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Disagreement on social media and stock trading volume: The Indonesian context

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Abstract. This research intends to test the relationship between disagreements on social media and stock trading volume using the Indonesia Stock Exchange (IDX) as a research object. The Covid-19 pandemic has made the use massively of social media to invest in Indonesia's capital market There has been an increasing number of investors in the IDX. They trade and discuss stocks online. The research question is whether the information on social media has worhted for Indonesian investors. Research on the relationship between social media features and stock market features, especially using trading volume, has never been done in Indonesia. To do this, we tested the influence that the number of posts and disagreements on Telegram social media has on stock trading volume in IDX. The test was done using multivariate regression method. The results show that discussions on social media have a positive and significant effect on stock trading volume, while disagreements do not significantly affect it.

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1. INTRODUCTION

This study aims to answer the question of whether information posted on social media matters for investors in Indonesia. It is important to provide this answer because there has never been any research linking social media features with capital market in Indonesia, especially using trading volume data. This research is exceedingly relevant presently because the combination of the Covid-19 pandemic and advances in social media technology has increased the number of investors. Data from the Indonesian Central Securities Depository shows that the number of investors has increased by more than 300% from 2.5 million people in 2019 to 7.86 million people in January 2022. The impact of the Covid-19 pandemic on financial markets has been broadly investigated in the literature (Rizvi et al., 2021; Hu et al., 2021; Chiah & Zhong, 2020). Meanwhile, advances in information and communication technology (ICT) have increased public participation in the capital market. Advances in internet technology, for example, facilitate access to the capital market through the presence of online brokers who have stimulated online trading (Turri et al., 2007). The earliest study on this issue by Barber and Odean (2002) showed that online trading often harms investors. This does not hinder the migration of investors from offline to online though, as online trading makes investing easier and cheaper (Bhasin, 2005), and even free of charge (Hu et al., 2021). Thus, technological advances have increased the number of investors.

Internet technology allows capital market information such as accounting disclosures, results of fundamental and technical analysis, and other disclosure information to be spread among investors in real-time (Blankespoor et al., 2018; Bartov et al., 2018). The existence of social media such as Reddit, Twitter, Whatsapp, Telegram, Wechat, Sina Weibo, and so on, further encourages investors to have conversations, share opinions, and discuss each other online and in real-time (Eierle et al., 2022). Even utilizing information posted on social media to make investment decisions has become a trend in the capital market (Yu et al., 2022). Chen et al. (2014) and Dong et al. (2021) discovered that investors' dependence on recommendations on social media is getting higher and has beaten advice from experts, similar to Nicholas's criticism in his book, The Death of Expertise (2017).

This phenomenon has invited a lot of research on the relationship between social media features and capital market features in various countries such as South Africa (Nyakurukwa & Seetharam, 2022), China (Zhang & Liu, 2021), and India (Mehta et al., 2021). The posting media used also vary, example, StockTwits (Cookson et al., 2021; Chang et al., 2021; Al-Nasseri et al., 2021; Audrino et al., 2020), Twitter (Nyakurukwa & Seetharam, 2022; Tan & Tas, 2021; Giannini et al., 2019), Facebook (Siikanen, 2018; Hasan & Wang, 2021), and Telegram (Tsuchiya, 2021). The Chinese version of social media is also widely used, for example WeChat (Zhang, 2021) and Sina Weibo (Xu et al., 2017). In Indonesia, this kind of research has not been portrayed. This condition has become a research gap which makes this research important to do. In detail, the research gap that we want to reduce, firstly, the impact of posting on social media - especially the impact of disagreements - on trading volume in the Indonesian Stock Exchange (IDX), to the best of our knowledge, has never been done. Second, the "Indonesian Investors" group on Telegram social media is famous and has many users in Indonesia. Third, most of the existing research used stock returns as a predictive target, including Chang et al. (2022), Nyakurukwa & Seetharam (2022), Tan & Tas (2021), Al Nasseri et al. (2021), and Wang et al. (2021), while this study will use stock trading volume as prediction target. Fourth, Telegram's social media is still rarely used, one of but it use by Tsuchiya (2021). Fifth, this research is the first to examine the impact of posting on stock values in bullish, bearish, and combined market conditions. Previous research did not differ the market conditions. This study proposes two hypotheses: First, information on the internet will be meaningful if the number of posts affects stock trading volume. Second, the meaning becomes useful when disagreements that arise in online discussions affect stock trading volume.

This research found posts on social media had a positive and significant effect on stock trading volume in bullish and combined market conditions but not in bearish market conditions. These results mean that information on social media is meaningful (Nyakurukwa & Seetharam, 2022). These results are proportionated with the latest findings that after posting using social media with the latest technology, the effect of information on social media on stock values is positive and significant. The disagreement hypothesis has a positive impact on trading volume, and a disagreement strengthens the influence of the number of postings on trading volume, which has not been affirmed in all market conditions. This finding is probably related to the culture of the Indonesian nation as a collectivist society. To be sure, this finding adds support to the unbiased prices hypothesis. Robustness check using the method of moment (MM) does not change the regression using the OLS method, posting has a positive and significant effect on trading volume on bullish and combined market conditions, and disagreements do not significantly affect trading volume.

The remaining paper proceeds as follows; a literature review will provide the progress of research in this field, a methodological approach that explains the data collection procedure and analysis technique, empirical results and discussion will propose the main work of this research. Finally, the conclusion will end this work.

2. LITERATURE REVIEW

Since Wysocki (1998; 1999; 2000) investigated the role of information posted on the internet in the capital market by correlating the number of posts on the Yahoo! Finance message board with stock returns, this topic has attracted many other researchers to update. Tumarkin & Whitelaw (2001), for example, used Raging Bull, then Das et al. (2005) used Yahoo! Finance, Raging Bull, The Motley Fool, and Silicon Investor, Zhang et al. (2012) used Theline!WallStreetPit, Leung & Ton (2015) used HotCopper, and Chang et al. (2022) used guba.eastmoney.com. Next, Dewally (2003) pioneered the use of newsgroups, which was replicated in May et al. (2019) by predicting stock returns on the Shanghai Stock Exchange (SSE) using the information posted on the Xueqiu newsgroup. Search engines were also used by Goel & Dash (2022), Wanidwaranan & Padungsaksawasdi (2022), Ben & Slim (2022) who used Google, and Xie & Wang (2017) used Baidu. Beside using newer posting media, the proxy for stock value is not limited to stock returns but involves another stock value particularly as trading volume, and price volatility.

The presence of social media increasingly facilitates the interaction of individual investors on the internet. Investors can discuss and share recommendations in real time . Chen et al. (2014) and Dong et al. (2021) noted that investors' dependence on recommendations on social media is getting higher. Researchers have also followed this development by looking for the relationship between postings on social media and stock values. StockTwits, a social media specifically created to share information about the capital market, is the most researched, including by Cookson et al. (2021), Chang et al. (2021), Al-Nasseri et al. (2021), and Audrino et al. (2020). Next is Twitter, for example by Nyakurukwa & Seetharam (2022), Tan & Tas (2021), and Giannini et al. (2019). The rests are Facebook (Siikanen, 2018; Hasan & Wang, 2021) and Telegram (Tsuchiya, 2021). The Chinese version of social media has also spawned a lot of researches, for example WeChat (Zhang, 2021) and Sina Weibo (Xu et al., 2017).

Preliminary literature studies show that the impact of posting on stock values is mixed. Wysocki (1998; 1999; 2000), Tumarkin & Whitelaw, (2001), and Sehgal & Song (2007), for example, found the positive effect of the number of posts on stock values. On the other hand, Das & Chen (2001), Dewally (2003), and Das et al. (2005) did not find a relationship between activities on the internet and stock values. The presence of social media has changed the results of research, most findings show a positive effect of postings on stock values, especially on stock returns (among others, Chang et al., 2022; Goel & Dash, 2022; Wanidwaran & Padungsaksawasdi, 2022; Ben & Slim, 2022; Nyakurukwa & Seetharam, 2022; Chang et al., 2021; Al-Nasseri et al., 2021; Tan & Tas, 2021; Zhang et al., 2021).

Based on these findings, the first hypothesis is built:

H_1: The number of posts affects stock trading volume

If posting in social media has meaning, indicated by the influence of the number of posts on trading volume, then a profound interpretation can be explored, namely content post. To prove this hypothesis, one of the content post, disagreements in discussions on social media, will be associated with stock trading volume.

The finance theory provides three hypotheses about disagreement (Hobs et al., 2018). First, disagreement is the cause of trade, known as the investor optimism hypothesis (Miller, 1977). The second is known the asymmetric information hypothesis (Varian, 1985). According to this hypothesis, the opinion difference among investors reflects on asymmetric information about firm values. The third is the no-trade theorem initiated by Milgrom & Stokey (1982). If there is no agreement on the price, then there will be no trade. This situation occurs when there is no price bias among investors, so it is known as the unbiased prices hypothesis.

Since the three hypotheses were created, many researchers have tried to test them. In recent decades, testing has become increasingly cautious (Daniel et al., 2021). This caution manifested in variable specifications (Awais & Yang, 2021). For disagreements, for example, there are many proxies (Hobbs, 2018) as partial least squares disagreement index (Huang et al., 2021) and correlation-based robust dynamic qualities (CBRDQ) (Chang et al., 2021). Media posting to convey disagreements is also selected, starting from StockTwits (Cookson et al., 2021; Chang et al., 2021; Al-Nasseri), Tweeter (Giannini et al., 2019; Nyakurukwa et al., 2022), Wechat (Zhang, 2021), and Sina Weibo (Xu et al., 2017). From the investors' side, it has separated between professional investors (analysts (Li & Li, 2021; Li et al., 2021), hedge funds (Nezafat et al., 2022)), and individual investors (Ma et al., 2022; Wang et al., 2021). The objects of the disagreement are also specific, such as a disagreement on the environment, social, and government (ESG) (Gibson et al., 2021), earning news (Giannini, 2019), earning announcement (Shen, 2022), and earning forecast (Li et al., 2021; Eierle et al., 2022).

For prediction targets, in general, there are still more studies on stock returns as an independent variable (Ma et al., 2022; Shen et al., 2022; Nezafat et al., 2022; Huang et al., 2021; Cao et al., 2021), but there has been an increase in the use of stock trading volume (Li & Li, 2021; Daniel et al., 2021; Cookson et al., 2021). Stock return proxies have also divided into cross-sections (Li & Li, 2022; Ma et al., 2022; Nezafat et al., 2022), time series (Hobbs et al., 2018), and market returns (Huang et al., 2021).

Of these various proxies, some were successful, and some were not, in proving the three hypotheses. Daniel et al. (2021), for example, proved succeed the investors'optimism hypothesis, in that high trading volumes are difficult to explain without a high level of disagreement. Meanwhile, the asymmetric hypothesis has been proven, among others, by Shen et al. (2022) and Huang et al. (2021). The proving of the two hypotheses shows that there is a positive influence of disagreement on stock trading volume. Those who support this finding include Cookson et al. (2021), Giannini et al. (2019), Cookson & Niessner (2020), Gibson et al. (2021), Li et al. (2021), Cao et al. (2021), and Huang (2021). Of course, some have proven the unbiased prices hypothesis (e. g., Hobbs et al., 2018). Here disagreements do not significantly affect the stock trading volume or have a negative effect (Li & Li, 2021; Ma et al., 2022; Shen et al., 2022; Nezafat et al., 2022).

As stated by Daniel et al. (2021), caution is needed in examining the impact of a disagreement. Results of the literature proved that there are still differences in findings regarding the impact of a disagreement on stock values.

Departing from this condition, the second hypothesis of this research is built:

H_{2a}: Disagreement affects stock trading volume
H_{2b}: Disagreement strengthens the effect of the number of posts on stock trading volume

In examining the two hypotheses, this paper proposes a model where the stock trading volume is the dependent variable, then the number of postings and disagreements is the independent variable. The model uses a control variable, a 45-most liquid stock price index (LQ 45). The use of stocks included in LQ 45 as a control variable is to anticipate the great attention of investors on the blue chips that may invest in the stocks.

Estimates are made on three market conditions: bullish, bearish, and a combination of both, using the OLS method. The data used is the stock trading volume in IDX, which was from Yahoo! Finance. Then the LQ 45 stocks data are taken from idx.co.id. Post data are from the 'Indonesian Investors' group on Telegram. The disagreement data uses the disagreement index calculated based on Das et al. (2015).

3. METHODOLOGY

The population of this study was 570 stocks listed on the Indonesia Stock Exchange until July 31, 2017. However, in the Indonesian Investor group on social media Telegram, are not posted all stock. Those who obtain the position do not necessarily meet the requirements requested. Therefore, this study used a sample with purposive sampling method, with the criteria of Wysocki (1998) as follows:

1. Not an initial public offering company in the last one year from the analysis period.
2. Get at least one post in a bullish or bearish market period.
3. Get at least one buy post in a bullish or bearish market period.
4. Get at least one sell post in a bullish or bearish market period.

This study used the primary and secondary data. Primary data was in the form of total posts, the number of buy posts, the number of sell posts, the number of neutral posts, and the number of uncategorized posts (see table 1). Determination of post category used the consensus technique. The consensus was from three people who did not know each other. Each post was read alternately by the three consensus participants, by giving a score of 1 for each category who agreed upon and -1 for the category that was not agreed upon. Disagreement data uses the disagreement index calculated based on Das et al., 2005.

For example, participant A gives a point of 1 for a post that is in the buy category, then this post is sent to participant B. If B agrees with A that the post is in the buy category, then B will add another point of 1, but if he does not admit on, then B will give -1 point. Next, continue the post forwarded to C, and C will repeat what B did. Thus, if all three agree that the post is in the buy category then this post will get a value of 3. If two agree and one disagrees, the post gets a value of 2 and is still in the buy category. If two people disagree, then the post will get a score of -1, and will not be used.

This research used the multivariate regression analysis method. This study did not test the normality test because many data posts were not normally distributed, which was insufficient. As Wysocki (1998) experienced, posts were only concentrated on five companies (Apple Computer, Intel, Oracle, Starbucks, and MCI Worldcom). The post unevenness makes the post-distribution not normal. To compensate, the variable number of posts is taken logarithmically (logP) according to the suggestion of Hair et al. (2018: 106). Estimates are on three market conditions: bullish, bearish, and a combination of both.

Table 1

Posting category

Category	Posted Sentences Contain
Buy	1. Words: buy; bullish 2. Optimistic tone 3. Positive statement 4. Good news 5. Statement of owning shares 6. Negative response to sell posts
Sell	1. Words: Sell; bearish 2. Pessimistic tone 3. Negative statement 4. Bad news 5. Stetement of not owning shares 6. Negative response to buy posts
Neutral	Words: hold, wait and see
Uncategorized	Other than words, include sentences, statements, and responses belonging to the three categories

Source: *own compilation*

Here are the regression models to be tested:

$$TV_{iBull} = \alpha + \beta_1 LogP_{iBull} + \beta_2 D_i + \beta_3 LogP_{iBull} * D_i + \beta_4 LQ45_i + \varepsilon_1 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

$$TV_{iBear} = \alpha + \beta_1 LogP_{iBear} + \beta_2 D_i + \beta_3 LogP_{iBull} * D_i + \beta_4 LQ45_i + \varepsilon_2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

$$TV_{iBull-Bear} = \alpha + \beta_1 LogP_{iBull-Bear} + \beta_2 D_i + \beta_3 LogP_{iBull-Bear} * D_i + \beta_4 LQ45_i + \varepsilon_3 . (3)$$

Regression models 1, 2, and 3 were used to test hypotheses 1, 2_a, and 2_b. $\mathbf{TV_i}$ is the cumulative trading volume of the bullish, bearish, and combined periods of each stock. $\mathbf{LogP_{iBull}}$, $\mathbf{LogP_{iBear}}$, and $\mathbf{LogP_{iBull\text{-}Bear}}$ the number of posts that each stock received in its bullish, bearish, and combined periods[1]. $\mathbf{D_i}$ is a disagreement among investors as measured by the disagreement index suggested.

LQ 45 is a control variable, namely, the 45 most liquid stocks used to calculate the most leading index, LQ 45 Index (See table 2 for complete variables operational definition). The LQ 45 index used to anticipate investors' attention on leading indicators, so they tend to pay attention to stocks that are included in the leading index. The use of this leading index as control variables follows Awais & Yang (2021).

[1] Needs analysis adjusts with time. For example, the number of open-to-close postings only counts the number of postings received by each stock from the opening to the closing of the exchange (Antweiler & Frank, 2004; Wysocki, 1998). This study uses close-to-close posting to match trading volume and stock price data.

Table 2

Variables operational definition and measurement

Variable	Operational Definition	Measurement
TV_{ibull} (Trading Volume in bullish period)	Number of shares traded in the bullish period	The number of daily stock trades is calculated close to close for the period 8 August 2020-19 March 2021
TV_{ibear} (Trading Volume in bearish period)	Number of shares traded in the bearish period	The number of daily stock trades is calculated close to close for the period 8 August 2019-19 March 2020
$TV_{iBull\text{-}Bear}$ (Trading volume in combined period)	Number of shares traded in the combined period	The number of daily stock trades is calculated close to close for the period 8 August 2019-19 March 2021
$LogP_i$ (Post)	Number of daily posts for bullish, bearish and combined periods	Total daily posting of each share for the period 8 August 2019-19 March 2020, the period 8 August 2020-19 March 2021, and the period 8 August 2019-19 March 2021, then the logarithm is taken
D_i (Disagreement)	Disagreement between posters manifested by buy and sell posts in bullish, bearish, and combined periods	$\left\lvert \frac{\lvert \text{Buy Posts} - \text{Sell Posts} \rvert}{\text{Buy Posts} + \text{Sell Posts}} - 1 \right\rvert$
LQ 45 (Leading index)	The leading index that made up of the 45 most liquid stocks (dummy variable)	Taken from 45 shares of LQ 45 members in the period of 8 August 2019-19 March 2020 for bearish market condition, 8 August 2020-19 March 2021 period for bullish market condition, and 8 August 2019-19 March 2021 for combined market condition. Value 1 for shares that are members of the LQ 45 index and 0 for others

Source: *own compilation*

4. EMPIRICAL RESULTS AND DISCUSSION

The descriptive statistics (table 3) showed that the number of posts in bearish market conditions reached 778 thousand, while in bullish market conditions was only 406 thousand. The mean of posts in bearish market conditions is 6,980, with a standard deviation of 12.03. In bullish market conditions, it means of posts is 3,180 and a standard deviation of 3.35. Following what happened to the number of posts, that there were more buy and sell in bearish market conditions than on bullish market conditions. Sell and buy, posting in bearish market conditions, are 589 thousand and 137 thousand, with a mean of 5,660 and 1,320, respectively. In bullish market conditions, the number of buy and sell posts is 179 thousand and 66 thousand, with a mean of 2,320 and 860, respectively. With a much greater number of posting in a bearish market, the deviation is also a large. This finding provides information that investors tend to seek information when the market is in a bearish condition compared to when the market is in a bullish condition. Furthermore, for combined market conditions, the number of posts reached 1.18 million, with a mean of 4,950 and a standard deviation of 9.34. The number of buy posts is 768 thousand, and sell posts is 203 thousand, with a mean of 4,070 and 1,120, respectively.

Although, in bearish market conditions, the more number of posts, the stock trading volume is more in bullish market conditions. In a bullish market condition, stock trading volume reaches 200 million shares with means of 26 million, while in a bearish market condition, the stock trading volume is only 155 million with a mean of 15 million. From these findings, information obtains that the condition of in bearish market, investors tend only discuss, so they make fewer trades. On the other hand, in a bullish market investor will likely trade more. Furthermore, in both market conditions is found that there are always more buy posts than sell posts. This finding is the same as previous findings, including when information was still using traditional media. Dewally (2003), for example, reported a ratio of buy-to-sell recommendations of 30:1 when the market is in a good mood and 7:1 when the market is in a bad mood.

Table 3

Descriptive statistics

Variables	N	Max	Min	Mean	Std Deviation
Bullish					
LogPost	406	16	1	3.18	3.35
Number of buy posts (thousands)	179	11	0	2.32	2.35
Number of sell posts (thousands)	66	15	0	.86	1.95
D	-	1	0	.20	.31
TV	2,005.27	189.64	.0002	26.04	39.30
Bearish					
LogPost	778	101	1	6.98	12.3
Number of buy posts (thousands)	589	79	1	5.66	9.50
Number of sell posts (thousands)	137	22	0	1.32	2.96
D	-	1	0	.23	.29
TV	1,551.14	203.90	.0001	14.91	30.82
Combine					
LogPost	1.184	112	3	4.95	9.43
Number of buy posts (thousands)	768	81	1	4.07	8.67
Number of sell posts (thousands)	203	24	1	1.12	2.76
D	-	1	0	.24	.30
TV	3,556.41	223	.0018	19.64	35.21

D is disagreement, and TV is the total trading volume of shares in hundreds of thousands of lots, 1 lot = 100 share

Source: *own calculation*

4.1. Information in social media is meaningful

In finding out the meaning of interactions on social media for Indonesian investors, this study links the number of posts with stock trading volume. Following the increasing capabilities of individual investors and the development of ICT, the discussion media has turned into uploaded posts by investors using various applications such as Telegram in this study. The hypothesis proved that one (H_1) is hypothesized, the more posts of a stock receive, the greater the trading volume becomes, whether the market is bullish, bearish, or a combination of both.

The regression models 1, 2, and 3 showed that the H_1 test gave mixed results. In bullish market conditions, the LogPost coefficient (β_1) is 45.102 and is significant at α 0.01 (see table 4). While in bearish market conditions, the LogPost coefficient value (β_1) = 15.061 and is insignificant. For combined market conditions, the regression results show the LogPost coefficient value (β_1) = 26.539 and is significant at α 0.01. With a result like this, then H_1 can be supported in bullish and combined market conditions.

In bullish market conditions, investors make investments based on discussions on social media to get strong evidence. It showed included stock in the LQ 45 index are significant at α 0.05 in influencing stock trading volume, but the direction is negative (β_4 = -27.976). It means that the shares included in LQ 45 index do not encourage investors to invest.

In bearish market conditions, H_1 is unsupported. When the market is in a bearish condition, the most influential factors on investors' investment decisions is LQ 45 stocks. It indicated by the positive and significant coefficient values of the LQ 45 variable. The coefficient value of LQ 45 (β_4) is 25.451 with a significance level of 0.05. In combined market conditions, again LQ 45 shares factor does not play a role in investment decisions. It proved by the coefficient value of LQ 45 (β_4) which is negative (-3.667) and not significant.

The LogPost variable significantly affects the stock trading volume and can support H_1 in both bullish and combined market conditions. In these two market conditions, the coefficient value of the LogPost variable is the largest. Hence, it is understandable that in a bullish market, the only factor that affects stock trading volume is the posts or the discussions on social media. The LQ 45 variable is significant in both bullish and bearish market conditions, but only supports the hypothesis in bearish market conditions. Thus, in bearish market conditions, the factor that most influences investment decisions are the blue chips stocks. In combined market conditions, investors still prioritize discussions on social media as a basis for investment decisions. These findings indicate the truth of the signal that investors make investment decisions based on the discussions on social media, although not in all market conditions. In bearish market conditions, investors pay more attention to LQ 45 stock. Thus, pieces of information in social media have an essential meaning in investing in the capital market.

4.2. Information in social media is not useful

Furthermore, to dig deeper into the meaning of the information posted on social media, it will test whether the content of the posting, namely disagreement, affects the stock trading volume. When posting, investors get responses from the other investors who also posts so that discussions occur on social media. According to Tumarkin & Whitelaw (2001), investors can influence each other to discuss on social media. In such discussions, of course, they do not always agree. Sometimes a bid (buy post) from one investor gets the opposite response (sell post) from another investor. Disagreements like this become one of the hypotheses of stock trading, thereby increasing trading volume. In obtaining the evidence, this study builds hypothesis 2_a (H_{2a}). H_{2a} testing was done by re-regressing models 1, 2, and 3. From the results obtained, disagreement does not significantly affect stock trading volume in all market conditions. Even in bearish market conditions, the disagreement effect on trading volume is negative.

If we look at table 4, in a bullish market condition, the coefficient of D variable (β_2) is 24.101 and is not significant. In bearish and combined market conditions, the D variable (β_2) coefficients are -5.061 and 9.670 and are insignificant. With a result like this, then H_{2a} is unsupported.

Table 4

Regression results using the OLS method

Variable	Bullish	Bearish	Combined
Constant	13.976 (1.923)*	-2.974 (-1.430)	3.009 (1.718)
LogPost	45.102 (3.047)***	15.061 (1.984)	26.539 (2.999)***
D	24.101 (2.056)	-5.980 (-2.086)	9.670 (2.507)
LogPost*D	-18.096 (-1.849)	-6.022 (-1.732)	-3.667 (-1.447)
LQ 45	-27.976 (-3.343)**	25.451 (3.663)**	-7.752 (-1.573)
F	2.619***	3.278***	2.988***
R^2	0.401	0.301	0.286

The reported of t-statistics is in parentheses, and significance level is denoted with asterisk for * $\varrho < 0.10$, ** $\varrho < 0.05$, and *** $\varrho < 0.01$.

Source: *own calculation*

In theory, disagreement increases trading volume, and hypothesis 2_b (H_{2b}) states that a high-level disagreement can increase the influence of the number of posts on trading volume. The regression results show the same thing with the disagreement influence independently, namely, the role of disagreement moderator is unsignificant. Even the coefficient values in the three market conditions are negative. The coefficient value of LogPost*D (β_3) in bullish market conditions is -18.096, while in bearish and combined market conditions, it is -6.022 and -3.667, respectively. Thus, H_{2b} is not supported.

For robustness check Moment Method (MM) was used. Although the regression with MM showed better results by a higher R^2 and a lower residual standard error (RSE), the regression results did not change, posting had a positive and significant effect on stock trading volume, and disagreements did not significantly affect stock trading volume. R^2 for bullish, bearish, and combined market conditions with classical standard errors were respectively 40.1%, 30.1%, and 28.6 while R^2 for bullish, bearish, and combination market conditions using the MM standard error were respectively 43.7%, 32.2 %, and 29.1% (see table 5). In addition to comparing R^2 and RSE, the t-test on RSE examines robustness where the results show that all differences in RSE are unsignificant.

Table 5

Regression results using the MM method

Variable	Bullish	Bearish	Combined
Constant	14.045 (2.010)*	-2.674 (-1.043)	2.991 (1.018)
LogPost	44.851 (3.043)***	14.988 (1.309)	25.997 (2.659)***
D	24.371 (2.729)	-6.321 (-2.670)	8.897 (1.917)
LogPost * D	-17.867 (-1.334)	-5.914 (-1.176)	-3.011 (-1.049)
LQ 45	-23.122 (-3.342)**	21.841 (3.742)**	-5.887 (-1.328)
F	2.914***	2.978***	2.958***
R^2	.437	.322	.291

The reported of t-statistics is in parentheses, and significance level is denoted with asterisk for * $\varrho < 0.10$, ** $\varrho < 0.05$, and *** $\varrho < 0.01$.

Source: *own calculation*

4.3. Discussion

Based on the result of the test of the first hypothesis, there are two fascinating things to discuss. First, the role of discussions on social media about investment activities is different in the two market conditions. This finding has never existed in previous studies. In bullish and combined market conditions, posting plays a pivotal role in influencing investment activity, namely increasing trading volume. This finding supports previous works, especially by Wysocki (1998; 1999; 2000). But more importantly, this finding is in line with the development of social media technology where the presence of social media with newer technology has changed the research results, which substantially indicate a positive effect of posting on stock values, especially on stock returns (Chang et al., 2022; Goel & Dash, 2022; Wanidwaran & Padungsaksawasdi, 2022; Ben & Slim, 2022; Nyakurukwa & Seetharam, 2022; Chang et al., 2021; Al-Nasseri et al., 2021; Tan & Tas, 2021; Zhang et al. al, 2021).

On the other hand, in bearish market conditions, posting does not affect stock values. This finding means that supporting parties find no evidence of posting effect on stock values, especially those who used old social network such as Das & Chen (2001), Dewally (2003), and Das et al. (2005). Second, the insignificant effect of posting on stock trading volume in bearish market conditions is contrary to the descriptive statistics results which show that investment activity will not follow posts. Another interpretation states that in bearish market conditions, investors tend to expect more postings than in bullish market conditions. There is a possibility that in bearish market conditions, investors are more active in seeking information via postings.

Theoretically, the finding of a positive and significant effect of posting on stock trading volume can be additional evidence for predicting stock values using information sourced from the latest technology. Before the internet information media attracted the attention of researchers, there had been many studies on the information effect on stock values disseminated through traditional media such as newspapers, radio, television, polling institutions, to the oldest one through coffee houses in Amsterdam (Leinweber & Madhavan, 2001). While the results obtained from discussions in traditional media still provide various alternative findings, the latest information media is already waiting for its turn. Therefore, this study finds additional evidence of the positive and significant effect of stock value information disseminated via the Internet.

Empirically, in the context of the Indonesian capital market, it is interesting to ask why investors make investment decisions based on discussions on social media. There are three potential answers. First, it is demanding to obtain data from official sources. Even if it succeeds in getting it, its accuracy still needs to be questioned. Second, there is a possibility of the capability of investors conducted investment analysis. As is known, the tradition of investing in shares in Indonesia has not been too long when compared to that in developed countries. Therefore, the ability of investors to conduct investment analysis—especially financial analysis—has not yet met the required level of capability. Even in societies with established investment traditions, it does not guarantee that investors can conduct analysis (Rose, 2001 and Rose et al. 2004)). Third, as theorized by behavioral finance, in analyzing information investors are influenced by psychological bias. This causes them to tend to ignore fundamental financial data and prioritize nonfinancial information such as discussion on social media.

The result of the second hypothesis test, for adherents of optimism hypothesis and asymmetric information hypothesis, it will be difficult to accept this result. Most theories and empirical findings indicate a positive and significant impact of disagreement on stock trading volume. Daniel et al. (2021) reviewed of development of research on disagreements in the capital market over the last few decades has succeeded in proving the optimistic investor hypothesis. His findings indicated that high trading volumes are difficult to explain without a large level of disagreement. While Shen et al. (2022) and Huang et al. (2021) confirmed the existence of the asymmetric information hypothesis. The proving of the two hypotheses shows that there is a positive influence of disagreement on trading volume. This evidence received much support from other findings, including of Cookson et al. (2021), Giannini et al. (2019), Cookson & Niessner (2020), Gibson et al. (2021), Li et al. (2021), Cao et al. (2021), and Huang (2021).

However, for adherents of the no-trade theorem like Hobbs et al. (2018), that disagreements do not affect trading volume is not surprising. Thus, the proven of influence of the disagreement on stock trading volume in this study adds support to the unbiased prices hypothesis initiated by Milgrom & Stokey (1982). This finding complements the literature on the role of disagreements in the capital market accompanying previous findings (Li & Li, 2021; Ma et al., 2022; Shen et al., 2022; Nezafat et al., 2022), particularly in the Indonesian context. Another theoretical explanation that does not prove H_{2a} and H_{2b} in bearish market conditions is the herd behavior. According to this theory, individuals usually confirm the majority of other individuals, then follow their decisions (Shiller, 2006; Fromlet, 2001). This theoretical explanation implicitly admits that IDX investors behave in the herd. Because investment decisions occur due to the behavior of the agreement, namely following the opinion of the majority of market participants. Thus, investors in IDX tend to avoid disagreements when making investments.

For the empirical explanation, there is a link to culture. According to Hofstede (1980; 2001), the culture of nations can classify—as collectivists or individualist. Eastern countries, such as Indonesia, are part of a collectivist society. Because the culture is a collectivist society, there is a possibility that Indonesian people are not comfortable with disagreements, especially those expressed in front of the interlocutors, including in discussions on social media. It is from the various meetings where there are rarely face-to-face arguments. The determined outcome of the deal is often by the leader or people with dominant influence. Even if there is a disagreement, what may happen is gossiping outside the forum. This behavior may also carry over when discussing social media investment decisions making. This cultural factor found the investment decisions influence in the capital market (Perez et al., 2021). The two explanations above are sufficient to explain the insignificant affect of a disagreement moderator on the effect of the number of postings on stock trading volume. In all market conditions, the affect of the moderator is negative and insignificant. It provides information that investors in IDX honestly tend to avoid disagreements and tend to follow the opinion of the crowd or behave in the herd, as suited to a collectivist society.

5. CONCLUSION

The presence of the internet and its applications, including social media, has shifted investment activities from offline to online media. Investors are increasingly dependent on information on social media. Investors trust recommendations on social media more than that from expert advice. The question is, does social media information have a meaning that can be useful? In answering this question, we tested two hypotheses, namely the effect of the number of posts and disagreements on social media on the stock trading volume.

The results showed from the first hypothesis that posts on social media have a positive and significant effect on stock trading volume is proven in the bullish and combined market conditions. It interpreted that information posts on social media have increased the stock trading volume. These results are answer the first question; namely, the information posts on social media have a meaning for Indonesian investors.

Then from the second hypothesis that a disagreement has a positive affect on trading volume and a disagreement strengthens the effect of the number of posts on stock trading volume, both have not proven in all market conditions. It means that investors in Indonesia tend to follow the opinion of market participants majority when making investment decisions, or there is no disagreement. This behavior of following the beliefs of the majority of market participants is known as the herd behavior. Thus, herd behavior has a place in IDX.

This study brings four contributions. First, adding literature on the impact of posting on social media on stock values for the Indonesian context, thus complementing similar studies from other countries. Second, adding literature on the use of Telegram social media that is still rarely used (Tsuchiya (2021). Third, the insignificant effect of disagreement on the stock trading volume at IDX, adding literature in supporting the unbiased price hypothesis (Hobbs, 2018), and adding literature on the role of culture in the capital market of collectivist society (Perez et al., 2021), especially in the Indonesian context. Fourth, this study provides literature on the impact of posting on social media on stock values in different market conditions.

The limitation of this research is, first, the category of posts used the consensus method. Although this method is more accurate (Das & Chen, 2001), it is slower. Machine-learning and deep-learning methods are faster. Second, the use of Telegram social media, although quite active, there are still not too many posts, so the posts collected are not sufficient. For further research, in proving the influence of cultural collectivism factors on the investment behavior of Indonesian investors is interesting. Finding the answer to why buy posts always outnumber sell posts is also quite challenging.

Author Contributions

Conceptualization, S.W (100%); methodology S.W. (50%) and I.R.S (50%); validation, S.W (40%) and I.R.S (60%); formal analysis, S.W (50%) and I.R.S (50%); investigation, S.W. (50%) and I.R.S (50%); writing—original draft preparation, S.W. (70%) and I.R.S. (30%); writing—review and editing, S.W. (40%) and I.R.S. (60%) . All authors have read and agreed to the published the manuscript. S.W. = Sawidji Widoatmodjo, I.R.S = Ignatius Roni Setyawan

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