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The Aggregate of Earnings and Announcement Returns with the Help of Twitter Using "Wisdom of Crowds" Theory and "Macro Accounting" Theory: Evidence from NYSE and Nasdaq

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Abstract

This study aims to predict the aggregate of earnings and announcement returns with the help of this purpose, by a selection of Twitter social media as a media approved by the US Stock Exchange and Securities Organization, data related to 345 companies selected from the list of top 500 companies in the United States, for the four years 2016-2019 (Market participant tweets about sample companies from October 2015 to March 2020), extracted and used Was analyzed from Stata software. The results showed that the volume of earnings news published by companies on Twitter could predict earnings surprises, and the content of earnings news published by companies on Twitter can predict earnings surprises. The results also showed that the volume of earning news published by companies on Twitter could predict announcement returns and the content of earning news published by companies on Twitter can predict announcement returns. The results can also be considered a strategy in content analysis of market-quality news based on a list of specialized financial words.

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1. Introduction

Accounting earnings and stock returns are among the essential information influencing investors' decisions in the capital market. With the advancement of information technologies, in addition to quantitative accounting earning information, it is essential to pay attention to the published news and quality information about accounting earnings and stock returns (Watts and Zimmerman, 1978). With the development of information technologies, users of accounting information have gained access to complementary information resources. Investors can access multiple sources to reduce their information gap with companies and other stakeholders, but they may not consider all information sources due to time constraints. Thus, despite the vast amount of data in popular publishing environments such as databases, websites, the press, financial advisory channels, and analysts, there is the potential for significant and sometimes influential information on various aspects of decision-making to be overlooked (Richins et al., 2017). investors 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. However, the past decade has witnessed an explosion in new sources of information that are easily accessible to capital market participants. With the rise of the Internet, individual investors increasingly rely on each other as peer-to-peer sources of information (e.g., Yahoo! Finance, Silicon Investor, and Raging Bull). By far, 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 about stocks instantaneously to a wide audience (Bartov et al., 2018).

The last decade has seen the emergence of new information sources, such as social media, making it easier for market participants to access information. The main difference that can be made between popular publishing channels and social media is that in the approach of publishing by popular media such as the press, the company does not know when investors will receive the information. The press also tends to cover the news of more visible companies, which attracts more readers (Miller, 2006). In contrast, a company using social media can:

1-Publish information to followers directly and without intermediaries.

2-Control the release schedule.

3-Send multiple, duplicate (or similar) messages related to similar information events over several days.

4-Also, know the exact number of followers.

While Twitter undoubtedly is an exciting and emerging new source of information to the capital market, it is unclear whether it will be useful to investors. On the one hand, 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 users comment on it. Finally, Twitter's short format (up to 140 characters) and ease of information search 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.

With the advent of Twitter in March 2006, many companies considered Twitter to be a communication channel for transmitting financial information to investors. As the communication channel mentioned, it changed the methods of publishing company news and the processing of news by users. Following a post from the CEO of Netflix on his personal Facebook page, the company's stock price rose 6.2% in just one day (Bloomberg, 2013). This prompted the Securities and Exchange Commission (SEC) to consider the impact of social media. The Securities and Exchange Commission

(SEC), in a statement issued on April 2, 2013, allowed companies to use social media, especially Twitter, to convey information to investors (Securities and Exchange Commission, 2013; Bartov et al., 2018). The statement provides a formal form of corporate information dissemination, and corporate executives will be directly responsible for the content of Twitter news. The Securities and Exchange Commission's statement on social media reassures investors that corporate tweeting is relevant (Al Guindy, 2017).

On the other hand, with the increasing importance of Twitter in the stock market, the symbol of "cashtag ($)" was introduced by the mentioned social media and made it possible for market participants to tweet about the shares of each company. Twitter has allowed its users to use the slaughter symbol to convey their views on the stock to a wide range of users. Discussions of tweets and interactions between market participants are important in several ways. First, according to the voluntary disclosure theory, companies often spread positive news on social media While tweeting to market participants. It shows a greater variety of tweet content because it conveys collective opinions and not just company opinions and neutralizes companies' strategic dissemination of news (Al Guindy, 2017). Second, gathering participants' opinions on Twitter can be interpreted as a measure of the " Wisdom of crowds" theory. The theory of Wisdom of crowds refers to the phenomenon that the aggregation of information from individuals with diverse and independent views and opinions will lead to better predictions than the predictions of any member of the group or even experts. Thus, the possibility of multidimensional communication on Twitter allows the participants' tweets and comments, including positive, negative and neutral comments, to be transferred to the market. Twitter allows market participants to express their opinions freely. The aggregation of information provided by a wide range of market participants will provide stakeholders with even more accurate information from the opinions of experts and analysts. This is because information intermediaries such as the press and financial analysts often seek to impose their views on others, and the mere reliance of investors on these channels will lead to inaccurate forecasts in capital markets (Stevens and Williams, 2004). In contrast, contributors' tweets provide the opinions of a diverse and broad group of independent users on a timely basis (Bartov et al., 2018).

On the other hand, the information from tweets may be uninformative or even intentionally misleading because Twitter is an unregulated platform with potentially anonymous users. For example, in two days in January 2013, a series of damning but false tweets on two stocks— Audience Inc. (ticker symbol: ADNC) and Sarepta Therapeutics, Inc. (ticker symbol: SRPT)— sent their prices plunging by 28 percent and 16 percent, respectively.

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 investors; another investigates whether information from Twitter predicts the overall stock market; and a third analyzes the relation between Twitter activity and investor response to earnings news.

However, the intriguing question of whether firm-specific information from Twitter is useful in predicting a firm’s earnings and stock returns has not been addressed. In this paper, we fill this gap in the literature by examining whether information from individual tweets about a firm can help investors predict the firm’s earnings and announcement returns. Specifically, we explore the following three research questions: (1) Does the aggregate opinion from individual tweets pertaining to a firm predict its quarterly earnings? (2) Does the aggregate opinion from individual tweets predict the stock price reaction to the firm’s earnings realizations? (3) Does the information environment quality of a company explain the cross-sectional variation in the predictive ability of the aggregate opinion from individual tweets (if it exists)? Gaps and contributions included in the present study relationship between the function of the mass media, with emphasis on two main elements of awareness and information, play an important role in speculating on changes in stock prices and investment decisions. Nowadays, everyone knows the importance and status information for investment decisions. Thus, the function of the mass media, emphasizing two main elements of awareness and information, plays an important role in speculating on changes in stock prices and investment decisions. Researchers in various countries pay less attention to this subject. This study attempts to influence the media to examine the investment decision in stock. In this study, the mass media, including Twitter, investment decision criteria, participation in the stock, and stock options have been adopted. The theoretical foundations, research method, findings, discussion, and conclusion are stated in the research.

2. Literature Review

2.1 Twitter and predicts the overall stock market

In recent years, academic literature has begun to study the role Twitter plays in the capital market. One strand of this literature investigates how companies exploit this new channel to communicate with investors. Blankespoor et al. (2014) show that firms can reduce information asymmetry among investors by broadly disseminating their news using Twitter to send market participants links to press releases and other traditional disclosures. Jung et al. (2018) find that roughly half of S&P 1500 firms have created either a corporate Twitter account or a Facebook page, with a growing preference for Twitter. Lee et al. (2015) show that firms use social media channels like Twitter to interact with investors to attenuate negative price reactions to consumer product recalls.

Another strand of this literature investigates whether information from Twitter predicts the overall stock market. Bollen et al. (2011) show that aggregate mood inferred from textual analysis of daily Twitter feeds can help predict changes in the Dow Jones Index. Similarly, Mao et al. (2012) find that the daily number of tweets that mention S&P 500 stocks is significantly associated with the levels, changes, and absolute changes in the S&P 500 Index. A third strand of this literature analyzes how Twitter activity influences investors' response to earnings. Curtis et al. (2014), who focus on the overall social media (Twitter and Stock Twits) activity over 30-day rolling windows, find 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.

In addition to the literature on Twitter, a broad stream of research has examined investors' use of Internet search engines, financial websites, forums, and other social media platforms. This research has provided mixed evidence on whether this information helps predict future earnings and stock returns. Using Google search volume as a proxy for investors' demand for financial information, Da et al. (2011) find that increases in Google searches predict higher stock prices in the near term followed by a price reversal within a year, while Drake et al. (2012) show that the returns-earnings relation is smaller when Google search volume prior to earnings announcements is high. Examining Internet bulletin boards, Hirschey et al. (2000) find that investment reports in Motley Fool predict stock returns. In contrast, Tumarkin and Whitelaw (2001) find no link between message board activity on Raging Bull and stock returns. Antweiler and Frank (2004) and Das and Chen (2007) find that the volume of messages on message boards, such as Yahoo! or Raging Bull, is associated with stock return volatility, not stock returns. More recently, Jame et al. (2016) show that crowdsourced earnings forecasts on the Estimize platform provide incrementally value relevant information to the capital market to predict earnings and calibrate the market's earnings expectation. Finally, Chen et al. (2014) demonstrate that information in user generated research reports and commentaries on the SeekingAlpha portal helps predict earnings and long-window stock returns following the report posting date. However, unlike investing portals such as SeekingAlpha that publish paid, full-length reports from registered users after verifying their credentials and vetting the quality of the submissions, there is little control or monitoring on an open platform like Twitter.

However, What this literature left unexplored is whether firm-specific information from individual tweets is useful in predicting the firm's earnings and stock returns, the very question we examine in our paper.

2.2 Wisdom of Crowds Theory

The Wisdom of the Crowds concept goes back over a century and refers to the phenomenon that the aggregation of information provided by many individuals often results in predictions that are better than those made by any single member of the group or even experts. Surowiecki (2004) presents numerous case studies and anecdotes to illustrate the Wisdom of Crowds. One classic example from the turn of the 20th century is Sir Francis Galton's surprising finding that the crowd at a county fair accurately predicted the weight of an ox when their individual guesses were averaged. The crowd's average (or median) prediction was closer to the ox's true weight than most crowd members' estimates and even closer than any of the estimates made by cattle experts. Similarly, a trial by jury can be understood as a manifestation of the Wisdom of Crowds, especially when compared to a trial by a judge, the single expert. Berg et al. (2008) analyze the ability of the Iowa Electronic markets to predict election results and find that the markets' prediction shows no bias and a remarkable ability to predict high-profile elections, outperforming polls conducted by experts. Recent papers that build on the Wisdom of Crowds notion show that user-generated research reports and commentaries posted on the SeekingAlpha portal help predict stock returns in several long-term intervals following the report posting date (Chen et al. 2014) and that the content of tweets can be used to predict future returns around Federal Open Market Committee (FOMC) meetings (Azar and Lo 2016).

In related work, Hong and Page (2004) show analytically that a diverse group of intelligent decision-makers reach reliably better decisions than a less diverse group of individuals with superior skills and conclude that under certain conditions, "diversity trumps ability" (p. 16386).

Building on this, Moldoveanu and Martin (2009), by collecting heterogeneous problem solvers, will always beat out a single expert problem solver." This is relevant to the research questions of this paper because anecdotal evidence suggests that Twitter has the most diverse set of users among social media platforms. In contrast, traditional information intermediaries such as financial analysts tend to "herd" to the consensus viewpoint (Jegadeesh and Kim 2010) and produce inefficient earnings forecasts (see, e.g., Abarbanell 1991; Abarbanell and Bernard 1992; Stevens and Williams 2004), perhaps because they belong to a rather small and homogenous group (see, e.g., Welch, 2000; Hong et al., 2000).

To summarize, if the Wisdom of Crowds and the value of diversity and independence apply to the information on the Twitter platform, this information may help predict a firm's earnings and announcement returns.

2.3 Macro accounting theory

a severe wave of accounting research under the heading of macro accounting seeks to use accounting information and data in financial statements to forecast Indicators. Macroaccounting emphasizes economists' view of seasonal accounting (Bekhradi Nasab et al., 2020). The emergence of a new theory of "macro accounting" with a new wave of accounting research over the last decade tries to explain and use the Aggregate information of interim accounting statements in economic forecasts. Macroaccounting theory suggests that economists and macroeconomic forecasters use Aggregate accounting information at the macroeconomic level. For example, accounting earnings are used to predict GDP, cost stickiness is used to predict unemployment, and the ratio of book value to market value is used to predict inflation. Earnings growth dispersion contains information about trends in labor reallocation, unemployment change, and aggregate output (Bekhradi Nasab et al., 2022). using macro accounting theory and numerous types of research by Bekhradi Nasab et al. (2020, 2022), aggregate accounting information is used to predict accounting earnings and stock returns.

2.4 Aggregate opinion and predict earnings surprises

Our first research question asks, can the aggregate opinion from individual tweets regarding a company, expressed by individuals just before its earnings announcement, predict its earnings? An implication of the Wisdom of Crowds and the value of diversity and independence concepts is that the aggregation of opinions derived from individual tweets may help in predicting earnings. This would be the case when individual tweets reflect the opinions of a large and diverse group of people making independent and timely assessments of a company's future earnings. Specifically, positive aggregate opinion may suggest company performance that exceeds prior expectations, while negative aggregate opinion may suggest company performance that disappoints prior expectations (Bartov et al., 2018).

As an example of direct-access information technology (DAIT), social media uses web-based approaches to create an interactive communication platform, enabling individuals and communities to share and refine their opinions. The company's decision to disseminate information through social media channels is a developed perspective on the disclosure strategy (Jung et al., 2018). In the disclosure strategy, the nature and different levels of disclosure, as well as publication channels, are examined. Thus, the multiplicity of publishing channels can improve public awareness of company disclosures and, by reducing the existing information gap, create a better understanding for the investor. Suppose the company expects to improve its information environment by increasing the level of disclosure. In that case, it can be expected that increasing the channels of publishing and transmitting news from such channels, such as Twitter, as a source of complementary awareness will reduce information asymmetry. In the first post-US Securities and Exchange Statement, Blankespoor et al. (2014) examined "The Role of Publishing in Market Liquidity: Evidence for Companies' Use of Twitter" and found that Publishing Company News Through Twitter reduces information asymmetry and increases liquidity. Al Guindy (2017) considered the role of social media in financial markets. He also examined the relationship between companies' use of social media and cost reduction of capital, as well as the role of Twitter in improving the information environment. Comparative results before and after the US Securities and Exchange Commission statement show that companies have become more inclined to spread the news via Twitter after the announcement. The results show that Twitter is a complementary source of information for investors and that using Twitter reduces information asymmetries between companies and investors, thus reducing the cost of capital. Jung et al. (2018) examined the relationship between news releases via Twitter and market reaction and concluded that the number of followers of news via Twitter and republishing news by followers affects market reaction. As companies tweet about earnings announcements and more followers receive the tweet, the abnormal difference between the buying and selling prices decreases, indicating a reduction in information asymmetry. In the first hypothesis of the research, the volume and content of earning news published by companies on Twitter social media is considered and its relationship with earnings surprises is examined:

H1. The volume of earnings news published by companies on Twitter can predict earnings surprises.

H2. The content of earnings news published by companies on Twitter can predict earnings surprises.

2.5 Aggregate opinion and predict announcement returns

Our second research question examines the relation between the aggregate opinion from individual tweets written just prior to the earnings announcement and the market response to earnings. The presence of complementary information in the capital market improves the market information environment and, ultimately, improves stakeholder decision-making (Warren et al., 2015). From a theoretical point of view, given that Twitter has the most user diversity among social media, the concept of collective insight into Twitter becomes relevant. The theory of collective insight refers to the phenomenon that the aggregation of information from individuals with diverse and independent views and opinions will lead to better predictions than the predictions of any member of the group or even experts. On the importance of informing the Twitter social media environment in terms of increasing market participants Wisdom crowd, Bollen et al. (2011) found that the Wisdom crowds inferred from the textual analysis of participants' daily tweets could predict changes in the Dow Jones index. Mao et al. (2012) found that the number of daily tweets of market participants about the top 500 Standard & Poor's (S&P500) stocks was significantly related to the level of change in the stock index. Curtis et al. (2014) examined the tweets posted by market participants in the Stock twit environment and found that tweeting at the social media level had a significant relationship with earnings. Al Guindy (2017) considers the role of Twitter in improving the information environment by increasing the Wisdom crowd of investors. The results showed that if Twitter news caused a positive feeling in investors, stock returns would be higher; otherwise, stock returns would be lower. This effect is especially pronounced when there is no consensus among financial analysts. Bartov et al. (2018) examined the opinions of people who follow corporate tweets and found that aggregating their opinions predicts future quarterly earnings and corporate earnings returns. In the second hypothesis of the research, the volume and content of earning news published by companies on Twitter social media are considered and its relationship with earnings surprises is examined:

H3. The volume of earnings news published by companies on Twitter can predict announcement returns.

H4. The content of earning news published by companies on Twitter can predict announcement returns.

3. Research Methodology

This research used Excel software to collect and classify raw data and Stata software for multivariate regression analysis. To collect data on the theoretical framework of the research and its background, articles published on the website of the American Accounting Association (www.aaa.com) between 2014 and 2019 have been used. The statistical knowledge used includes descriptive statistics to describe and present statistical characteristics of variables and parameters and inferential statistics include estimation and estimation of coefficients.

Twitter data, including the volume and text of tweets posted on the corporate Twitter page and the number of corporate Twitter followers on the date of each tweet, was used to modify the content variable of the tweets using the Python language and " Application Programming Interface (API)" and Web scraping techniques. Has been extracted. These techniques automatically collect data. There are also tweets related to market participants' opinions about each sample company, which are extracted by adding the slash symbol ($) to the beginning of the companies' Twitter IDs. This data also includes the volume and text of the participants 'tweets and the number of participants' followers on the history of each tweet. In order to extract data related to the measurement of independent variables (volume and content of tweets), the total tweets of the sample companies from the beginning of October 2015 to March 2020, including 550,000 tweets, were extracted in the first stage. In the second stage, the tweets published in the research estimation period, i.e. the 58 days before the earning announcement (2-to-60), were filtered and the number of tweets reached 179495. In the last step, the tweets were re-filtered to separate the tweets containing the earning announcement information, in which the number of tweets reached 9145. Also, to extract market participant tweets, in the first stage, the total market participant tweets about sample companies from the beginning of October 2015 to March 2020, including 450,000 extracted tweets. In the second stage, the tweets posted in the research estimation period were filtered. At this stage, the number of tweets reached 130,905. In the last step, the separation of tweets containing news of earnings announcements was done, and the number of tweets reached 20,037. It should be noted that the identification of tweets containing earning announcement information has been done based on the analysis of the content of the tweets and using the word list introduced by Bartov et al. (2018). The necessary condition is the presence of at least one of the words representing the earning announcement news in the desired tweet. Market data in this study were the maximum and minimum three-day stock prices to measure the dependent variable and were extracted manually from the relevant website (www.investing.com). To collect market data by referring to the mentioned site, first, identify the date of the earnings announcement of each company and separately for each financial period and then, based on it, estimate the period of 60 calendar days before the announcement of earnings to 2 days before the date It is an earning announcement, it has been specified. Market data are then extracted for the estimated and event periods (the three days around the earnings announcement). The estimation period is based on a calendar because the basis for extracting Twitter data is also the estimation period, and the basis for tweeting companies and other Twitter users is not based on the working days of the stock market. On the other hand, the three days around the earnings announcement are the stock exchange's working days. Control variable data were manually extracted from corporate financial statements and websites (www.gurufocus.com, www.investing.com, www.fortune.com, www.siccode.com, www.sec.gov).

The statistical population consists of the top 500 companies in the US stock market from 2016 to 2019. These companies account for 80% of the value of the US stock market and include 500 large and active companies. This is one of the most important indicators of the overall performance of the US stock market. In the first step to determine the sample size, the companies on the list of the top 500 companies on the US stock exchange were selected at least once during the research period (from November 2015 to March 31, 2019). At this stage, the number of companies was 642. The initial list of companies was extracted from the relevant website. In the next step to select a statistical sample, the following items were considered:

1 company that has an official Twitter page.

2- Companies that joined Twitter in early November 2015 or earlier.

3-Companies listed on the New York Stock Exchange and the Nasdaq Stock Exchange.

It should be noted that companies with basic information and incomplete companies were excluded from the statistical sample. These companies numbered 21; Also 8 companies that the ratio of market value to negative book value (negative property rights)

They were also left out. With this selection, the final statistical sample reached 345 companies.

Regression model of hypotheses following the research Bartov et al. (2018) As follows:

Equation (1)

$$ESURP = \alpha + \beta_1 \sum OPI_{[-10:-2]} + \beta_2 PRIOR\_ESURP + \beta_3 EXRET_{[-10:-2]} + \beta_4 RP\_OPI + \beta_5 SIZE + \beta_6 MB + \beta_7 ANL + \beta_8 INST + \beta_9 Q_4 + \beta_{10} LOSS + \varepsilon$$

Equation (2)

$$EXRET_{[-1:+1]} = \alpha + \beta_1 \sum OPI_{[-10:-2]} + \beta_2 EXRET_{[-10:-2]} + \beta_3 RP\_OPI + \beta_4 ANL + \beta_5 INST + \beta_6 Q4 + \beta_7 LOSS + \varepsilon$$

In these models:

ESURP: In Equation (1), the dependent variable, ESURP, is the earnings surprise, measured using either

EXRET: In Equation (2), the dependent variable, EXRET [-1; +1], is Carhart's (1997) buy-and-hold abnormal stock returns for the firm over the three-day window, [-1; +1], multiplied by 100. OPI [-10; -2], the test variable in Equation (2), captures the aggregate opinion at the firm-quarter level extracted from individual tweets written in days -10 to -2.

OPI: The primary challenge underlying our research design is the estimation of OPI. Along with prior research, we use textual analysis to quantify the opinions expressed in individual tweets. Since performing textual analysis using any word classification scheme is inherently imprecise (Loughran and McDonald, 2011), we measure OPI using Several alternatives and considerably different textual analysis methodologies. Independent research variables include the publication, number and content of earnings news published by companies and market participants.

1-Firms Earnings Announcement Tweets (FEAT): This variable is two-digit. So, if the company has at least one earning announcement tweet in the estimation period, it is equal to one and otherwise zero (Jung et al., 2018).

2-Firms Earnings Announcement Tweets Frequency (FEAT-F): This variable is logarithmically one plus the number of earning Tweets posted by each company on Twitter during the estimation period (Jung et al., 2018).

3-Firms-TONE (FTONE): Textual analysis was used to measure the content of the companies' earnings announcement tweets. For this purpose, after selecting the tweets containing earning announcement news based on the dictionary list[1] of Bartov et al. (2018), the content analysis of the tweets was performed using the word list provided by Loughran and McDonald[2] in 2011. According to the textual analysis based on the list of words mentioned in previous studies, content analysis based on the negative words in this list is more accurate (Bartov et al., 2018). Therefore, content 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 weighting method for each tweet is based on the number of followers of the company's Twitter page and multiplying the number of negative words in each tweet by one plus the logarithm of one plus the number of followers on the earning announcement date. Then, the total number of weighted negative words in the tweets during the estimation period is multiplied by -1 and divided by one plus the total number of positive and negative words in the tweets (Bartov et al., 2018).

Equation (3)

$$FTONE = -1 \times \frac{\left(\sum\left[Tweets\ for\ Each\ Negative\ Number\ of\ Words \times [1 + (log1 + Number\ of\ Followers)]\right]\right)}{(1 + Negative\ and\ Positive\ Number\ of\ Words)}$$

4-Individuals Earnings Announcement Tweets (IEAT): earning Posting on Twitter: This variable is defined as a two-value variable; So that if the company in the estimation period has at least one earning announcement tweet from the market participants, it is equal to one and otherwise it is equal to zero.

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, erning, proforma, pro-forma, results, revenue, sales, yearend, year-end.

2- The LM Vocabulary was introduced in 2011 by Loughran and McDonald to analyze k-10 reports, which is a modification of the Harvard Vocabulary. This dictionary is specifically related to the language of finance and has been tested in capital market research to evaluate the content of reports, the text of calls, as well as tweets.

5-Individuals Earnings Announcement Tweets Frequency (IEAT-F): The variable is logarithmically one plus the number of earning announcement tweets posted by market participants on Twitter during the estimation period.

6-Individuals-TONE (ITONE): The content variable of the messages posted by market participants on Twitter is measured the same way as the content variable of the earning tweets posted by companies.

The control variables are as follows.

INST: Number of shares held by institutional investors scaled by total shares outstanding as of the quarter end date.

LOSS: Indicator variable equal to one if earnings before extraordinary items (IBQ) is strictly negative in the prior quarter, zero otherwise.

MB: Ratio of market value to book value of equity ([CSHOQ*PRCCQ]/CEQQ).

MVE is the market value of equity (CSHOQ*PRCCQ).

RP_OPI: Total number of traditional news events classified as positive less total number of traditional news events classified as negative during the nine-trading-day window [-10; -2], where day zero is the quarterly earnings announcement date, using the RavenPack database. Each positive or negative traditional news event is weighted by RavenPack's ESS (Event Sentiment Score), rescaled to range between 0 and 1, where higher values indicate the sum of the ESS scales stronger sentiment, and the measure rescaled.

SIZE: Natural logarithm of MVE.

SUE: Standardized unexpected earnings are measured using quarterly diluted earnings per share excluding extraordinary items (EPSFXQ) and applying a seasonal random walk with drift model.

ANL: Natural logarithm of one plus the number of analysts in the latest I/B/E/S consensus analyst quarterly earnings per share forecast prior to the quarter-end date.

Q4: The indicator variable is equal to one if the quarter is the fourth fiscal quarter or zero otherwise.

3.1 Research findings

Table (1) presents our sample's descriptive statistics on Twitter activity and variables.

Then, in order to choose between panel regression models and OLS, the F-Limer test was used, and finally, the panel regression model was selected as the appropriate model. After selecting the panel regression model as a suitable model, the choice between fixed effects panel regression models and random effects panel regression was made using the Hausman test.

The results of the Hausman test showed that the panel was selected with random effects. The merger test was used to test the integrated data model against random effects, which showed that there is no ability to integrate temporal and spatial effects in the model.

Table 1. Descriptive statistics of quantitative variables used in the panel regression

Variables	Mean	Max	Min	S.d
FEAT-F	0/532	1/69	0	0/5
FTONE	-1/19	0	-4/809	1/406
IEAT_F	0/92	1/78	0	0/47
ITONE	-1/57	0	3/37	0/95
ESURP	0/01	0/04	-0/007	0/01
EXRET	45/33	81/29	3/63	14/4
SIZE	4/33	5/58	3/18	0/48
ANL	0/07	0/92	-0/29	0/15

MB	5/9	96/43	0/55	11/63
LEVE	0/3	0/81	0/01	0/17
Q4	67	1	0	48/66

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 showed that the assumption of variance homology of the remaining models was not established. Also, the serial autocorrelation study results between the rest of the models showed that the underlying assumptions of variance homogeneity and lack of serial autocorrelation are not established for the above models. Therefore, the least generalized quadratic regression model is used to solve the problems of variance inequality and serial autocorrelation. The following are the results of testing the hypotheses in Tables (2) and (3).

Table 2. The results of the first and second Hypotheses test

$$\boldsymbol{ESURP} = \alpha + \beta_1 \sum \boldsymbol{OPI}_{[-10:-2]} + \beta_2 \boldsymbol{PRIOR\_ESURP} + \beta_3 \boldsymbol{EXRET}_{[-10:-2]} + \beta_4 \boldsymbol{RP\_OPI} + \beta_5 \boldsymbol{SIZE} + \beta_6 \boldsymbol{MB} + \beta_7 \boldsymbol{ANL} + \beta_8 \boldsymbol{INST} + \beta_9 \boldsymbol{Q_4} + \beta_{10} \boldsymbol{LOSS} + \varepsilon$$

Variable	**Coefficient (t-statistic)**			
	ESURP			
	FEAT-F	**FTONE**	**IEAT_F**	**ITONE**
	Model I	**Model II**	**Model III**	**Model IV**
Intercept	-1.0683*** (-14.12)	-1.4254*** (-15.36)	-0.3678*** (-6.78)	-0.5426*** (-6.63)
OPI	0.0235 (0.02)	0.1547*** (7.63)	0.0254 (1.67)	0.0365* (1.86)
PRIOR_ESURP	0.3624*** (46.52)	0.9784*** (54.47)	0.1648*** (11.73)	0.1657*** (11.89)
$EXRET_{[-10;-2]}$	0.0126*** (5.87)	0.0248*** (5.58)	0.0125*** (5.71)	0.0247*** (5.47)
RP_OPI	0.5698*** (5.76)	0.4985*** (5.47)	0.1745*** (2.74)	0.5269*** (2.89)
SIZE	0.4985*** (8.86)	0.4896*** (11.76)	0.7589*** (4.75)	0.5963*** (4.01)
MB	-0.1564** (-2.11)	-0.7598 (-0.16)	0.2596 (0.76)	0.2657 (1.11)
ANL	-0.5968*** - (-3.16)	0.6512** (-2.57)	0.5496 (0.45)	0.4785 (0.88)
INST	0.8965** (2.64)	0.7319 (0.93)	0.8164*** (5.54)	0.7518*** (5.12)
Q4	0.8569*** (7.11)	0.8753*** (8.25)	- 0.1547*** (-4.67)	- 0.2658*** (-4.89)
LOSS	0.5677*** (16.88)	0.5932*** (16.77)	-0.4587** (-2.13)	-0.5789** (-2.11)

The results of Table 5 show a significant difference between companies that do not have earnings tweets and companies that do not, and there is a positive relationship between the number of earnings announcement tweets published by companies earning surprise. And there is meaning. In other words, with the increase in the number of earnings tweets posted by companies on the Twitter page, earning surprise increases. There is also a significant positive relationship between the negative content of earning tweets published on each company's official Twitter page and earning surprises. In other words, with the increase in the level of positivity of corporate earning tweets, earning surprise increases.

Table 3. The results of the third and fourth Hypotheses test

$$EXRET_{[-1:+1]} = \alpha + \beta_1 \sum OPI_{[-10:-2]} + \beta_2 EXRET_{[-10:-2]} + \beta_3 RP\_OPI + \beta_4 ANL + \beta_5 INST + \beta_6 Q4 + \beta_7 LOSS + \varepsilon$$

Variable	Coefficient (t-statistic)			
	ESURP			
	FEAT-F	FTONE	IEAT_F	ITONE
	Model I	Model II	Model III	Model IV
Intercept	-1.6354*** (-11.45)	- 1.5987*** (-11.65)	- 0.6958*** (-6.65)	-0.1267*** (-6.59)
OPI	0.26987*** (4.44)	0.5987*** (9.56)	0.2957** (2.89)	0.6587* (2.01)
$EXRET_{[-10;-2]}$	0.2654*** (8.56)	0.3651*** (8.77)	0.5987*** (5.21)	0.1658*** (5.11)
RP_OPI	0.5698*** (6.25)	0.4563*** (6.26)	0.2514*** (3.14)	0.4584*** (3.33)
ANL	-0.5265*** - (-3.06)	0.6598** (-2.17)	0.2471 (0.36)	0.5624 (0.67)
INST	0.6528** (2.63)	0.2651 (0.85)	0.9531*** (5.45)	0.8569*** (5.49)
Q4	0.5987*** (7.77)	0.5698*** (8.54)	-0.6257*** (-5.85)	-0.4598*** (-5.43)
LOSS	0.0698*** (19.58)	0.0596*** (19.09)	-0.2657** (-3.59)	-0.3659** (-3.15)

The results of Table (6) show that announcement returns in companies with earning announcement tweets are significantly different from companies that do not have earning announcement tweets. A positive relationship exists between the number of earning announcement tweets companies publish and announcement returns. Further, there is meaning. In other words, as the number of earning tweets posted by companies on the Twitter page increases, the earning of earnings announcements increases. A positive and significant relationship exists between the negative content of earning tweets published on each company's official Twitter page and the announcement returns. In other words, with the increase in the level of positivity of corporate earning tweets, the announcement returns increase.

4. Conclusion

The dramatic increase in the use of social media these past few years had a significant impact on the capital market. Firms use social media to communicate with their investor base and increasingly, individual investors use social media to share information and insights about stocks. We examine whether the aggregate opinion from individual tweets prior to a quarterly earnings announcement (a recurring, price-moving event scrutinized closely by market participants) is useful in predicting a company's quarterly earnings and announcement returns. We analyze a broad sample of individual tweets written in the nine-trading-day period leading up to the firms' quarterly earnings announcements in the four years 2016–2019 (Market participant tweets about sample companies from October 2015 to March 2020). Two alternative measures of aggregate opinion from individual tweets serve as our test variables. We find that the aggregate Twitter opinion helps predict quarterly earnings after controlling for other determinants of earnings, including aggregate opinion from traditional media sources. We also find that the aggregate Twitter opinion predicts abnormal returns around earnings announcements.

The overall results show that differences in the source of earning news on Twitter will positively affect earning surprise and announcement returns. Also, the existence of a significant relationship between the volume and content of tweets containing earning news from companies and earning surprise and announcement returns shows that social media, as a multidimensional communication channel, is a source for disseminating information with wide coverage. In other words, publishing additional news through social media channels can be considered as a complementary source of information to improve the information content of earning or strategic publication of news by companies. Accordingly, investors active in the web environment are advised to consider social media as a channel for disseminating information with wide coverage and to benefit from the benefits of this communication channel, along with other sources of information, to increase their awareness of investment decisions. On the other hand, in order to eliminate the negative effects of social media, it is recommended that users use caution and vigilance when using social media as a source of information. Companies that use social media to publish news are also advised to use a uniform policy to publish information on social media to maintain their credibility; otherwise, the credibility of the news will be challenged. The research results show the great importance of publishing information (general market and economy information and financial and accounting information of companies) on the intention of real investors to invest in the stock market. Therefore, the development of information and information technology and transparency in the stock exchange will play an effective role in encouraging more segments of society to invest in the stock exchange and, consequently, increase the country's market efficiency and economic development. On the other hand, with the development of information technology in the stock market, it will be possible to predict future market behaviors. Therefore, there is a need for more appropriate information for stock market investors to make decisions through television, newspapers and the Internet (in the fields of education, marketing communications and providing political, economic and financial news to companies) as well as providing real news and information, timely and up to date. Access to investors is emphasized through a variety of mass media. The results of testing the hypotheses are consistent with the results of research by Jung et al. (2018) and Bartov et al. (2018).

Finally, considering the importance of social media in financial markets worldwide, it is suggested that in future research, the role of social media on various aspects of the market, improving information transparency and information quality characteristics in the form of empirical research and comparing the results. Also, the effects of each social media in the financial markets will be compared by comparing popular media and social networks in the country and social media worldwide. Comparing the information environment inside the country with abroad, in terms of related field characteristics and common mechanisms for publishing information through social media channels can be more informative about the existing differences.

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