Do Twitter Sentiments Really Effective on Energy Stocks? Evidence from Intercompany Dependency

Yılmaz, Emrah Sıtkı and Ozpolat, Aslı and Destek, Mehmet Akif

Gaziantep University, Gaziantep University, Gaziantep University

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Emrah Sitki Yilmaz
Department of Accounting and Tax Applications
Gaziantep University, Gaziantep, Turkey
ORCID: 0000-0003-2741-4222
esyilmaz@gantep.edu.tr

Asli Ozpolat
Department of Management and Organization
Gaziantep University, Gaziantep, Turkey
ORCID: 0000-0002-1769-3654
ozpolat@gantep.edu.tr

Mehmet Akif Destek
Department of Economics
Gaziantep University, Gaziantep, Turkey
ORCID: 0000-0002-2514-9405
adestek@gantep.edu.tr

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ABSTRACT: The study aims to examine the effects of social media activities on stock prices of the energy sector. In this respect, the sample covers the monthly period from 2015m6 to 2020m5 has been observed. Energy stocks as S&P 500 index (SP), stock market volatility index (VIX), trade-weighted USD index (USD) and Brent oil prices (OIL) have been used as independent variables. Accordingly, three different models have been created to analyze the link between returns, volatility and trading volume and Twitter sentiments by using Augment mean Group. As a result, we found that Twitter sentiment values have no significant impact on the returns and volatility of the companies. Tweets, on the other hand, appear to have a favorable impact on company trading volume values.

Keywords: social media, Twitter, Energy Sector, Stock Prices

1. Introduction

Classical financial theory accepts that investors act rationally and that irrational behaviors are not effective in determining stock prices. (Zhang et al. 2018: 50). The efficiency of capital markets and rationality is possible in the presence of all available information about stock prices. In addition, according to the efficient market hypothesis, there is the symmetrical distribution of information in the market for the prediction of future values of stock prices. Therefore, the efficient market hypothesis states that all information that will require investors to act rationally is available in the market. In this context, social media is used as an important tool for the distribution of information to the public. Companies can make shares that can affect the company's value and increase their brand values through their social media accounts. (Sun et al, 2020). Social media is expressed as both hardware and technological innovation software (Web 2.0) covering content creation, interaction, and interoperability. Social media has recently become very important for companies in terms of establishing direct relations with customers and investors and ensuring information transparency (Wang and Kim, 2017: 15). Therefore, technological developments affect the interaction of organizations with current and potential customers. Especially the emergence of Web 2.0 technologies and the increasing popularity of social media has allowed it to be more direct and interactive. This form of communication, where users can easily share information, has an important place in the information sharing of companies. (Siamagha et al., 2015:89). According to "we are social's digital around the World" (2021) report, the number of internet users in the world is 4.88 billion, which is 62% of the world's population, and the number of social media users is 4.55 billion. According to the report, there are 2.895 million active users on Facebook and 436 million active users on Twitter. When we look at the size of the numbers in general, it is seen that social media tools such as Google, Facebook and Twitter have the potential to affect companies' volatility, trading volume and daily stock prices. In addition, social media also affects the moods and tendencies of investors.

Positive investors may be more optimistic about the risks and returns of financial assets. (Sun et al, 2019; Reboredo and Ugolini , 2018). According to these approaches, which are examined within the scope of behavioral economics studies, bad mood, and anxiety cause investors to have negative tendencies and can affect investment decisions and asset prices. (Kaplanski and Levy, 2010: 174). Figure 1 shows the effects of mood changes on investors' decisions.

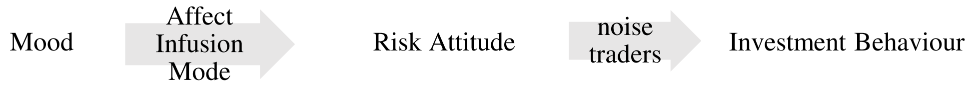

Fig. 1. Link Between Mood and Investment Behavior (Nofer and Hinz ;2015:232)

The stress level of individuals and therefore investors can be directly affected by bad or positive moods and even social media sharing with other people. (see, for example, Mitchel and Phillipps, 2007; Hirshleifer and Shumway, 2003; Wann et al,1994). Saunders (1993) in her study on the New York stock market between 1927-1989, stated that stock returns are lower on cloudy days than on sunny days. Therefore, in the light of technological developments, the effect of social media shares on investors' decisions, in general, includes findings worth investigating.

In this context, the study aims to measure the effect of social media activities on stock prices of energy firms. From this view, the models have been estimated using monthly data from 2015 m6 to 2020m5 for the energy sector, which are 20 companies in S&P 500. For this purpose, three different models were created. While the first model analyzed the tweet sentiment relationship on stock returns, the effects on volatility and trade volume were examined in the other models. Augmented Mean Group (AMG) analysis was used in the estimation of the models. To the best of our knowledge, the contributions of this study to the existing literature are three-fold: i) this is the first study to observe the impact of twitter sentiment values on energy firms' return values using with second generation panel data methodologies which allows the possible cross-sectional dependence among observed firms. ii) Besides firm's returns, we also examine the impact of twitter sentiment on firms' volatility and trading volume values and this situation gives us a chance to more accurate inferences. iii) to avoid possible omitted variable bias, this study also uses the S&P 500 index, oil price, USD index and stock market volatility index as independent variables.

From point of this view, the study frame is generally prepared as the following: Section 2 is reviewed the studies and findings on the effect of social media and stock prices. Section 3 describes data and methodology. The results are given in Section 4 and based on the results, conclusions and policy recommendations are in section 5.

2. Literature Review

There are very few empirical studies examining the relationship between firms' social media activities and firm value. When these studies are examined, empirical studies generally focus on tweeter sentiment, google search queries and Facebook activities. The main point in the studies is whether investors' tendencies are affected by activities that affect individual mood, such as daily news and social media. (see for example, Bollen et al, 2011; Mao et al, 2012; Mittal and Goel, 2012; Siganos et al, 2017; Bakar et al, 2014; Guo and Ji, 2013; You et al., 2017; Tajvidi and Karami , 2017; Bartov et al. 2018; Siikanen et al. 2018). When previous studies are examined, the relationships between social media and firm value, trading volume, volatility and stock prices have been examined using various empirical methods. because of empirical studies are predominantly that social media affects the decisions of investors and because of these effects, social media sensitivity has a spillover effect between stock prices and firm value. Schaupp The findings obtained and Belanger (2014) concluded that the contributions of social media to companies are internal operations, marketing, customer service and sales. Sun et al. (2019) stated that social media has a positive effect on firm value and increases not only communication between firms and the public but also firm promotion and brand value. In addition, the existence of an inverted U-shaped relationship between stock prices and company news and investors' attention was also obtained. Similarly, Zu et al. (2019) examined the relationship between social media input intensities and firm performance of companies in the China Stock Market between 2010 and 2014. According to the results of the study, an inverted U-shaped relationship was obtained between firm performance and input density. In addition, it was concluded that the size of the firm increased the social media input density, and the tendencies of the investors were positively affected. Giannini et al. (2019) obtained the existence of a strong relationship between social media and the stock market. Accordingly, fluctuations in stock prices are directly affected by social media activities. Tonghui et al. (2020) applied Granger causality analysis in their study for the CSI 300 index and found that there was a high correlation between fluctuations in stock markets and social media. They concluded that social media plays a key role, especially in fluctuations in crisis and boom periods. According to Diebold and Yilmaz (2014), which supports these results, there is a bidirectional distribution effect between renewable energy stock and social media. Majumdar and Bose (2019). They concluded that the social media activities of manufacturing companies increase the value of the company. Wang and Kim (2017), in their study on 232 companies, found that social media made a positive contribution to customer relationship management and increased the performance of the company in a certain way. Zhang et al. (2018) obtained the existence of a strong causal relationship between daily happiness sentiment from twitter and stock returns. Accordingly, the existence of a causal relationship between investors' tendencies and stock returns indicates that future prices of financial assets can be predicted. In other words, the validity of the efficient markets hypothesis is supported. Kim and Kim (2014), Da et al. (2015) and López-Cabarcos et al. (2017) have reached findings that support this result in their studies.

When the studies examining the relationship between the stock market and Facebook, twitter and Google sentiment are examined, it is concluded that most investors and stock prices are positively affected by the Facebook, Twitter, and Google activities of the companies. In one of these studies, Li et al. (2017) found that there is a positive relationship between twitter activities of firms, stock returns and trading volume. In addition, there is a bidirectional relationship between daily happiness and market variables. Ronco et al. (2015) found that twitter volume and sentiment influenced abnormal stock returns, while Meinusch and Tilman (2015) concluded that the number of tweets also influenced interest rates, Exchange rates and asset prices. Rao and Srivastava (2013) concluded that the effect of twitter sentiment on oil, gold and market indices is remarkably high. Sprenger et al (2014) examined the relationship between twitter micblogging and stock market and found associations between stock return and trading volume and tweet sentiment. Lazzini et. al. (2021), investigated the effects of social media on the Italian stock market during the Covid-19 period. The main purpose of the study is to investigate the effect of social media activities on the extreme volatility of the stock market in an environment of uncertainty caused by covid, with Granger causality analysis. According to the results obtained, there is a strong relationship between the frequency and intensity of Twitter usage and stock market tendency.

In addition to these studies, there are some studies that indicate the effect of social media on stock prices by two channels: the hoarding aversion effect (managerial bad news hoarding behaviors) and the magnified market reaction effect (the power of market reaction when the bad news is published). Related to these, Rakowski et al. (2020) state that social media strengthens the basic information about a firm and thus can eliminate the problem of asymmetric information. Hence, tweets including consciousness on social media, not only support the timing of information about companies but also increase the effectiveness of managers. In that case, the manager’s behaviors have a crucial impact on stock prices through social media. Hossain et. al. (2021) study the nexus between future stock prices and the number of tweets and the findings support the positive effect on variables. Therefore, the results state the hoarding aversion effect. Contrary to this view, sharing all information, especially bad news, via social media can cause a negative reaction in the market. Jin and Myer’s (2006) indicate that sharing bad news negatively affects the market. Their studies support the magnified market reaction effect. At this stage, reference is made to the distinction between bad and good news. In addition, it is stated that online fake news can significantly reduce the value of the company. Velichety and Shrivastava (2022) find that fake online news could cause approximately USD 2.11 Million in equity depreciation over a ten-day period, and by creating uncertainty, 67.17 million fake tweets could cause a loss of approximately 10 million USD.

One of the most recent studies in this field is Zaman et.al. (2022), in which Elon Musk's tweets examine the relationship between Bitcoin prices. As a result of the analysis, it was concluded that Elon Musk's tweets increased bitcoin prices. In addition, it was stated in the study that these increases were not significant, and the tweet sensitivity of bitcoin prices was low. Similarly, Hamraoui and Boubaker (2022) examined the effects of twitter on stock returns for 22 Tunisian companies. They found that although tweet numbers do not give highly effective results, they can be used for price volatility.

On the contrary, some research indicates that there is no link between social media and stock prices and firms value. Reboredo and Ugolini (2018) examined the relationship between Twitter sentiment and stock prices for 17 clean energy companies in their study on the renewable energy sector. The findings show that twitter sentiment is not sufficient for future price prediction, volatility, or trade volume. At the same time, it is stated that the spread effect is moderate, the spread effect of volatility and trade volume is asymmetrical. Similarly, Jung et al. (2017) examined the strategic information dissemination strategies of companies and the dissemination channels they use in this context. For dissemination, they found that firms' Twitter quarterly earnings announcements were less likely to spread via Twitter. Nofer and Hinz (2015) examined the effect of 100 million tweets on investors in Germany between 2011 and 2013. As a result of the study, no relationship was found between twitter mood states and the stock market.

There are few studies involving Facebook data. Among these studies, Siganos et. Al (2017), in their study on Facebook data, found that there is a positive relationship between Facebook shares of companies and asset prices. Karabulut (2013) examined the effect of Facebook's Gross National Happiness index on investor sentiment and stated that this index is effective in estimating US daily returns. When we look at the studies examining the effects of Google searches on stock markets, it is concluded that Google searches are an effective tool in estimating asset prices and affecting asset prices. Guo and Ji, (2013) investigated the relationship between oil prices and Google volume search queries and found the existence of a long-term relationship between the variables. Similarly, Han et al. (2017) concluded that Google search queries are effective on daily oil prices. Afkhami et al (2017), in their study for different markets, concluded that Google search activities have a wide impact on the behaviour of investors. Vozlyublennaia (2014), using S&P 500 Nasdaq and Dow Jones data, examined the relationship between stock market values of small and medium-sized enterprises and Google queries and stated that investors were temporarily affected by Google queries.

Finally, there are studies examining the effects of media on stock crashes and jumps. One of these studies, Aman (2013), concluded in his study that while the media has an intense effect on a stock crash, it does not have a positive effect on stock jumps. Comparable results were found in Miller (2006), Huberman and Regev (2001), Chan, (2003), Fang and Peress, (2009), Tetlock, (2007), Tetlock et al., (2008) and Bushee et al., (2010) is also observed in their studies. Accordingly, media activities have an impact on firm activities, value, and investors' decisions.

3. Empirical Model, Data and Methodology

3.1. Model and Data

In order to observe the impact of Twitter sentiment on energy stocks, we observe the sample covers the monthly period from 2015m6 to 2020m5. Following the study of Reboredo and Ugolini (2018), we construct three empirical models as follows:

$$Return_{it} = a_0 + a_1 TS_{it} + a_2 SP_{it} + a_3 VIX_{it} + a_4 USD_{it} + a_5 OIL_{it} + u_{1it} \quad (1)$$

$$Volatility_{it} = a_0 + a_1 TS_{it} + a_2 SP_{it} + a_3 VIX_{it} + a_4 USD_{it} + a_5 OIL_{it} + u_{2it} \quad (2)$$

$$Trading\ Volume_{it} = a_0 + a_1 TS_{it} + a_2 SP_{it} + a_3 VIX_{it} + a_4 USD_{it} + a_5 OIL_{it} + u_{3it} \quad (3)$$

where Returns is monthly returns of each firm, volatility indicates monthly volatility of stocks for each firm and trading volume implies monthly trading volumes of firms. As a proxy for twitter sentiment, we used the natural logarithm of tweet activities of each firm. In addition, we also benefitted from some regressors which are accepted as the crucial factors that affect the energy stocks as S&P 500 index (SP), stock market volatility index (VIX), trade-weighted USD index (USD) and Brent oil prices (OIL).

For sentiment analysis, we used a machine learning approach involving the use of natural language processing to the identification of utterances that indicate authors' opinion-based attitudes towards items (Li & Hovy, 2017). Consistent with the previously accepted methodology for researching energy firms in the UK (Mogaji et al., 2020), customer tweets were collected as a direct representation of their interactions with brands and other clients. Python was utilized for twitter mining and sentiment analysis, notably Twitterscraper and Textblob. Textblob contains a vast vocabulary document and can effectively do practically any activity involving idea mining. It combines natural language processing (NLP) and machine learning concepts to analyze the words in a phrase or tweet and determine if the message as a whole is positive or negative (Mogaji and Erkan, 2019; Mogaji et al., 2020; Textblob, 2022).

After separating tweets that were unrelated to the issue or lacked feeling, 61011 tweets were used for 20 energy companies in this instance.

In addition, during the we first obtained monthly high prices (H), low prices (L), opening prices (O), closing prices (C) and monthly trading volume data of each company from Yahoo finance database. We applied some transformations to get the dependent variable values. For the monthly returns data, we used the first difference of the natural logarithm of each firm's closing prices. For monthly trading volume data, we used the logarithm of firms' monthly traded shares. Finally, we used the Garman and Klass (1980) volatility approach to obtain monthly volatility values as follows:

$$\sigma_{k,t} = \sqrt{0.511(h_t - m_t)^2 - 0.019(c_t(h_t + m_t) - 2h_t m_t) - 0.383c_t^2} \tag{4}$$

where $h_t = \ln(H_{k,t}/O_{k,t})$, $m_t = \ln(L_{k,t}/O_{k,t})$ and $c_t = \ln(C_{k,t}/O_{k,t})$. In addition, the S&P 500 index data is sourced from the Yahoo!Finance, VIX data and trade-weighted USD index data is obtained from Federal Reserve Bank of St. Louis, Brent oil prices are obtained from the Energy Information Administration database.

[INSERT FIGURE 2 HERE]

According to Figure 2, in general, it is seen that the volatility of the firms' return rates increased in the same periods, so there is a close relationship between the rate of return and volatility. When we look at the tweet sentiment series, it can be stated that the effect on return rates, volatility, and volume is limited. In the next step, the econometrically tested results of this effect are included.

3.2. Methodology

Second-generation panel methods were used in the study. Accordingly, first, the cross-sectional dependence between the variables was examined. First-generation tests neglect cross-section dependency. Accordingly, the units in the panel do not affect each other. However, shock occurring in one unit also has effects on other units. Therefore, it is necessary to investigate whether there is a dependency between the units in panel analysis. This dependence between units is expressed as cross-sectional dependency and the dependency is analyzed with the cross-sectional dependency tests developed by Breush Pagan (1980) and Pesaran (2004). The CD test developed by Pesaran (2004) is calculated as follows.

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij}\right) \tag{5}$$

In the model, T represents the time dimension in the panel, N represents the cross-sectional dimension and the OLS correlation estimate of the residuals. Accordingly, when the T value is small and the N value is large, the CD test allows asymptotic normal distribution. In addition, the null hypothesis is established according to this asymptotic distribution and expresses the slope of the coefficients in single and multiple breaks (Pesaran, 2004:1-7). To determine the existence of the relationship between the variables after the cross-section dependence, coefficient estimation was made with AMG analysis. The most important advantage of this test is that it is not necessary to make unit root and cointegration estimations.

Augment Mean Group (AMG) panel estimator is developed by Eberhardt and Bond (2009), Bond and Eberhardt (2013). The AMG estimator is an analysis method that was developed by including the "common dynamic effect" in the analysis and offers the opportunity to make regression specific to the groups in the panel. The "common dynamic effect" is included as a dummy variable in the analysis. The model created accordingly is defined in 3 stages: In the first stage of the AMG test (1) numbers are modelled variables are estimated to be first degree stationary with dummies. Accordingly, the models can be written as follows:

$$Return_{it} = a_0 + a_1 TS_{it} + a_2 SP_{it} + a_3 VIX_{it} + a_4 USD_{it} + a_5 OIL_{it} + \sum_{t=2}^{T} P_t(\Delta D_t) + u_{1it} \tag{6}$$

$$Volatility_{it} = a_0 + a_1 TS_{it} + a_2 SP_{it} + a_3 VIX_{it} + a_4 USD_{it} + a_5 OIL_{it} + \sum_{t=2}^{T} P_t(\Delta D_t) + u_{2it} \quad (7)$$

$$Trading\ Volume_{it} = a_0 + a_1 TS_{it} + a_2 SP_{it} + a_3 VIX_{it} + a_4 USD_{it} + a_5 OIL_{it} + \sum_{t=2}^{T} P_t(\Delta D_t) + u_{3it} \quad (8)$$

In the model, ΔD_t represents first-differences of dummy variable; p_t is coefficient of a dummy variable. At the second stage of the analysis, p_t the parameter is counted in the model as a common dynamic process (φ_t).

$$Return_{it} = a_0 + a_1 TS_{it} + a_2 SP_{it} + a_3 VIX_{it} + a_4 USD_{it} + a_5 OIL_{it} + d_i(\varphi_t) + u_{1it} \quad (9)$$

$$Volatility_{it} = a_0 + a_1 TS_{it} + a_2 SP_{it} + a_3 VIX_{it} + a_4 USD_{it} + a_5 OIL_{it} + d_i(\varphi_t) + u_{2it} \quad (10)$$

$$Trading\ Volume_{it} = a_0 + a_1 TS_{it} + a_2 SP_{it} + a_3 VIX_{it} + a_4 USD_{it} + a_5 OIL_{it} + d_i(\varphi_t) + u_{3it} \quad (11)$$

At the last stage, the model parameters indicate the average over the panel. The models are as follows:

$$Return_{it} = a_0 + a_1 TS_{it} + a_2 SP_{it} + a_3 VIX_{it} + a_4 USD_{it} + a_5 OIL_{it} + u_{1it} \quad (12)$$

$$Volatility_{it} = a_0 + a_1 TS_{it} + a_2 SP_{it} + a_3 VIX_{it} + a_4 USD_{it} + a_5 OIL_{it} + u_{2it} \quad (13)$$

$$Trading\ Volume_{it} = a_0 + a_1 TS_{it} + a_2 SP_{it} + a_3 VIX_{it} + a_4 USD_{it} + a_5 OIL_{it} + u_{3it} \quad (14)$$

4. Empirical Findings

In the first stage of empirical analysis, we investigated the cross-section dependency assumption, which was neglected in previous studies and one of the main starting points of this study. As is known, it is an expected situation that the stock values of companies operating in the same sector in financial markets will be affected by each other. In this direction, the obtained cross section dependency test results are presented in Table 1. According to the findings, null hypothesis, which indicates that intercompany dependency is not valid, is strongly rejected in all 3 models where returns, volatility and trading volume variables are used as dependent variables, respectively.

[INSERT TABLE 1 HERE]

In the next stage, we examined the effects of regressors with an estimator that allows for inter-company dependency achieved in the previous stage. Accordingly, we used the Augmented Mean Group (AMG) estimator developed by Eberhardt and Teal (2010) and Bond and Eberhardt (2009) while estimating the coefficient. There are several reasons for using this estimator, except that it allows cross-sectional dependence. That is, AMG estimator is resistant to non-stationary variables, whether cointegrated or not (Eberhardt & Teal, 2010). Therefore, they do not require the preliminary test (neither to determine the existence of cointegration nor to verify that all variables have the same order of integration) required by other heterogeneous, non-stationary panel estimators such as Fully Modified OLS and Dynamic OLS. Also, both CMG and AMG estimators are resistant to serial correlation (Pesaran, 2006; Eberhardt & Teal, 2010).

[INSERT TABLE 2 HERE]

First of all, the findings we obtained by testing the effects of variables for 3 different models at the panel level are shown in Table 2. According to the findings, a statistically significant effect of Twitter sentiment on returns and volatility is not valid. On the other hand, twitter sentiment increases the trading volume values of energy companies on a panel basis. Similarly, the effect of the S&P 500 index and the USD index on firm stocks is insignificant. The increase in stock market volatility decreases the returns; however, it appears that it increases the volatility of firm stocks and trading volumes. Finally, it is found that the increase in oil prices only increases the returns.

AMG estimator is used for each company to analyze the effects of twitter sentiment on returns, volatility, and trading volumes on a company-by-company level, in addition to the panel findings. Table 3 shows the impact of Twitter sentiment on corporate returns for the energy companies examined. When the statistics are analyzed in terms of twitter sentiment, it is shown that 3 of the 20 companies have positive statistical significance. Twitter, on the other hand, has no statistically significant impact on the remaining 17 companies. Furthermore, in 10 of 20 firms, an increase in the S&P 500 index value has a positive and statistically significant influence on firm returns. For 19 of the 20 firms, the increase in the stock market volatility index value has a negative effect on firm volatility. Surprisingly, the impact of the USD index on company returns is statistically insignificant. Finally, an increase in oil prices raises the value of 13 of the 20 companies' returns.

[INSERT TABLE 3 HERE]

Table 4 shows the effect of independent variables on firm volatility values on a firm-by-firm basis. When the data is analyzed, it can be shown that increasing twitter sentiment reduces corporate volatility for 5 of the 20 companies, while increasing it for 3 of the 20. For four of the twenty companies, an increase in the S&P 500 index reduces firm volatility. The effect is statistically insignificant for the remaining 16 firms. The conclusion is that when the volatility index rises, so does the volatility of all enterprises.

[INSERT TABLE 4 HERE]

Finally, Table 5 presents the findings on the effects of twitter sentiment on company trading volumes. When the results are analyzed, twitter sentiment has a positive and significant effect in seven of the twenty organizations studied, while it has a negative effect in one. In 18 of the 20 companies, however, the effect of an increase in the S&P 500 index on trading volume values is statistically insignificant. Similarly, the impact of a higher USD index on 18 of the 20 enterprises is statistically insignificant. The increase in the volatility index is found to have a beneficial impact on the trading volume values of all 20 companies. While an increase in oil prices reduces trading volume values in three of the twenty corporations, it improves volume values in six of the twenty.

[INSERT TABLE 5 HERE]

When all of the findings are considered together, it is concluded that the twitter sentiment values have no significant impact on the returns and volatility of the companies. Tweets, on the other hand, appear to have a favorable impact on company trading volume values. The interesting finding here is that an increase in trading volume generated by positive sentiment in tweets has no impact on company returns. In addition, oil prices are the most influential factor on firm returns values when assessed on a panel basis, but the S&P 500 index is the most effective element when evaluated on a firm basis.

5. Concluding Remark

According to the efficient market hypothesis, there is symmetric information in the markets and individuals/investors can access all the information that will require them to make rational decisions in the market. For this reason, social media activities have been controversial in terms of evaluating the markets recently. At this stage, it is stated that social media activities can affect the investment behaviour of individuals positively or negatively.

In this study, the effects of companies' social media activities on firm returns, trade volume and volatility were examined. The tweet sensitivities of 20 energy companies traded in the S&P 500 were examined between 2015m6 and 2020m5. Three different models were created to measure the relationship between Twitter sentiment (TS) and return, trade volume and volatility. In these models, the S&P 500 index (SP), stock market volatility index (VIX), trade-weighted USD index (USD) and Brent oil prices (OIL) variables are the control variables. The models were tested with AMG analysis. According to the results obtained, tweeter sensitivity does not affect firms' returns and volatility. However, the trade volume is affected. In this result, it should be noted that positive tweets do not affect the trade volume. Therefore, according to the results of our study, it is possible to say that only negative tweets have an impact on the investment decisions of individuals, contrary to the behavioral economics findings. However, this effect is not effective on volatility and returns. Therefore, it can be concluded that the tweet sensitivity of the companies included in our study has a limited effect on their investment decisions.

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