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The Effect of Social Media Sentiment on the Returns of the Istanbul Stock Exchange[1]

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Abstract

The objective of this research is to investigate the relationship between investor attention based on social media and financial market activity in terms of the Istanbul Stock Exchange (ISE). The main goal of the study is to reveal the direction and strength of the relationship between the number of tweets on Twitter and the trading volume for a relevant stock that is a constituent of the BIST 30 index. In this context, the period from 1 January 2020 to 31 December 2020 is examined, and the daily tweet and trading volume datasets are transformed into weekly frequency datasets by considering the ISE trading days. The collected data set has been analysed with unit root tests, causality analyses, and the AR(1) corrected Fixed Effects regression model. Results show a statistically significant, positive, and powerful relationship at the 1% significance level between the number of posted tweets and stock market trading volume, and also reveal unidirectional causality from trading volume to the number of tweets.

1.Introduction

Financial markets are dynamic systems where information flows quickly and intensively, and economic, political, and psychological factors are reflected in prices simultaneously. The classical finance approach, based on the Efficient Market Hypothesis (EMH) and the rational investor assumption, asserts that publicly available information is quickly reflected in prices, and that investors cannot systematically earn over-normal returns (Fama, 1970). However, developments in information

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technologies, especially over the last 30 years, the popularisation of internet-based technologies and social media have evolved the knowledge generation and dissemination considerably. This transformation complicates the explanation of investors' behaviours and price formation processes only within classic financial models. Therefore, concepts such as behavioural finance and investor sentiment have come into the forefront.

Social media platforms offer a new communication medium where users share their comments, expectations, concerns, and excitement about financial assets instantly. Especially, the Twitter (X) platform is seen as a feedback channel that reflects the sentiments and expectations of investors, thanks to its intensive use of hashtags and high levels of interaction. Thus, any changes in the volume of tweets related to a specific stock can be evaluated as attention to that stock and can create vicarious influence on investors' buy-sell decisions (Tetlock, 2007). Behavioural finance literature emphasizes that investors exhibit some biases in their decision-making processes, such as cognitive limitations, emotional responses, herd behaviour, overconfidence, and loss aversion (Kahneman and Tversky, 1979). Social media provides an environment that consolidates these biases and allows them to spread quickly. Especially, the psychological tendency named as fear of missing out (FOMO) shows that rapid increases in attention and social media posts about specific stocks can motivate investors to follow other investors' behaviour rather than rational analysis. In such an environment, whether discussions and expectations intensified around specific stocks on social media have a remarkable impact on trading volume becomes an important research question.

Istanbul Stock Exchange (ISE) is a market with increasing depth and significant trading volume for both domestic and foreign investors. Especially during times of high investor activity, the potential effects of news, comments, and rumors that spread on social media can become more apparent. The BIST 30 index of ISE contains the largest companies in terms of market capitalization and trading volume. These companies are intensely followed by both individual and institutional investors. Therefore, stocks in the BIST 30 index provide an appropriate sample to examine the relation between investor attention based on social media and trading volume.

In this research, the effect of social media on financial markets is discussed in relation to the volume of Twitter posts based on related stocks and the trading volume of BIST 30 stocks. The research mainly assumes that the number of tweets about relevant stocks reflects investor attention and discussion intensity, and, accordingly, this knowledge can be reflected in market trading volume. In other words, the study investigates whether an increase in the intensity of social media discussions about a stock during a specific period is associated with an increase in trading volume during the same period or the following period. Thereby, to what extent investor sentiment based on social media is reflected in the microstructure of the market and liquidity dynamics is tested empirically.

The sample for the research comprises stocks that were part of the BIST 30 index during the period from 1 January 2020 to 31 December 2020 and remained BIST 30 constituents for at least a quarter. The chosen period spans the time when global uncertainty rose, pandemic-related shocks occurred, and social media use intensified. In this context, daily trading volume data and tweets containing the names of relevant stocks have been collected, and the dataset has been transformed to weekly frequency based on the trading weeks of the Istanbul Stock Exchange. Thus, the weekly total number of tweets and the weekly trading volume for each stock have been obtained in a series.

In the study, the dataset has been examined using descriptive statistics first, and subsequently, the series' stationarity has been evaluated using unit root tests. Simultaneous relationship between variables is revealed by Pearson correlation coefficients. To investigate the direction of the causal relationship between social media activities and trading volume, Granger causality tests are applied. Thus, the study analyses whether tweet volume based on stocks is a statistically significant "precursor" to trading volume. Similarly, whether changes in trading volume emerge as a trigger for social media activity is analysed.

The contribution of this research to the literature can be evaluated in several ways. Firstly, international literature examining the relationship between social media sentiment and financial markets primarily focuses on developed countries. Emerging markets like Turkey are relatively less examined. This research aims to contribute to this gap by focusing on stocks in the BIST 30 index and systematically examining the relationship between investor attention based on social media and trading volume in Turkey's capital market. Later, the volume of tweets used in the study is discussed as a basic indicator of attention, rather than complex sentiment-classifying algorithms based on content analysis. Lastly, findings on the effects of investor psychology and social interactions on market micro-structures are discussed by interpreting the social media-trading volume relation through a behavioural finance lens. In the context of implementation, findings from the relationship between social media and trading volume can provide implications for both individual and institutional investors, portfolio managers, and market makers. For instance, observing sudden increases in social media interest in certain stocks, coupled with substantial increases in trading volume, might suggest that social media-based signals could be used as a complementary indicator in market surveillance, risk management, or early warning mechanisms. On the other hand, unidirectional or bidirectional causality findings between trading volume and social media activities can contribute to a better understanding of herding and knowledge flow in the market.

The scope of the research includes the stocks that are constituents of the BIST 30 index for at least one quarter during the period from 1 January 2020 to 31 December 2020. Mergers and structural changes in the chosen period on constituents of the BIST 30 index have been considered. Stocks that have non-traded days in the time period or do not have significant observations in the dataset are also weeded out. The social media dataset includes only tweets containing a stock name from publicly available accounts for the chosen time period. Geographical, linguistic, and technical filters have been applied to possibly obtain a dataset that reflects the behaviour of native investors. In this research, the contents of tweets are not subjected to text-based sentiment classification; instead, the number of tweets is used as an indicator of attention. Therefore, this brings with it both the study's strengths and methodological limitations. These issues are discussed in detail in the later parts of the research.

While the methodology is presented in the third chapter of the research, the study adopts a quantitative, empirical research design. Financial data is obtained from the Istanbul Stock Exchange database, and social media data from the X API. After the data consolidation and transformation into weekly frequencies, stationary tests, correlation analysis, and the Granger causality test are applied to the dataset. Thus, the possible effect of social media activity on trading volume is examined within econometric frameworks based on time-series analysis.

2. Theoretical Context: Fear of Missing Out and Investor Sentiment

One concept that has emerged in recent years within the framework of Behavioural Finance is FOMO. In the psychological literature, FOMO is characterized as a cognitive state arising from the fear of being left out of rewarding opportunities, experiences, or successes that others are enjoying (Przybylski et al., 2013). Thus, emphasizes that sentiment is closely related to the comparison process. Social media enables individuals to observe what others are doing, what decisions they are making, and what consequences they are facing. Therefore, it has become one of the medium through which FOMO is most intensely fed. When others gain high profit from a specific stock, investors come to believe that others caught the opportunity or bought the stock at the right time. This realization evokes intense feelings of regret and dissatisfaction. In the context of Prospect Theory, individuals define “profit” and “loss” from their reference point and experience losses more intensely than earnings (Kahneman and Tversky, 1979). In the case of FOMO, missing potential earnings could be perceived as a real loss in memory, even if there was no direct loss. This can increase the willingness to take risks (Kahneman and Tversky, 1979; Przybylski et al., 2013).

In conclusion, FOMO is a concept that links social media-driven behavioural dynamics to excessive risk-taking and over-trading in stock markets. Investors can make decisions not only based on financial dynamics but also on what others do and how much they earn. This leads us to recognize that FOMO is a constituent of understanding financial market operations. Therefore, considering the effect of FOMO on investor psychology in studies examining the relationship between social media and search behaviour and stock markets provides a consistent interpretive basis.

Another concept that has come to the forefront in recent years is investor sentiment. Investor sentiment is defined as a constituent that cannot be explained with the framework of classical finance and reflects the optimism and pessimism of investors, based on a psychological and cognitive basis (Baker and Wurgler, 2006). During high sentiment, the perception of risk decreases, and asset prices tend to rise, whereas they exhibit the opposite dynamics during low sentiment. Traditional studies used indirect indicators such as surveys, trading volumes, the number of new public offerings, and data on short positions to measure investor sentiment. In conjunction with the popularity of social media platforms, sentiment indices were started to be produced directly with the text mining and sentiment analysis methods (Tetlock, 2007; Bollen et al., 2011).

This research aims to examine the relationship between the presence of stocks on social media and trading volume on the stock market from a behavioural finance perspective. To that end, investor attention and sentiment over time will be examined quantitatively using time-series data on how often the names of specified stocks are posted on the X platform. The proxies for investor attention and sentiment will be compared with stock market trading volumes. Similarities between the oscillations of social media and the search behaviours of investors and market activity will be examined. In the context of behavioural finance, investors with bounded rationality cannot analyse all the stocks with the same perspective; instead, they follow the trend of assets that are more visible on social media (Barber and Odean, 2008). Consequently, heightened visibility on social media and search engines enhances the salience of specific stocks, making them more cognitively available to investors. According to the attention-driven buying hypothesis, this increased visibility ensures that these stocks enter the investors' consideration sets, directly influencing trading decisions (Barber and Odean, 2008). Empirical evidence confirms that simultaneous spikes in search engine queries and social media activity (e.g., tweet counts) are significantly correlated with increased stock market trading volume (Da et al., 2011; Bollen et al., 2011).

It is also important to consider that vice versa of this relationship. Rapid changes in prices or trading volume can lead investors to search for relevant stocks on social media more. Hence, causality can be not only unidirectional but also mutual (Fekrazad et al., 2022). For this reason, this research will consider not only correlations but also timing, delays, and potential feedback. Observing increases in social media indices and search activity on the eve of high-volume trading periods indicates a shift from attention to transactions. However, observing changes in these indicators after high trading-volume periods reflects an interaction between transactions and attention, conversely.

In conclusion, sentiment based on social media and search volume indices enables us to analyse the literature highlighted by behavioural finance empirically. In this research, the frequency with which stock names appear on X is analysed in relation to trading volumes on the stock market. This is important in understanding the relationship between the flow of information and knowledge, investors' behaviours, and the liquidity of stock markets. On the one hand, the obtained findings will provide insights into how markets work. On the other hand, they will reveal how effective social media and search data are for understanding investors' behaviours.

3. Literature Review

In this part, empirical studies that examines relationship between the social media-based indicators and financial markets are collected systematically and evaluated. In this context, studies are examined in terms of social media activities, investor attention indicators, sentiment measurements, market behaviour and social media effects during crisis.

Chen et al. (2011) have studied effects of traditional media sentiment and social media sentiment on stock market by comparing them and found that effect of negative words used in articles negatively correlates with share returns. Bolaman (2011) discussed the efficient market hypothesis and examined the behavioural finance. Existence of relationship between overconfidence and trading volume is proved by using Granger Causality Test. Oprean and Tanasescu (2014) analysed the behavioural finance factors explain the trading volume evolution on Romania and Brazil capital markets. The results shown that in both capital market trading is effected by investor's irrational behaviours and the rationality hypothesis can be rejected for both capital markets.

Rancho et al. (2015) have worked on the relations between Twitter sentiment and financial markets. As a result of this work, they have found low Pearson correlation and Granger causality for the time series. Nguyen et al. (2015) have proposed a framework which predicts the direction of stock price movements by using social media sentiment analysis. Study shows that the proposed method outperforms the model based solely on historical prices with better result of 2.07% and better accuracy of 9.83%.

Reed (2016) analysed the effect of the consumer sentiment on the stock market prices by collecting data from Twitter. In conclusion, it is found that talk intensity of economic activities not only cause shifts in the daily stock market prices but also has a significant negative effect. Chouse et al. (2016) have analysed investors' activities on social media and impact of medias shared by investors on the Chicago Board Options Exchange Market Volatility Index (VIX). Results show that variable has no effect on technical investors except the time period, but variables also have significant effect on non-technical investors.

Sul et al. (2017) have analysed the effect of social media sentiment on the returns of shares and found that tweets for a specific firm from accounts who has less than 171 followers had a remarkable impact on the stock's returns for next trading day, the next 10 days, and the next 20 days. Tan (2019) has analysed the effects of investor attention, social media activity and social media on the individual share returns and trading performance. The results of the thesis indicate that Twitter sentiment and the number of tweets have a remarkable effect on stock returns and any increase in SVI, effects the stock price of firm with the higher returns and this effect is stronger especially for small stocks.

Affuso and Lahtinen (2019) have analysed the effect of social media sentiment and geography on share returns and study shows that negative tweets have much larger impact than positive tweets on share returns. Langroudi (2019) has analysed the role of social media on stock prices of four Turkish football teams which are traded on the Istanbul stock exchange. The study found that using different data together has a better accuracy than using them separately.

Allen et al. (2019) have worked on the influence of daily financial news sentiment on the stock returns. In this work, results of analysis shows that sentiment scores have a remarkable influence on Dow Jones companies returns with delay. Kwatra (2020) has examined the behavioural aspect of Finance by analysing its impact on stock markets during the coronavirus pandemic. The research explains the overconfidence bias by showing the GDP growth projections published by Moody's data in India during the coronavirus pandemic.

Cruz et al. (2021) have worked on the effect of Twitter posts on some of the global stock market indices like Dow Jones, S&P 500 and FTSE 100, during H1N1 and Covid-19 pandemics. In conclusion, researchers found that there is a remarkable effect of sentiment on twitter posts on the financial indices during both pandemic especially Covid-19 pandemic.

Ren et al. (2021) have analysed effect of the social media sentiment on mass media sentiment. Researchers have found that if there is a remarkable relationship between social media sentiment and mass media sentiment, mass media sentiment has become more persisting. Mehta et al. (2021) investigated correlation between social media sentiment and companies' stock prices and found that

Long Short-Term Memory (LSTM) framework has %92,45 accuracy score to predict future prices of shares.

Derer (2022) has analysed the behavioural finance effects on sports club's stocks who can be traded on Istanbul Stock Exchange (ISE). To conclude, research has shown that different clubs has been effected by different events. Zhang et al. (2022) have worked on the effect of social media rumors on China stock markets. In conclusion, It is found that IFFRI has positive effect with the time of "t-1" and "t" but has negative effect with the period of "t+1" over the stock market volatility.

Rosa (2022) examined the social media sentiment influence on stock prices of global companies traded on Dow 30 and found no meaningful relationship between social media sentiment and stock prices. Maqsood et al. (2022) have examined the social media sentiment on the stock markets of European Union countries in connection with Brexit event. In conclusion, finding of research shows that sentiment analysis of Brexit events promotes the stock exchange prediction better with a deep learning model comparing with machine learning models specifically for highest contributor countries.

Hamraoui et al. (2022) have studied the Twitter sentiment for the companies traded on Tunisian financial market. As a result of research, low Pearson correlation and Granger causality estimates between the times series have been found. Fekrezad et al. (2022) have examined the two-way connection between social media sentiment and stock market for companies traded on the S&P 100. In conclusion, researchers have found that if there was any increase in volume of negative tweets about company, cause lower returns and higher short volume of companies' stocks within an hour/day.

Avila (2023) has worked on the effect of tweet sentiment on returns of stocks of companies work in biotechnology sector, by focusing on the effect of social media sentiment on decision-making processes of investors. To conclude, it is found that there is a complex interaction between tweet sentiment and stock market performance. Nyakurukwa and Seetharam (2023) have examined the articles and development of social media sentiment analysis about stock market. Their research shown that most of the study has been made by using computer and mathematical sciences domains.

Sevinç (2024) has analysed the effects of social media and forums on financial markets. To conclude, this research shows that posts shared on Twitter and İnvesting.com have different effects under the influence of different market conditions. Dilik (2024) has worked on the influence of the social media posts on share stocks volatility. As a result, research shows that positive posts have positive influence on returns and negative posts have negative influence on returns.

Peivandizadeh et al. (2024) have proposed a model that predicts the share prices by combining social media analysis and stock market data and researchers have demonstrated that both the Off-policy PPO component and the TLSTM architecture were more decisive in the performance gain. Akgül (2025) has examined the social media -in case of Telegram- effect on investment decisions of investors by the aspect of behavioural finance. This research shows that in the events of positive contents investors make hasty decisions by effect of FOMO and in the events of negative contents investors make rapid sales by the effects of panic.

Boz (2025) studied on relationship between social media and volatility of leading technology companies traded on financial markets by using text mining and deep learning. As a result of research different results has been obtained from different models and parallelism between price and sentiment scores obtained from analysis found to be limited but significant. Aksöz (2025) has analysed the relation between Twitter Happiness Index and global stock indexes, and significant relationships have been found between twitter happiness index and examined financial markets.

4. Data and Methodology

In this section, the framework of the empirical analysis is presented to examine the impact of social media interactions on financial markets during the COVID-19 pandemic, based on the "Noise Trading" hypothesis and "Investor Attention" theories within behavioral finance. Within the scope of the study, a comprehensive panel dataset was constructed by combining market data on companies traded on the BIST 30 index with tweet counts representing investor attention on Twitter. Panel Data Analysis was preferred as the methodological approach for its ability to consider both the time (weekly) and cross-sectional (company) dimensions simultaneously.

The behavioral finance literature suggests that investors cannot process all available information perfectly or homogeneously. Instead, they make decisions within the context of limited attention, cognitive biases, and social interactions (Barberis and Thaler, 2003). This perspective allows for evaluating social media activities not just as communication but also as a measurable proxy for investor attention and sentiment. Rather than focusing on daily fluctuations, this analysis uses weekly aggregated data to filter out daily noise, allowing observation of overall tendencies and medium-term trends.

The population of interest for this research consists of stocks traded on Borsa Istanbul (BIST). However, to ensure the reliability of the findings and to focus on the most liquid assets, the sample is restricted to the constituents of the BIST 30 Index. There are several theoretical and practical reasons for limiting the sample to the BIST 30. Firstly, stocks with low trading volume often exhibit statistical instability and microstructure noise (Karpoff, 1987). BIST 30 includes the largest and most liquid companies in Turkey, ensuring continuous trading activity and minimizing data quality problems. Secondly, for a study based on "investor attention," the selected stocks must be familiar to the public. Large-cap companies attract significant attention from individual investors, the financial press, and institutional funds, generating a sufficient "footprint" on social media platforms (Sprenger et al., 2014). The study period is defined as January 1, 2020, to December 31, 2020. This specific timeframe was chosen because 2020 marks the emergence of the COVID-19 pandemic, a period characterized by global financial uncertainty and high volatility. Literature suggests that during such high-uncertainty periods, individual investors intensify their use of social media as an information source and a platform for interaction (Baker et al., 2020). Therefore, this period provides a suitable laboratory to observe the dynamics of "noise trading" and "herding behavior".

The dataset was constructed by merging financial market data with social media interaction data.

- Financial Data: Daily trading volume data was obtained from Istanbul Stock Exchange database.
- Social Media Data: The number of tweets containing the ticker symbols (e.g., #GARAN, #ASELS) of the relevant stocks was collected via the Twitter (X) API. To ensure data quality, posts from both accounts and repetitive spam content were filtered out to the extent possible.

Although the BIST 30 index nominally comprises 30 companies, its composition changed during the year due to corporate actions. Specifically, companies like Soda Sanayi (SODA) and Trakya Cam (TRKCM) were merged into Şişecam (SISE) in the last quarter of 2020. To maintain time-series continuity and prevent structural breaks, a balanced panel approach was adopted that includes all major constituents present during the year. Consequently, the final sample consists of 31 unique stocks.

The data were collected weekly. While financial data is available daily, a weekly aggregation was preferred to:

1. Minimize the daily noise and extreme volatility often observed in high-frequency data.
2. Better observe the medium-term trends of investor attention.
3. Align the trading volume with the broader wave of social media discussions.

The year 2020 spans 53 weeks in terms of data calendar continuity. Therefore, with 31 companies observed over 53 weeks, the final dataset constitutes a strongly balanced panel with a total of 1,643 observations.

Two main variables are used in the empirical analysis. Trading volume as the dependent variable and the number of tweets as the independent variable.

To prepare the data for econometric analysis, namely Panel Regression and Granger Causality, the logarithmic transformation was applied to both series. Taking the natural logarithm (ln) of the variables serves several purposes. These are,

1. Scaling: It reduces the scale differences between companies with very high and very low raw volumes.
2. Normality: It approximates the distribution of the series to a normal distribution.
3. Homoscedasticity: It helps stabilize the variance of the series.
4. Elasticity: It allows the regression coefficients to be interpreted as "percentage changes" (elasticity) rather than unit changes.

The variables used in the model are defined in Table 1 below.

Table 1. Definition of Variables

Variable Type	**Variable Name**	**Variable code**	**Definition and Transformation**
Dependent variable	Log-Trading volume	LN_VOLUME	The natural logarithm of the total weekly trading volume (TL) of the stock. ($\ln\sum Volume_{i,t}$)
Independent Variable	Log-Tweet Count	LN_TWEET	The natural logarithm of the total weekly number of tweets mentioning the stock's ticker. ($\ln\sum Tweets_{i,t}$)

In this research, the relationship between weekly digital attention indicators, namely Twitter interaction intensity and weekly trading volume for stocks in the BIST 30 index, is analyzed for the period of 2020, which is the main period for the COVID-19 pandemic. The research hypotheses are derived from the "Investor Attention" and "Noise Trading" theories in the behavioral finance literature. The study aims to test both the contemporaneous relationship via Panel Regression and the direction of causality via Panel Granger Causality tests between the variables. In this context, the basic hypotheses to be tested are presented below:

H_1: There is a statistically significant and positive relationship between social media attention and trading volume.

$H_{1a:}$ An increase in the weekly logarithmic number of tweets (LN_TWEET) regarding a specific stock leads to a statistically significant increase in the weekly logarithmic trading volume (LN_VOLUME) of that stock.

H2: Social media attention Granger-causes trading volume

H2a: Past values (lags) of weekly tweet volume (LN_TWEET) contain statistically significant information to predict the current values of weekly trading volume (LN_VOLUME).

$H_{3:}$ Trading volume Granger-causes social media attention.

$H_{3a:}$ Past values (lags) of weekly trading volume (LN_VOLUME) contain statistically significant information to predict the current values of weekly tweet volume (LN_TWEET).

Evaluating H_2 and H_3 together intends to reveal whether the relationship between digital attention and trading volume is unidirectional, bidirectional (feedback), or neutral (no causality) in the short run. Meanwhile, H1 focuses on the magnitude and direction of the simultaneous effect.

In this study, Panel Data Analysis is employed to investigate the relationship between the financial performance of BIST 30 companies and social media interactions. Panel data is a method that combines time-series and cross-sectional data dimensions. This method was preferred over simple time-series or cross-sectional analyses because it offers more degrees of freedom, reduces multicollinearity among variables, and effectively controls for firm-specific heterogeneity (Baltagi, 2005). The econometric analysis process is structured in four main stages. Initially, the stationarity of the series is tested using Panel Unit Root Tests. Subsequently, the appropriate regression specification is determined, with the Fixed Effects Model as the focus. Following this, autocorrelation issues are addressed to estimate the final model with an AR (1) Adjustment. Finally, the direction of the relationship is examined via the Panel Granger Causality Test.

5. Analysis And Discussion

This chapter presents the results of the econometric analysis examining the relationship between the trading volumes of companies listed on the BIST 30 index and Twitter interactions, which serve as a proxy for social media attention. The analysis process begins with the presentation of descriptive statistics for the variables, proceeds with stationarity, unit root, and causality tests, and concludes with the estimation of the panel regression model designed to test the research hypotheses.

Table 2 presents the descriptive statistics for the logarithmic trading volume (LN_VOLUME) and logarithmic tweet count (LN_TWEET) variables used in the analysis. The dataset consists of a balanced panel with a total of 1,643 observations (31 companies * 53 weeks).

Table 2. Descriptive Statistics definition of Variables

	LN_VOLUME	LN_TWEET
Mean	20.83312	5.447456
Median	20.78411	5.476464
Maximum	24.28318	7.436028
Minimum	17.77558	1.791759

Std. Dev.	1.014211	0.671402
Skewness	0.187372	-0.394419
Kurtosis	2.936399	3.969454
Jarque-Bera	9.890705	106.9393
Probability	0.007116	0.000000
Sum	34228.82	8950.170
Sum Sq.	714782.1	49495.84
Sum Sq. Dev.	1688.999	740.1822
Observations	1643	1643

As presented in Table 2, the descriptive statistics reveal important insights regarding the distribution of the variables. A close examination of the central tendency measures indicates that the mean (20.83) and median (20.78) values for LN_VOLUME are remarkably similar. A comparable convergence is observed for LN_TWEET, with a mean of 5.44 and a median of 5.47. This proximity suggests that the logarithmic transformation successfully centered the data, minimizing the potential distortion caused by extreme outliers. Regarding the dispersion of the series, the standard deviation values indicate sufficient variation to explain the relationship in the regression analysis.

In terms of distribution characteristics, the LN_VOLUME variable exhibits a skewness of 0.18, while LN_TWEET shows a skewness of -0.39. In statistical literature, skewness coefficients falling within the range of -0.5 to +0.5 are generally accepted as evidence of an approximately symmetric distribution. Since both variables remain well within these boundaries, the assumption of symmetry is satisfied. Regarding the tail behaviour, LN_VOLUME has a kurtosis of 2.93, which is extremely close to the normal distribution benchmark of 3. On the other hand, the LN_TWEET variable displays a kurtosis value of 3.96, indicating a leptokurtic distribution. This suggests that social media attention occasionally experiences intensity spikes, which is consistent with the viral nature of information diffusion on digital platforms. Finally, while the Jarque-Bera test statistics lead to the rejection of the null hypothesis of perfect normality ($p < 0.05$), the large sample size of the study (N=1,643) implies that these deviations are not severe enough to violate the asymptotic assumptions required for the Fixed Effects model estimation, as supported by the Central Limit Theorem (Wooldridge, 2013).

Before proceeding with the regression analysis, it is crucial to examine the stationarity of the variables to avoid spurious regression. In this study, two different panel unit root tests are employed to ensure robustness:

1. Levin, Lin & Chu (LLC) test, which assumes a common unit root process.
2. Im, Pesaran & Shin (IPS) test, which allows for individual unit root processes across cross-sections.

The tests were conducted at level with an intercept specification. Table 3 summarizes the comparative results of these tests for logarithmic trading volume (LN_VOLUME) and logarithmic tweet counts (LN_TWEET). Detailed test outputs and statistics for each cross-section are presented in Appendix A.

Table 3. Panel Unit Root Test Results (Level - Intercept)

Variables	Test Method	Statistic	Prob.	Result
LN_VOLUME	Levin, Lin & Chu (t*)	-6.22	0.0000***	Stationary I(0)
	Im, Pesaran & Shin (W-stat)	-8.0294	0.0000***	Stationary I(0)
LN_TWEET	Levin, Lin & Chu (t*)	-9.0371	0.0000***	Stationary I(0)
	Im, Pesaran & Shin (W-stat)	-11.5181	0.0000***	Stationary I(0)

Note: *** indicates statistical significance at the 1% level. Full EViews outputs are available in Appendix A.

As presented in Table 3, both the LLC and IPS tests yield consistent results. The probability values for LN_VOLUME and LN_TWEET are statistically significant at the 1% level ($p < 0.01$) across both test specifications. Therefore, the null hypothesis of a unit root is strongly rejected. These findings confirm that the series are stationary at levels, denoted as I(0). This implies that the variables have a constant mean and variance over time, eliminating the need for differencing. Consequently, the subsequent correlation and regression analyses will be performed using the level values, allowing for the interpretation of long-term relationships.

Following the confirmation of stationarity, a Pearson Correlation Analysis was conducted to examine the direction and strength of the linear relationship between the variables. While correlation does not imply causation, it provides preliminary evidence regarding the synchronization between social media attention and market activity. Table 4 presents the correlation matrix for the variables used in the study.

Table 4. Pearson Correlation Matrix

Covariance Analysis: Ordinary			
Sample: 1/03/2020 12/31/2020			
Included observations: 1643			
Correlation			
Probability	LN_VOLUME	LN_TWEET	
LN_VOLUME	1.000000		

LN_TWEET	0.736469	1.000000	
	0.0000	-----	

Note: Values in parentheses represent probability (p-values). *** indicates statistical significance at the 1% level

The results in Table 4 indicate a strong, positive, and statistically significant relationship between trading volume and tweet counts ($r = 0.736$, $p < 0.01$). This coefficient suggests that weeks with high social media interaction (LN_TWEET) are strongly associated with higher trading volumes (LN_VOLUME) for BIST 30 companies. The fact that the correlation is close to 0.74 supports the theoretical expectation that investor attention drives trading activity. However, to determine the direction of this relationship (i.e., whether tweets drive volume or volume drives tweets), a causality test is required.

To determine the direction of the relationship between trading volume and social media attention, the Panel Granger Causality Test was conducted. Given the rapid information processing in financial markets, the test was performed using 1 lag to capture the immediate subsequent effects. The null hypothesis (H_0) posits that the independent variable does not Granger-cause the dependent variable. Table 5 summarizes the test results.

Table 5. Dumitrescu-Hurlin Panel Causality Test Results

Pairwise Granger Causality Tests				
Date: 12/24/25 Time: 02:37				
Sample: 1/03/2020 12/31/2020				
Lags: 1				
Null Hypothesis:	Obs	F-Statistic	Prob.	Decision
LN_TWEET does not Granger Cause LN_VOLUME	1612	0.09324	0.7601	Fail to reject H0
LN_VOLUME does not Granger Cause LN_TWEET		14.8969	0.0001	Reject H0

Note: *** indicates statistical significance at the 1% level.

The results in Table 5 reveal a distinct causal structure. The null hypothesis that "Trading Volume does not Granger Cause Tweets" is strongly rejected ($p < 0.01$). This indicates a unidirectional causality running from trading volume to social media interactions. This result means that volume drives attention. This finding supports the "Visibility Hypothesis," suggesting that high trading activity draws investor attention to specific stocks, subsequently generating more discussions and "buzz" on social media platforms in the following period. Conversely, the hypothesis that tweets cause volume is not rejected at 1 lag ($p = 0.76$). This implies that social media sentiment is absorbed into the market prices and volume instantaneously, within the same week, rather than with a delay. Therefore, past tweets do not predict future volume, which is consistent with the Efficient Market Hypothesis. Since the causal impact of tweets on volume appears to be contemporaneous rather than lagged, the Panel Regression Analysis in the next section is essential to quantify this simultaneous relationship.

Following confirmation that the variables satisfy the stationarity conditions, the study proceeds to the final stage of the analysis: model estimation. The Granger causality tests performed in the previous section indicated a unidirectional causality running from Trading Volume to Tweet counts, supporting the visibility hypothesis. However, no lagged causality was found from Tweets to Volume. Given the rapid nature of financial markets, it is considered that the impact of social media attention on trading volume occurs contemporaneously rather than with a delay. In this direction, the Fixed Effects model has been estimated to test the direction, magnitude, and statistical significance of this simultaneous relationship. At this stage of the analysis, the relationship between the dependent variable, LN_VOLUME, and the independent variable, LN_TWEET, is tested using the Fixed Effects estimator, which accounts for firm-specific individual effects. The results of the baseline model, estimated without any correction procedures, are presented in Table 6.

Table 6. Baseline Fixed Effects Regression Results

Dependent Variable: LN_VOLUME				
Method: Panel Least Squares				
Sample: 1/03/2020 12/31/2020				
Periods included: 53				
Cross-sections included: 31				
Total panel (balanced) observations: 1643				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	15.90044	0.139891	113.6632	0.0000
LN_TWEET	0.905501	0.025577	35.40281	0.0000
	Effects Specification			
Cross-section fixed (dummy variables)				
R-squared	0.754623	Mean dependent var		20.83312
Adjusted R-squared	0.749902	S.D. dependent var		1.014211
S.E. of regression	0.507205	Akaike info criterion		1.499481
Sum squared resid	414.4408	Schwarz criterion		1.604738
Log likelihood	-1199.824	Hannan-Quinn criter.		1.538515
F-statistic	159.8200	Durbin-Watson stat		0.696202
Prob(F-statistic)	0.000000			

Note: *** indicates statistical significance at the 1% level.

The results indicate a positive and highly significant relationship between social media attention and trading volume. The coefficient for LN_TWEET is 0.9055 ($p < 0.00$), which is statistically significant at the 1% level. Since both variables are in logarithmic form, the coefficient represents an elasticity. This implies that, ceteris paribus, a 1% increase in the number of tweets leads to approximately a 0.91% increase in trading volume. The high R-squared value (0.75) suggests that the model explains approximately 75% of the variation in trading volume, indicating a powerful goodness of fit. However, a critical examination of the diagnostic statistics reveals a potential issue. The Durbin-Watson statistic is 0.69, which is significantly lower than the benchmark value of 2.0. This indicates the presence of positive autocorrelation in the residuals. While the presence of autocorrelation does not bias the coefficient estimates (they remain consistent), it invalidates the standard errors, making the t-statistics unreliable. Therefore, to ensure valid statistical inference, it is necessary to re-estimate the model using Heteroskedasticity and Autocorrelation Consistent (HAC) / Robust Standard Errors.

As identified in the baseline model, the low Durbin-Watson statistic (0.69) indicated the presence of serial correlation in the residuals. In financial time series data, it is common for the current value of a variable to be influenced by its past values (persistence). Ignoring this structure can lead to inefficient estimates and misleading inferences. To address this issue and ensure the robustness of the results, the model was re-estimated by including a first-order autoregressive term AR(1) within the Fixed Effects framework. This specification explicitly models the serial dependence in the error term. The results of the corrected Panel AR(1) Fixed Effects Model are presented in Table 7.

Table 7. Final Panel Regression Results (Fixed Effects with AR(1))

Dependent Variable: LN_VOLUME				
Method: Panel Least Squares				
Sample (adjusted): 1/10/2020 12/31/2020				
Periods included: 52				
Cross-sections included: 31				
Total panel (balanced) observations: 1612				
Convergence achieved after 7 iterations				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	16.76728	0.144769	115.8213	0.0000
LN_TWEET	0.753012	0.025723	29.27404	0.0000
AR(1)	0.669585	0.018800	35.61695	0.0000
	Effects Specification			
Cross-section fixed (dummy variables)				
R-squared	0.857044	Mean dependent var		20.85638
Adjusted R-squared	0.854147	S.D. dependent var		0.998856
S.E. of regression	0.381470	Akaike info criterion		0.930689

Sum squared resid	229.7749	Schwarz criterion		1.040933
Log likelihood	-717.1355	Hannan-Quinn criter.		0.971611
F-statistic	295.8243	Durbin-Watson stat		2.147476
Prob(F-statistic)	0.000000			
Inverted AR Roots	.67			

Note: *** indicates statistical significance at the 1% level.

Upon examining the findings in Table 7, it is observed that with the inclusion of the AR(1) term, the Durbin-Watson statistic rose to 2.147, indicating that the autocorrelation problem has been completely eliminated. The explanatory power of the model (R2) reached a very high level of 85.7%. This ratio implies that approximately 86% of the variation in the trading volume of BIST 30 companies is explained by tweet counts, past-period effects (momentum), and firm-specific fixed characteristics. The remaining 14% stems from factors not included in the model, such as balance sheets, financial statements, and macroeconomic data. This result proves that the volatility in trading volume during the pandemic period was driven much more by investor attention and market momentum than by traditional financial data. The coefficient of the LN_TWEET variable, which tests the study's central hypothesis, was 0.753 and statistically significant at the 1% level ($p < 0.00$). As the model reveals, there is a simultaneous and very strong positive relationship between the number of tweets and trading volume. This coefficient is interpreted as follows:

"During the Covid-19 pandemic, a 1% increase in social media attention (tweet count) towards BIST 30 stocks leads to approximately a 0.75% increase in the trading volume of the relevant stock."

This finding suggests that investors do not wait to digest news but act immediately upon hearing the "Noise." It is statistically confirmed that the intensity of social media noise is associated with a simultaneous surge in trading volume, rather than a delayed reaction. The results obtained strongly support the "Herding Behavior," "Investor Attention," and "Noise Trading" theories in the Behavioral Finance literature. In summary, the physical isolation during the pandemic rendered investors more sensitive to the information flow on digital platforms, making social media interaction one of the most significant determinants of market liquidity.

6. Conclusion and Recommendations

In this study, the impact of social media interactions on the trading volume of BIST 30 companies was empirically examined during the COVID-19 pandemic, a period characterized as one of the highest levels of historical uncertainty in financial markets. While the traditional "Efficient Market Hypothesis" argues that investors are rational and act solely on fundamental information (balance sheets, interest rates, etc.), this study is grounded in the "Behavioral Finance" perspective, which argues that investors are influenced by "noise" in social media.

Within the scope of the analysis, panel data were used, covering 53 weeks for 31 companies. The key findings obtained from the unit root tests, causality analyses, and the AR(1) corrected Fixed Effects regression model, along with the recommendations developed in light of these findings, are presented below.

The empirical results of the study reveal a statistically significant, positive, and strong relationship at the 1% significance level between the tweets used on the Twitter platform—representing social media activity—and stock market trading volume. The elasticity coefficient of 0.753 obtained from the analysis indicates that a 1% increase in the number of tweets about BIST 30 stocks leads to an approximately 0.75% increase in the relevant stock's trading volume.

The Granger Causality tests provided a critical finding regarding the direction of this relationship. The analysis detected a unidirectional causality running from Trading Volume to Tweet counts, supporting the visibility hypothesis. This suggests that high trading activity draws attention to stocks, subsequently generating social media buzz. However, no lagged causality was found running from Tweets to Volume. This lack of lagged predictability, combined with the powerful relationship found in the regression analysis, proves that the interaction between social media and financial markets occurs simultaneously. Investors respond to the information flow on social media not with weekly delays, but with instantaneous reactions. The fact that the model's explanatory power reached 86% demonstrates that during crisis periods like the pandemic, the vast majority of volatility in trading volume is determined by investor attention and psychological factors rather than financial ratios.

These results strongly support the "Investor Attention" theory in the literature, as well as the "Herding Behavior" and "Noise Trading" hypotheses. The physical isolation and uncertainty of the pandemic led individual investors to social media to obtain information and track market trends. Although increasing interaction on Twitter creates "noise" in stock prices independent of rational data, the tendency of investors to follow these signals and act collectively, herding psychology, directly transformed the concentration of attention on the stock into trading volume that is liquidity.

In light of the findings, recommendations for market stakeholders can be developed as follows. Individual and institutional investors should follow not only fundamental and technical analysis data but also Digital Market Sentiment when making portfolio decisions. The study has shown that the volume of social media interactions is a concurrent indicator of market liquidity. Particularly during periods of crisis and uncertainty, strategies should be developed with the expectation of volatility and volume increases in heavily discussed stocks on social media. Executives of BIST 30 companies also must recognize that stock performance depends not only on financial success but also on corporate communication and brand perception. Since the "noise" generated about the company on social media directly affects trading volume, it is vital for companies to engage in professional social media management, establish transparent communication with investors through digital channels, and manage information pollution (disinformation) promptly. Market regulators should prioritize rule-making, acknowledging how sensitive trading volume is to social media interactions. This situation indicates that social media provides a conducive ground for market manipulation, such as pump-and-dump schemes. It is recommended that regulatory bodies accept social media platforms as a source of financial data and implement AI-supported surveillance mechanisms to detect manipulative activity on these channels.

This study demonstrates that during periods of high uncertainty, the explanatory power of traditional asset pricing models based solely on fundamental data diminishes. Therefore, academicians should reconsider the strict rationality assumptions of the Efficient Market Hypothesis in their curriculum and theoretical frameworks. It is recommended to integrate "Digital Sentiment" as a new risk factor or pricing variable into standard financial models such as CAPM or Fama-French. Furthermore, the intersection of finance and data science is becoming increasingly critical; thus, academic programs should prioritize teaching Big Data analytics and Natural Language Processing (NLP) techniques to understand the microstructure of modern financial markets better. Although this research provides significant empirical evidence regarding the relationship between social media and stock market activity, there are three main limitations that frame the scope of the interpretability of the findings. Firstly, the study covers the period from January 1, 2020, to December 31, 2020. This timeframe corresponds to the peak of the COVID-19 pandemic, a period characterized by extraordinary uncertainty and volatility significantly above historical averages. While this context provides a unique opportunity to observe behavioral patterns during a crisis, the strong "herding behavior" observed in this period may differ in calmer market conjunctures. Therefore, the findings should be interpreted specifically within the context of crisis periods.

Secondly, the transformation of time series to a weekly frequency constitutes a methodological constraint. Consolidating trading volume and tweet numbers as 53 weekly totals was necessary to filter out daily noise and focus on the main trend. However, this aggregation smooths out sudden news effects or short-term sentiment shocks that occur on specific days. This limitation explains why the contemporaneous relationship is strong while the lagged causality is less observable in the short run.

Thirdly, the measurement of digital attention contains structural constraints inherent to social media data. Although filtration methods were applied, it is practically impossible to exclude bot accounts or non-investor interactions from the dataset completely. Therefore, the variable used in the analysis (LN_TWEET) should be treated as a strong proxy for investor attention rather than as a flawless measure of individual investor sentiment.

In conclusion, these limitations define the boundaries of the research rather than invalidating the results. The study successfully demonstrates the dominant role of social media on trading volume during high-uncertainty periods, contributing valuable insights to the behavioral finance literature. Building on the findings and methodological limitations discussed in this study, several avenues for future research are proposed to enrich the behavioral finance literature further. Since this study used weekly data to observe medium-term trends, future studies should employ daily or high-frequency (intraday) data to enable more precise observation of the speed of information transmission and market microstructure. Additionally, while this research focused on "investor attention" through interaction volume, future researchers are encouraged to incorporate Natural Language Processing (NLP) and Sentiment Analysis methods. Distinguishing between positive, negative, and neutral sentiments would provide a deeper understanding of how the tone of digital information influences market direction, rather than just the volume of attention. Furthermore, since this research centers on trading volume, the effects on stock prices, return volatility, and abnormal returns should be examined in future models to determine whether social media noise creates only liquidity or also causes price inefficiencies. Finally, comparative studies could be conducted between crisis and non-crisis periods, or between developed and emerging markets, to test the universality and persistence of the "herding behavior" observed in this research.

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