exchange.

Companies with incomplete fundamental information were excluded from the sample.

Eight companies with a negative market value ratio to book value (negative equity) were also excluded. After applying these items, the sample size turned out to be 345 films.

### 3.4. Models Testing Hypothesis

The regression model of the hypotheses is designed by modeling and modifying the Bartov, Faurel and Mohanram (2019):

Model (1) $ABRETURN_{it} = B_0 + B_1\,TONE_{it} + \sum controls_{it}$

Model (2) $ABTURNOVER_{it} = B_0 + B_1\,TONE_{it} + \sum controls_{it}$

Model (3) $ABSPREAD_{it} = B_0 + B_1\,TONE_{it} + \sum controls_{it}$

Model (4) $ABRETURN_{it} = B_0 + B_1\,OTONE_{it} + B_2\,ETONE_{it} + \sum controls_{it}$

Model (5) $ABTURNOVER_{it} = B_0 + B_1\,OTONE_{it} + B_2\,ETONE_{it} + \sum controls_{it}$

Model (6) $ABSPREAD_{it} = B_0 + B_1\,OTONE_{it} + B_2\,ETONE_{it} + \sum controls_{it}$

### 3.5. Variables

#### 3.5.1. Dependent Variables

*ABRETURN:* Abnormal share returns are measured as the difference between three-day absolute size-adjusted returns and the mean three-day absolute size-adjusted returns in an estimation period, divided by the standard deviation of the mean absolute size-adjusted returns in the estimation period. The estimation period begins 60 calendar days before the earnings announcement date and ends 2 days before that (Jung et al., 2018).
*ABTURNOVER:* Abnormal share turnover is measured as a three-day volume divided by outstanding shares minus the average three-day turnover in the estimation period. The estimation period begins 60 calendar days before the earnings announcement date and ends 2 days before that (Jung et al., 2018).

*ABSPREAD:* Abnormal spreads are measured as the three-day average spread (ask minus bid price, divided by their mean) minus the average three-day spread in the estimation. The estimation period begins 60 calendar days before the earnings announcement date and ends 2 days before that (Jung et al., 2018).

### 3.5.2. Independent Variables

*TONE:* The tone of the disseminated tweets was measured using textual analysis. After selecting the tweets containing earnings announcement news based on the vocabulary of Bartov, Faurel and Mohanram (2019), the analysis of the positive or negative tone of the tweets was performed based on a wordlist developed in Loughran and McDonald's (2011) analysis of 10-K filings (LM wordlist)[i]. According to the textual analysis based on the LM word list in previous research, tone analysis based on the negative words in this list is more accurate. Therefore, tone analysis is based on the number of negative words in each tweet. First, we identify the number of negative words in each tweet and assign a weight to each tweet. The weighing method for each tweet is based on the number of followers of the company's Twitter account, multiplying the number of negative words in each tweet by one plus the log of one plus the number of followers of the company's Twitter account on the earnings announcement date. Then, the sum of the weighed negative words of the tweets during the estimation period is multiplied by -1 and divided by one plus the total number of positive and negative words of the tweets, as follows:

$$TONE_{it} = \frac{-1 \times \sum [\text{number of negative words per tweet} \times [1+(\log 1+\text{number of followers})]]}{1+ \text{the total positive and negative words of tweets}_{it}}$$

After quantifying the tone of earnings announcement tweets, the mentioned variable has been divided into two components: the tone of tweets containing original news (OTONE) and the tone of tweets containing existing news (ETONE). Tweets containing existing news are tweets which meet one of the following conditions:

A: Re-tweets: These tweets are prefixed with "RT", and are also possible to identify.

B: Tweets containing hyperlinks: Tweets with a link to connect to the company's website or other websites.

Tweets that do not meet the requirements of A and B are in the group of tweets containing the company's original news. In order to calculate the tone variable of tweets containing original and existing news, after separation, each group of tweets (original and existing) is weighed and calculated as follows:

$$OTONE_{it} = \frac{-1 \times \sum [\text{number of original negative words per tweet} \times [1+(\log 1+\text{number of followers})]]}{1+ \text{the total positive and negative words of original tweets}_{it}}$$

$$ETONE_{it} = \frac{-1 \times \sum [\text{number of existing negative words per tweet} \times [1+(\log 1+\text{number of followers})]]}{1+ \text{the total positive and negative words of existing tweets}_{it}}$$

### 3.5.3. Control Variables

Based on the background research (Henry and Leone, 2016; Jung et al., 2018; Al Guindy, 2017; Bartov, Faurel and Mohanram, 2019), the control variable is derived from the criteria affecting the presence of firms in the social media Twitter and the Criteria affecting the news coverage on the social media, as follows:

*Un-sophisticated investors (UNSOPHI):* The unsophistication proxy is defined using the percentage of outstanding shares owned by individual retail investors, assuming that retail investors are less sophisticated than institutional investors. This variable is measured as one minus percentage of the shares held by the institutional investors of Company i for period t (Jung et al., 2018).

*The firm size (SIZE):* The firm size was measured as the natural logarithm of the market value of the firm's equity i at the end of period t (Al Guindy, 2017).

*Growth (GS):* The yearly sales growth is measured as the ratio of the total sales for the period t compared to period t-1 (Jung et al., 2018).

*Market-to-book value (MTB):* The market value to book value is measured as the market-to-book ratio of firm i for the period t (Jung et al., 2018).

*Leverage (LEVE):* This proxy is measured as the debt-to-asset ratio of firm i for the period t (Jung et al., 2018).

*The firm age (FIRMAGE):* This variable is measured as the number of years since a firm’s founding in the t-1 period (Bartov, Faurel and Mohanram 2019).

*The Loss (LOSS):* The loss variable is an indicator variable set to 1 (0 otherwise) if the firm actual earnings per share are less than one (Henry and Leone, 2016).

## 4. Findings

### 4.1. Descriptive Statistics of Quantitative Variables

This study's descriptive findings, including mean, standard deviation, minimum, and maximum observation, are presented in Table 1. It should be noted that the number of companies studied is 345 companies, and their information has been collected for 4 consecutive years. According to the results of descriptive statistics, on average, the sample companies' abnormal share returns, abnormal share turnover and abnormal spreads are 2.674 and 0.012and 0.011, respectively.

**Table 1.** The Descriptive Statistics of Quantitative Variables

| Variable | Symbol | Min | Max | Mean | Std. Dev |
|---|---|---|---|---|---|
| Independent | TONE | -3.370 | 0.000 | -1.576 | 0.953 |
| | OTONE | -3.373 | 0.000 | -1.547 | 0.982 |
| | ETONE | -3.471 | 0.000 | 0.500 | 0.900 |
| | PTONE | 0.000 | 1.000 | 0.386 | 0.320 |
| | NTONE | -1.000 | 0.000 | -0.474 | 0.338 |
| Dependent | ABRETURN | -0.903 | 14.522 | 2.674 | 3.153 |
| | ABTURNOVER | -0.015 | 0.090 | 0.012 | 0.017 |
| | ABSPREAD | -0.007 | 0.048 | 0.011 | 0.01 |
| Control | UNSOPHI (%) | 3.639 | 81.29 | 45.339 | 14.404 |
| | SIZE (log) | 3.189 | 5.583 | 4.337 | 0.485 |
| | GS | -0.290 | 0.922 | 0.078 | 0.155 |
| | MTB | 0.550 | 96.433 | 5.902 | 11.634 |
| | LEVE | 0.010 | 0.813 | 0.302 | 0.176 |
| | FIRMAGE | 1 | 205.09 | 67 | 48.669 |

Other descriptive statistics related to independent and control variables are also shown in Table 2.

**Table 2.** The Frequency Distribution of Loss Variable (LOSS)

| Variable | Dummy | | Valid % | N |
|---|---|---|---|---|
| LOSS | EPS > 0 | 0 | %96.9 | 1436 |
| | EPS < 0 | 1 | %3.1 | 46 |
| | | | %100 | 1482 |

The frequency distribution table (table 2) states that among the studied companies and in the years investigated, 1436 (96.9%) companies have positive earnings per share, and 46 companies (3.1%) have negative earnings per share (loss).

## 4.2. Inferential Statistics

### 4.2.1. Regression Model Type Identification Tests

In order to choose whether the panel regression models or OLS regression models, the F-Limer test was used, and finally, the panel regression model was selected as the appropriate model. After selecting the panel regression, the choice between fixed effects panel regression models and random effects panel regression was made using Hausman Test. The results of the Hausman Test indicated that the panel model was selected with random effects. The merger test was used to test the integrated data model against random effects, which showed no ability to integrate temporal and spatial effects in the model. After selecting the appropriate model, the stability of variance and serial autocorrelation of the model residues have been investigated using the parent test.

The results of the parent test demonstrated that the assumption of variance homology of the re-original models was not established. Also, the results of the serial autocorrelation study between the rest of the models suggest that the underlying assumptions of variance homogeneity and lack of serial autocorrelation are not established for the above models; therefore, to solve the problem of variance inequality and serial autocorrelation, the least generalized quadratic regression model is used.

### 4.2.2. Hypotheses Test Results

**Table 3.** Association between TONE and ABRETURN

| | Coefficient | Std. err. | Z | P>\|z\| | VIF |
|---|---|---|---|---|---|
| cons | 2.277 | 0.560 | 4.060 | <0.001 | 1.010 |
| TONE | -0.023 | 0.059 | -0.400 | 0.688 | 1.010 |
| UNSOPHI | -0.003 | 0.003 | -0.800 | 0.425 | 1.050 |
| SIZE | 0.027 | 0.120 | 0.230 | 0.820 | 1.070 |
| GS | -0.875 | 0.307 | -2.840 | 0.004 | 1.020 |
| MTB | 0.023 | 0.006 | 3.680 | <0.001 | 1.040 |
| LEVE | -0.402 | 0.340 | -1.180 | 0.237 | 1.030 |
| LOSS | -0.621 | 0.327 | -1.900 | 0.058 | 1.030 |
| FIRMAGE | -0.001 | 0.001 | -1.330 | 0.182 | 1.010 |

Table (3) results show no significant relationship between the negative tone of earnings news disseminated by market participants and abnormal share returns.

**Table 4.** Association between TONE and ABTURNOVER

| | Coefficient | Std. err. | Z | P>\|z\| | VIF |
|---|---|---|---|---|---|
| cons | 0.038 | 0.001 | 24.510 | <0.001 | 1.040 |
| TONE | 0.000 | 0.000 | 0.170 | 0.867 | 1.010 |
| UNSOPHI | 0.000 | 0.000 | 2.970 | 0.003 | 1.060 |
| SIZE | -0.007 | 0.000 | -22.750 | <0.001 | 1.110 |
| GS | -0.003 | 0.001 | -2.630 | 0.009 | 1.020 |
| MTB | 0.000 | 0.023 | 3.550 | <0.001 | 1.040 |
| LEVE | 0.000 | 0.001 | 0.920 | 0.355 | 1.030 |
| LOSS | -0.004 | 0.002 | -2.390 | 0.017 | 1.030 |
| FIRMAGE | 0.000 | 0.009 | 3.910 | <0.001 | 1.010 |

Table (4) shows no significant relationship between the negative tone of earnings news disseminated by market participants and the abnormal share turnover.

**Table 5.** Association between TONE and ABSPREADS

| | Coefficient | Std. err. | Z | P>\|z\| | VIF |
|---|---|---|---|---|---|
| cons | 0.025 | 0.001 | 16.700 | <0.001 | 1.030 |
| TONE | 0.011 | 0.000 | 0.030 | 0.972 | 1.010 |
| UNSOPHI | -0.000 | 0.023 | -2.000 | 0.045 | 1.050 |
| SIZE | -0.003 | 0.000 | -9.480 | <0.001 | 1.090 |
| GS | -0.002 | 0.000 | -3.420 | 0.001 | 1.020 |
| MTB | -0.000 | 0.000 | -1.550 | 0.121 | 1.040 |
| LEVE | 0.001 | 0.000 | 2.010 | 0.044 | 1.030 |
| LOSS | 0.003 | 0.001 | 2.230 | 0.026 | 1.030 |
| FIRMAGE | -0.010 | 0.007 | -1.440 | 0.150 | 1.010 |

The results of Table (5) show that there is not a significant negative relationship between the negative tone of the disseminated earnings tweets of market participants and the abnormal share spread.

**Table 6.** Association between OTONE, ETONE and ABRETURN

| | Coefficient | Std. err. | Z | P>\|z\| | VIF |
|---|---|---|---|---|---|
| cons | 2.180 | 0.568 | 3.830 | <0.001 | 1.010 |
| OTONE | -0.051 | 0.058 | -0.870 | 0.383 | 1.020 |
| ETONE | 0.052 | 0.059 | 0.880 | 0.381 | 1.020 |
| UNSOPHI | -0.002 | 0.003 | -0.560 | 0.575 | 1.060 |
| SIZE | 0.041 | 0.121 | 0.340 | 0.731 | 1.070 |
| GS | -0.857 | 0.299 | -2.860 | 0.004 | 1.020 |
| MTB | 0.023 | 0.006 | 3.700 | <0.001 | 1.040 |
| LEVE | -0.423 | 0.343 | -1.230 | 0.217 | 1.030 |
| LOSS | -0.601 | 0.329 | -1.830 | 0.068 | 1.030 |
| FIRMAGE | -0.001 | 0.001 | -1.570 | 0.117 | 1.010 |

The results of Table (6) show that there is no significant relationship between the negative tone of earnings tweets containing the original information disseminated by the market participants and abnormal share returns, as well as the negative tone of earnings tweets containing existing information disseminated by the market participants and abnormal share returns.

Table (7) shows a significant relationship between the negative tone of earnings tweets containing the original information disseminated by the market participants and the abnormal turnover of shares. However, there is no significant relationship between the negative tone of earnings tweets containing the existing information disseminated by the market participants and the abnormal turnover of shares.

**Table 7.** Association between OTONE, ETONE and ABTURNOVER

| | Coefficient | Std. err. | Z | P>\|z\| | VIF |
|---|---|---|---|---|---|
| cons | 0.040 | 0.001 | 25.730 | <0.001 | 1.040 |
| OTONE | 0.000 | 0.000 | 2.030 | 0.043 | 1.020 |
| ETONE | 0.000 | 0.000 | -1.390 | 0.166 | 1.020 |
| UNSOPHI | 0.000 | 0.000 | 3.310 | 0.001 | 1.060 |
| SIZE | -0.007 | 0.000 | -23.990 | <0.001 | 1.110 |
| GS | -0.003 | 0.001 | -2.560 | 0.010 | 1.020 |
| MTB | 0.000 | 0.023 | 3.440 | 0.001 | 1.040 |
| LEVE | 0.000 | 0.000 | 0.060 | 0.951 | 1.030 |
| LOSS | 0.005 | 0.001 | -2.540 | 0.011 | 1.030 |
| FIRMAGE | 0.000 | 0.009 | 3.850 | <0.001 | 1.010 |

Table (8) shows no significant relationship between the negative tone of earnings tweets containing the original information disseminated by the market participants and the abnormal share spreads. However, there is a significant relationship between the negative tone of earnings tweets containing existing information disseminated by the market participants.

**Table 8.** Association between OTONE, ETONE and ABSPREADS

| | Coefficient | Std. err. | Z | P>\|z\| | VIF |
|---|---|---|---|---|---|
| cons | 0.025 | 0.001 | 16.890 | <0.001 | 1.030 |
| OTONE | 0.000 | 0.000 | 1.490 | 0.137 | 1.020 |
| ETONE | -0.000 | 0.000 | -4.780 | <0.001 | 1.020 |
| UNSOPHI | -0.000 | 0.000 | -3.130 | 0.002 | 1.060 |
| SIZE | -0.003 | 0.000 | -9.370 | <0.001 | 1.090 |
| GS | -0.003 | 0.000 | -3.600 | <0.001 | 1.020 |
| MTB | -0.000 | 0.000 | -1.770 | 0.077 | 1.040 |
| LEVE | 0.001 | 0.001 | 1.340 | 0.181 | 1.030 |
| LOSS | 0.003 | 0.001 | 2.360 | 0.018 | 1.030 |
| FIRMAGE | -0.010 | 0.007 | -1.340 | 0.180 | 1.010 |

### 4.2.3. Additional Analyses

In the research background, two methods have been used to analyze the content of the tweets. In the first method, content analysis was done based on only the negative words of each tweet. This method has been used to measure the tone of the tweets in the main hypotheses of the research. The additional tweets' tone analyses using the second method and based on the LM vocabulary is an adjustment to the model presented by Al Guindy (2017). For this purpose, after selecting the earnings tweets, using the LM word list, the number of positive and negative words of each tweet has been identified. Subsequently, the tweet with more negative words is considered negative, and the tweet with more positive words is considered positive. Tweets with the same number of negative and positive words are zeroed and discarded. The details of the analysis are as follows:

*Step 1:* Identify the tone of each tweet as a percentage of the total positive and negative words in each tweet to increase the level of accuracy of content analysis. In other words, in a tweet whose content is identified as positive, the number of positive words equals the total number of positive and negative words, and the result is identified as a ratio.

*Step 2:* Modify the tone of each tweet based on the number of followers of the Twitter page on the date of the tweet; thus, the result of the calculation in the previous step is multiplied by one plus the logarithm of one plus the number of followers of the Twitter page on the date of the tweet.

*Step 3:* For each company in each period, the value is assigned to positive and negative tweets separately. For this purpose, the absolute value of the sum of the value of the positive and negative tweets identified in the previous step is subtracted. In the case of subtraction, once the value obtained from the sum of the positive tweets is adjusted and again, it applies to the value obtained from the sum of the adjusted negative tweets.

In the additional analysis of the study, three models have been examined as follows:

Model (1) $$ABRETURN_{it} = B_0 + B_1\,PTONE_{it} + B_2\,NTONE_{it} + \sum controls_{it}$$

Model (2) $$ABTURNOVER_{it} = B_0 + B_1\,TONE_{it} + B_2\,NTONE_{it} + \sum controls_{it}$$

Model (3) $ABSPREAD_{it} = B_0 + B_1 TONE_{it} + B_2 NTONE_{it} + \sum controls_{it}$

ABRETURN, ABTURNOVE, and ABSPREAD share abnormal returns, turnover and bid-ask spreads.

*PTONE* $_{it}$: The positive tone of the earnings tweets of the company's participants i in period t.

*NTONE* $_{it}$: The negative tone of the earnings tweets of the participants of the company i in the period t.

Control variables include UNSOPHI, SIZE, GS, MTB, LEVE, LOSS and FIRMAGE.

The test results of the additional models are as follows:

**Table 9.** Association between PTONE, NTONE and ABRETURN

| | Coefficient | Std. err. | Z | P>\|z\| | VIF |
|---|---|---|---|---|---|
| cons | 2.333 | 0.582 | 4.000 | <0.001 | 1.010 |
| PTONE | -0.318 | 0.205 | -1.550 | 0.122 | 1.130 |
| NTONE | -0.043 | 0.195 | -0.220 | 0.823 | 1.140 |
| UNSOPHI | -0.002 | 0.003 | -0.780 | 0.433 | 1.060 |
| SIZE | 0.040 | 0.121 | 0.330 | 0.738 | 1.070 |
| GS | -0.861 | 0.298 | -2.890 | 0.004 | 1.020 |
| MTB | 0.024 | 0.006 | 3.700 | <0.001 | 1.040 |
| LEVE | -0.351 | 0.339 | -1.040 | 0.300 | 1.030 |
| LOSS | -0.583 | 0.330 | -1.770 | 0.077 | 1.030 |
| FIRMAGE | -0.001 | 0.001 | -1.390 | 0.166 | 1.010 |

Table (9) shows no significant relationship between earnings tweets' positive and negative tone and the abnormal share return.

**Table 10.** Association between PTONE, NTONE and ABTURNOVER

| | Coefficient | Std. err. | Z | P>\|z\| | VIF |
|---|---|---|---|---|---|
| cons | 0.040 | 0.001 | 25.440 | <0.001 | 1.040 |
| PTONE | -0.001 | 0.000 | -2.130 | 0.033 | 1.130 |
| NTONE | 0.001 | 0.000 | 2.820 | 0.005 | 1.140 |
| UNSOPHI | 0.000 | 0.000 | 4.240 | <0.001 | 1.060 |
| SIZE | -0.007 | 0.000 | -23.710 | <0.001 | 1.110 |
| GS | -0.002 | 0.001 | -2.240 | 0.025 | 1.020 |
| MTB | 0.000 | 0.000 | 2.750 | 0.006 | 1.040 |
| LEVE | 0.000 | 0.001 | 0.670 | 0.503 | 1.030 |
| LOSS | -0.004 | 0.002 | -2.430 | 0.015 | 1.030 |
| FIRMAGE | 0.000 | 0.008 | 4.460 | <0.001 | 1.010 |

The results of Table (10) show a significant relationship between the positive tone (to negative coefficient) and negative tone (to positive coefficient) of earnings tweets and abnormal share turnover.

**Table 11.** Association between PTONE, NTONE and ABSPREADS

| | Coefficient | Std. err. | Z | P>\|z\| | VIF |
|---|---|---|---|---|---|
| cons | 0.025 | 0.001 | 17.350 | <0.001 | 1.030 |
| PTONE | -0.001 | 0.000 | -3.470 | 0.001 | 1.130 |
| NTONE | 0.000 | 0.000 | 1.880 | 0.060 | 1.140 |
| UNSOPHI | -0.000 | 0.024 | -1.710 | 0.087 | 1.060 |
| SIZE | -0.003 | 0.000 | -9.480 | <0.001 | 1.090 |
| GS | -0.002 | 0.000 | -3.530 | <0.001 | 1.020 |
| MTB | -0.000 | 0.000 | -1.590 | 0.112 | 1.040 |
| LEVE | 0.001 | 0.000 | 2.070 | 0.038 | 1.030 |
| LOSS | 0.003 | 0.001 | 2.300 | 0.022 | 1.030 |
| FIRMAGE | -0.009 | 0.007 | -1.250 | 0.210 | 1.010 |

The results of Table (11) show that there is a significant relationship between the positive tone (to negative coefficient) and negative (p-value of 0.060) tone (to positive coefficient) of earnings tweets and the abnormal share spreads.

## 5. Conclusion

The present study investigated the thematic relationship between earnings news disseminated by market participants on Twitter and market variables, including abnormal share returns, abnormal share turnover and abnormal share spreads. For this purpose, according to the official approval of Twitter, awareness of the capital markets by the Securities and Exchange Commission (SEC), data related to 345 firms from the list of US S&P 500 firms, for a period of four years: 2016-2019 were extracted and were analyzed by Stata software. The results prove no significant relationship exists between the negative tone of earnings news disseminated by market participants via Twitter and the market variables. These results were not in line with the findings of Al Guindy (2017); the results of Al Guindy (2017) explain that the negative tweets of the market participants lead to lower stock returns; furthermore, on days when the market participants' tweets are negative, the trading volume is abnormally high. It was also inconsistent with Bartov, Faurel and Mohanram (2019). Bartov, Faurel and Mohanram (2019) found a significant positive relationship between the negative tone of the market participants' tweets and the abnormal returns. On the other hand, sorting out the tweets into the original earnings tweets and existing earnings tweets showed no significant relationship between original and existing earnings tweets with abnormal returns. These results did not correspond to Bartov, Faurel and Mohanram (2019). They illustrate a significant positive relationship between the negative tone of the original tweets and the share return. In the Bartov, Faurel and Mohanram (2019) study, all financial tweets have been examined, not merely earnings tweets. In other words, the tweets analyzed in this study were more limited, which could be a reason for dissimilar findings. The results also show a significant relationship between the tone of the original earnings tweets and the abnormal share turnover. There is a significant relationship between the tone of existing earnings tweets and bid-ask spreads. Finally, additional analysis based on separating tweets into positive and negative showed a significant relationship between the tone of positive and negative tweets and the abnormal stock turnover and spreads.

The reasons for the inconsistency of the results with some previous studies are as follows:

- Focus on tweets containing earnings news in the present study.

- Previous studies have often been conducted before 2013 (before the Securities and Exchange Commission (SEC) stated on Twitter); the present study was carried out after the statement issuance.
- Differences in sources of the disseminated tweets, as some studies have analyzed tweets posted by firms and some by market participants. Previous studies have focused more on examining corporate tweets.

The results show that the market participants' dissemination of additional news through social media channels can be used to harmonise awareness in the capital markets. Therefore, along with the positive effects of social media on improving the information environment of the firms, users of the web environment are recommended to consider the quantitative and qualitative news disseminated on social media as a widely disseminated information channel and enjoy the benefits of this channel along with other information resources to increase their awareness of investment decisions. On the other hand, in order to eliminate the negative effects of social media based on the strategic dissemination of news on social media, it is recommended that users use social media as a source of information carefully and vigilantly. Finally, considering the importance of social media in financial markets, it is suggested that in future research, the impact of qualitative and quantitative news, the existing aspects of the market, such as reducing information asymmetry, improving information transparency and information quality characteristics, shall be addressed. Moreover, by analyzing and comparing new information channels and the level of news disseminated in domestic and global information environments, attempt to gain more awareness of the existing differences and apply them in advancing the capital market goals.

## Endnotes Terminology

| Endnote Number | Endnote Content |
|---|---|
| 1 | Adjusted, earning, ebit, ebitda, eps, expense, fiscal, gaap, gain, in the black, in the green, in the red, income, loss, noi, nopat, normalized, oibda, operating, per share, pro forma, profit, proforma, pro-forma, results, revenue, sales, yearend, year-end |
| 2 | Mega cap, Big cap, Mid cap, Small cap, Micro cap, Nano cap. |
| 3 | http://www.gurufocus.com, http://www.investing.com, http://www.fortune.com , http:// www.siccode.com, http://www.sec.gov |
| 4 | The word list used in the General Inquirer text-processing program, the Harvard IV-d dictionary, is available at: http://www.wjh.harvard.edu/~inquirer/spreadsheet_guide.htm |

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