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Twitter (X), Investor Sentiment, and Market Inefficiency: A Case Study of Indonesia

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Abstract−This study examines the impact of Twitter (X) sentiment on market inefficiency (proxied by stock mispricing) in Indonesia, based on an analysis of 600 observations. Stock mispricing, which arises due to inefficiencies in the capital market, is significantly influenced by investor sentiment. With the growing role of technology, social media platforms, particularly Twitter (X), have become valuable tools for measuring market sentiment. Using the Vector Autoregressive (VAR) model, our findings indicate that Indonesian stock prices in were undervalued by 19.5%, and Twitter sentiment had a significant negative effect on stock mispricing, suggesting that pessimistic sentiment can lead to deviations from fundamental stock values. These findings reinforce the behavioral finance perspective, which argues that investor emotions influence market movements beyond traditional financial indicators. The study also emphasizes the need for investors to consider both market fundamentals and sentiment trends on social media before making investment decisions. Given the growing role of digital platforms in shaping financial perceptions, understanding investor sentiment on Twitter can provide valuable insights for market participants.

Keywords: Stock Mispricing; Twitter (X); Investor Sentiment; Market Inefficiency.

1. INTRODUCTION

Since the introduction of the Efficient Market Hypothesis (EMH) by (Fama, 1970), public information has been regarded as a crucial factor in the stock market, as it is directly reflected in stock prices. However, Behavioral Finance theory argues that stock prices are not necessarily linked to available information due to their high volatility (Shiller, 1981). In an inefficient market (semi-strong or weak form efficiency), the reflection of information in stock prices occurs gradually, causing stock prices to deviate from their fundamental values, a phenomenon known as stock mispricing.

Stock mispricing significantly influences investment decisions. When stocks are overpriced, firms should issue shares to raise investment funding since the cost of capital is lower. Conversely, firms should refrain from selling shares when stocks are underpriced to avoid potential financial losses due to incorrect investment decisions (Mrad et al., 2024).

One of the primary factors contributing to stock mispricing is investor sentiment. Han et al. (2022) found that market mispricing, as indicated by market anomalies, is more likely to occur when investor sentiment persists. Previous studies also suggest that stock price fluctuations are significantly driven by investor sentiment (Verma & Verma, 2021). Furthermore, (Cheema & Fianto, 2024) demonstrated a significant relationship between stock mispricing and investor sentiment.

Various methods can be employed to measure investor sentiment, such as the New Investor Sentiment Index (NISI) proposed by (Gong et al., 2022) and the Consumer Confidence Index (CCI). However, with advancements in technology, social media has become an increasingly common platform for individuals to express their opinions, emotions, and ideas. Consequently, social media platforms can serve as valuable tools for gauging investor sentiment.

X, formerly known as Twitter, is one of the most widely used social media platforms for expressing public opinions and ideas. Due to its accessibility and brevity, Twitter serves as a popular source of concise public opinion. Additionally, the vast and diverse nature of Twitter data presents opportunities for researchers to enhance their understanding of public sentiment. Twitter is also considered a reliable representation of public sentiment since tweets are limited to 140 characters (Cam et al., 2024; Y. Wang et al., 2022).

The number of Twitter users has consistently increased over the years. By the end of 2018, Twitter had 321 million users worldwide. According to Statista (2024), Indonesia ranks fourth in terms of active Twitter users, following the United States and Japan—both of which are known for their strong-form market efficiency (Figure 1). Furthermore, the number of active Twitter users in Indonesia has continued to rise, with the most significant increase occurring in 2017, from 16.8 million to 18.9 million users (Figure 2).

Previous studies have demonstrated that stock market movements and returns can be predicted using Twitter-based sentiment analysis (Albahli et al., 2022; Duz Tan & Tas, 2021). Several studies have also explored the relationship between investor sentiment on Twitter and stock market behavior. However, most of these studies have focused on developed markets, such as the United States, which are characterized by higher market efficiency. In contrast, this study examines an emerging market, specifically Indonesia, which is known for its inefficiencies. While previous research has investigated investor sentiment in inefficient markets (Messaoud et al., 2023; Nyakurukwa & Seetharam, 2023; W. Wang et al., 2021), none have utilized news and mood data from Twitter as a means of measuring

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investor sentiment. Given the rapid advancement of technology, social media has become an essential medium for individuals to express opinions and emotions.

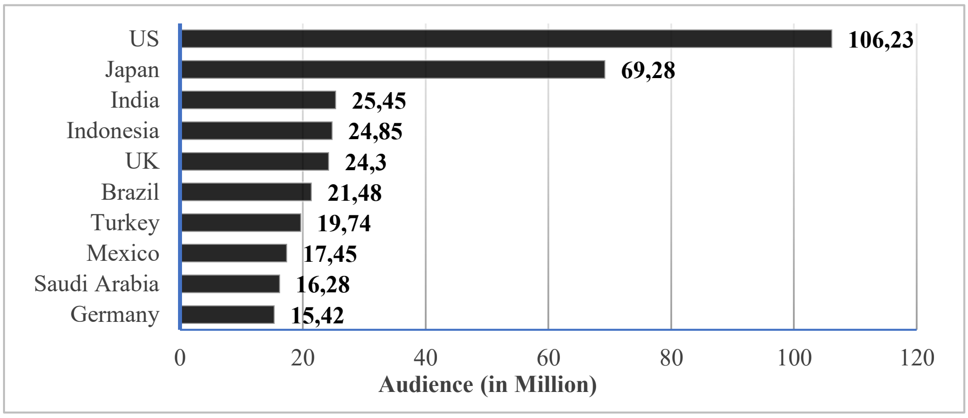

Figure 1. Number of Active Twitter Users based on Country as of April 2024 (in million)

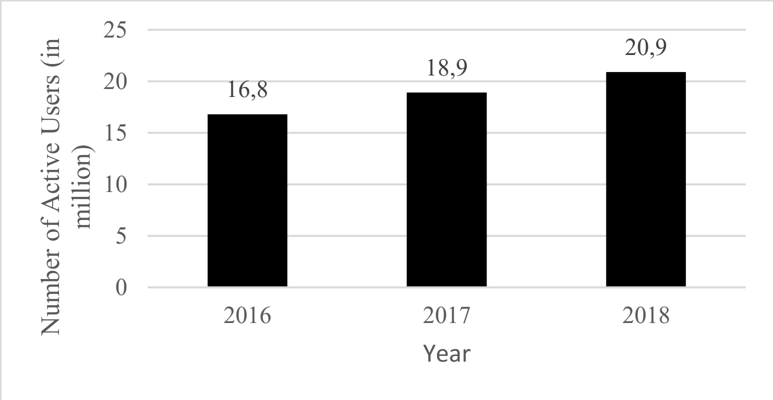

Figure 2. Number of Active Twitter Users in Indonesia in 2016 – 2018 (in million)

Therefore, the purpose of this study is to analyze the impact of investor sentiment on Twitter on market inefficiencies in Indonesia proxied by stock mispricing. To the best of our knowledge, this is the first study to examine the relationship between investor sentiment on Twitter and stock mispricing in an emerging market. The findings of this study can provide valuable insights for investment managers in assessing investor sentiment before making investment decisions.

2. RESEARCH METHODS

2.1 Basic Research Framework

In the era of globalization, social media has played a crucial role in the stock market. Previous research highlighted that social media, particularly Twitter, provides real-time public sentiment data that can be utilized to predict stock price movements (Albahli et al., 2022; Duz Tan & Tas, 2021). However, recent studies suggest that investor and public sentiment not only influence stock prices and returns but also contribute to market anomalies such as stock mispricing.

Han et al. (2022) show that shifts in sentiment persistence impact equity market anomalies and evaluate sentiment's predictive capacity for short-term returns. However, W. Wang et al. (2021) finds an inverse correlation between investor sentiment and future stock returns on a global scale. These differences are attributed, to some extent, to variations in cultural and institutional factors, as well as differences in intelligence and education levels, all of which are influenced by the degree of participation by individual investors in each market.

Verma & Verma (2021) finds that stock prices consistently fail to reflect their true fundamental values due to sentiment from both small and large firm investors. Small firms often experience disproportionately higher returns than large firms. This phenomenon, commonly referred to as the "small firm effect," suggests that investors may misprice small-cap stocks due to overestimating their growth potential (Quy Duong, 2024). As a result, stock mispricing is more pronounced in these firms, driven by speculative trading and less available public information (Zhang, 2022). A study analyzing A-share companies listed on the Shanghai and Shenzhen stock exchanges from 2010 to 2022 also indicate that stock returns are negatively correlated with the component reflecting investor expectations, suggesting that high book-to-market ratios may result from excessive market reactions rather than fundamental factors, leading to stock mispricing (Y. Liu, 2024).

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Based on those research, investor sentiment may affect stock prices away from its fundamental value. Additionally, firm size, especially small firms and high book-to-market firms are tend to have more effects on stock prices. Therefore, this study have basic research framework drawn as follows:

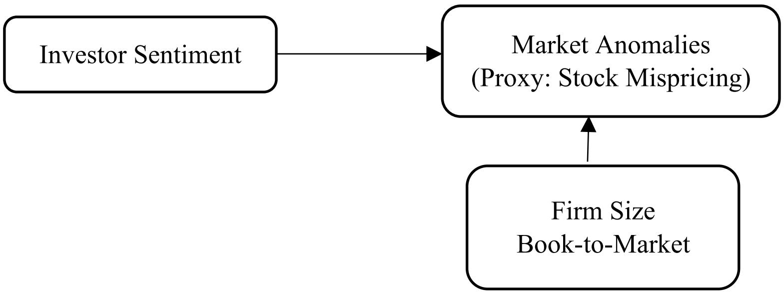

Figure 3. Research Framework

Moreover, based on previous research and research framework, the following hypothesis is proposed:
H1. Investor sentiment on Twitter has a negative effect on stock mispricing.

As mentioned above, the highest increased in number of active Twitter users occurred in 2017. Therefore, we use all shares data listed in Indonesia Stock Exchange in 2017. We obtain all price data and financial statements from Datastream. We use quarterly data, which is consist of price, market value, book value, tax payable, dividend payable, book-to-market ratio, and net income. For risk free rate proxy, we use government bond 10y yield. Whereas tweet data collected using Twint package in Anaconda 3.6.

2.2 Estimation of Stock Mispricing

To estimate stock mispricing, we use methodology in (D. Liu et al., 2016), who define fundamental or intrinsic value of market-to-book ratio as:

$$m_t - b_t = c + \sum_{\tau=1}^{\infty} \rho^{\tau-1} E_t(ROE_{t+\tau}) - \sum_{\tau=1}^{\infty} \rho^{\tau-1} E_t(r_{t+\tau}) \quad (1)$$

Where m_t is log of the market value, b_t is the log of book value; book value calculation is from the sum of common equity, deferred tax, and tax payable. c is a constant and estimated as c = k/1-ρ, where ρ = 1/ 1+ e^{d-p}, d – p is the average log dividend-price ratio for the period, and k = -log (ρ)-(1-ρ). r_t is excess stock return which is defined as log return of the stock minus the risk free rate; E_t is expectations operator, which is conditional expectations calculated using the estimated Vector Autoregressive (VAR) parameters; and ROE_t = log (1 + net income/book value) – risk free rate.

However, the intrinsic value is different from observed value, which depend on investor expectations when they price stocks. Besides, $\sum_{\tau=1}^{\infty} \rho^{\tau-1} E_t(r_{t+\tau})$ in eq. (1) is a discount factor in security valuation models related to both investor risk preference and equity risk premium. Thus, we divided observed log market-to-book value ratio into two components, those are fundamental value and mispricing term, ε_t, which is the difference between observed and fundamental log market-to-book value ratios.

$$m - b = m_t - b_t + \varepsilon_t = c + \sum_{\tau=1}^{\infty} \rho^{\tau-1} E_t(ROE_{t+\tau}) - \sum_{\tau=1}^{\infty} \rho^{\tau-1} E_t(r_{t+\tau}) + \varepsilon_t \quad (2)$$

In this study, the mispricing term will be divided into two components, these are earning mispricing and required return mispricing. To examine it, we use VAR estimation model at MB, ROE, and return with one lag and specified as:

$$\chi_t = B\chi_{t-1} + \zeta_t \quad (3)$$

Where χ_t is a 3x1 vector for three variables at time t, or $\chi_t = (MB_t, ROE_t, r_t)'$, and MB_t is observed log market-to-book value ratios. While B is 3x3 VAR coefficient matrix and ζ_t is 3x1 VAR vector, which is e_2 and e_3. e_2 vector defined as $e_2 = (0,1,0)'$ and used to estimate fundamental ROE. Whereas e_3 vector defined as $e_3 = (0,0,1)'$ and used to estimate fundamental return. To estimate fundamental ROE and return, we use eq. 4 and eq. 5 below.

$$\sum_{\tau=1}^{\infty} \rho^{\tau-1}[E_t(ROE_{t+\tau})] = \sum_{\tau=1}^{\infty} \rho^{\tau-1}[e_2'(B_x x_t)] = e_2'B(I - \rho B)^{-1} x_t \quad (4)$$

$$\sum_{\tau=1}^{\infty} \rho^{\tau-1}[E_t(r_{t+\tau})] = \sum_{\tau=1}^{\infty} \rho^{\tau-1}[e_3'(B_x x_t)] = e_3'B(I - \rho B)^{-1} x_t \quad (5)$$

After that, then we estimate earning mispricing and required return mispricing by comparing it to observed ROE and return. Finally, we examine stock mispricing which stated as:

$$\varepsilon_t = \left[\sum_{\tau=1}^{\infty} \rho^{\tau-1} E_t(ROE_{t+\tau}) - \sum_{\tau=1}^{\infty} \rho^{\tau-1} E_t(ROE_{t+\tau})\right] + \left[\sum_{\tau=1}^{\infty} \rho^{\tau-1} E_t(r_{t+\tau}) - \sum_{\tau=1}^{\infty} \rho^{\tau-1} E_t(r_{t+\tau})\right]$$

$$\varepsilon_t = \left[\sum_{\tau=1}^{\infty} \rho^{\tau-1} E_t(ROE_{t+\tau}) - \sum_{\tau=1}^{\infty} \rho^{\tau-1}[e_2'(B_x x_t)]\right] + \left[\sum_{\tau=1}^{\infty} \rho^{\tau-1} E_t(r_{t+\tau}) - \sum_{\tau=1}^{\infty} \rho^{\tau-1}[e_3'(B_x x_t)]\right]$$

$$\varepsilon_t = ROE_{\varepsilon_t} + r\_\varepsilon_t \quad (6)$$

Where:

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ROEε :$[\sum_{\tau=1}^{\infty} \rho^{\tau-1} E_t(ROE_{t+\tau}) - \sum_{\tau=1}^{\infty} \rho^{\tau-1}[e_2{}'(B_x x_t)]$, is the difference between ROE observed and ROE fundamental, defined as earning mispricing. positive ROEε indicating overvaluation, while negative ROEε indicates undervaluation

rε: $[\sum_{\tau=1}^{\infty} \rho^{\tau-1} E_t(r_{t+\tau}) - \sum_{\tau=1}^{\infty} \rho^{\tau-1}[e_3{}'(B_x x_t)]$, is the difference between stock return observed and stock return fundamental, defined as required return mispricing. If rε is positive, it indicates overvaluation, whereas if rε negative, it indicates undervaluation.

2.3 Estimation of Twitter Sentiment

To extract tweets from Twitter, we construct Phyton code in Anaconda. By using Twint package in Phyton code, we have collected approximately 3.464.646 of tweet from January 1st 2017 until December 31st 2017. A unique dataset has collected including the number of replies, number of retweets, and number of likes.

Due to casual nature of people usage in Twitter, raw tweets generally contain noisy dataset. Therefore, raw tweets have to be normalized by doing pre-processing steps. This steps including convert tweets to lower case, replace all URL link with the word URL, replace all user mention with USER_MENTION, and replace matched emoticons with EMO_POS or EMO_NEG. Finally, we remove RT as it is indicating retweets and classified as unnecessary feature for text classification.

In order to create finance and stock market related sentiment analysis, we use finance-related lexicon from Loughran and Mc Donald (2011). We construct our sentiment index by aggregating daily sentiment score of all tweets for each company into quarterly sentiment score. Following Leitch & Sherif (2017), it defined as the sum of positive words less the sum of negative words divided by a nominator of overall number of positive words and the number of negative words, or specified as follow:

$$\text{SentimentScore (SS)} = \frac{\text{Npos} - \text{Nneg}}{\text{Npos} + \text{Nneg}} \tag{7}$$

Where Npos as number of positive words, and Nneg as number of negative words of each tweets.

2.4 Control Variables

We use book-to-market (BM) and firm size as control variables in this paper. Book-to-market is measured by comparing book value and market value of each stocks, while firm size calculated using natural logarithmic of market capitalization of each stocks.

3. RESULTS AND DISCUSSION

3.1 Analysis on Stock Mispricing

The descriptive statistics about stock mispricing is shown in Table 1. This table reports quarterly stock mispricing. MB is the log of the observed market-to-book value ratio, while the Est. MB is the estimated or fundamental market-to-book value ratio based on Eq. (1). The equity mispricing is the difference between the observed MB and Est. MB. As specified in Eq. (6), earning mispricing is mispricing from earning estimation, while required return mispricing is from required return.

Table 1. Summary Statistics – Stock Mispricing

	MB	Est. MB	Equity Mispricing	Earning Mispricing	Required-Return mispricing
All Firm	16.10%	35.60%	-19.50%	-8.10%	-11.40%

In 2017, this table reports that log MB is 16.10%, while estimated MB is 35.60%. It indicates that log MB is lower than estimated MB so that it can be also indicate that stock price in 2017 is undervalued of 19.5%. Moreover, we divided stock mispricing into earning mispricing and required return mispricing. Table 1 shows that earning mispricing is -8.10% which indicates undervaluation; whereas required return mispricing is -11.40% which also indicates undervaluation. This result suggests that undervaluation is attributed to required-return mispricing.

3.2 Analysis on Twiter Sentiment

Table 2 illustrates the investor sentiment on Twitter in 2017. This table reports quarterly investor sentiment on Twitter. Sentiment score calculated by number of positive words less number of negative words divided by a nominator of the overall positive words and negative words, as specified in Eq (7).

Table 2. Summary Statistics – Twitter Sentiment

	Number of Tweets			
	Positive (%)	Negative (%)	Neutral (%)	Total
All Firm	608,225 (17.56%)	412,162 (11.90%)	2,444,259 (70.55%)	3,464,646

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Sentiment Score				
All Firm	Mean	Min	Max	SD
	0.379	-1.000	1.000	0.483

In Table 2, it is shown that from 3,464,646 tweets that were successfully obtained, 70.5% of tweets were neutral sentiment, 17.6% were positive, while 11.9% contain negative sentiment. Besides, on average, quarterly sentiment score is positive 0.379. This result indicates that most of Indonesian people tend to use Twitter to show opinions that are neutral and positive, compared to negative opinions.

3.3 Analysis of Twitter Sentiment on Stock Mispricing

By using fixed effects model in panel data as specified in Eq. (8), $\varepsilon_{i,t}$ is the stock mispricing, $SENT_{i,t}$ is investor sentiment, $BM_{i,t}$ is book-to-market, and $SIZE_{i,t}$ is firm size for stocks i at time t. R^2 is the adjusted R-square. "*" indicates significance at 10% level, "**" indicates significance at 5% level, "***" indicates significance at 1% level. The relationship between stock mispricing and investor sentiment on Twitter is shown in Table 3.

$$\varepsilon_{i,t} = \alpha_{i,t} + \beta_1 SENT_{i,t} + \beta_2 BM_{i,t} + \beta_3 SIZE_{i,t} + e_{i,t} \quad (8)$$

Table 3. Regression Result for The Mispricing and Investor Sentiment

	$\alpha_{i,t}$	$SENT_{i,t}$	$BM_{i,t}$	$SIZE_{i,t}$	R^2
Coeff	0.617	-0.022^{**}	0.195^{***}	-0.044^{*}	97.07%
t-stat	1.149	-2.007	5.226	-1.946	

From Table 3, we find that there is significant negative effect on stock mispricing and investor sentiment on Twitter with adjusted-R^2 of 97.07%. This result indicates that sentiment on social media, especially Twitter, is closely related to stock prices which affects its movements (Albahli et al., 2022; Duz Tan & Tas, 2021). Moreover, this result also confirms the behavioral finance theory which stated that investor sentiment may affect stock price to deviate from its fundamental.

3.4 Robustness Check

To identify whether the result remain the same if the measurement of sentiment variables is changed, we test robustness of our result. We use another proxy of investor sentiment, which are Bull Ratio (BullR), and specified as (Oliveira et al., 2017):

$$BullR_{i,t} = \frac{NBull_{i,t}}{NBull_{i,t} + NBear_{i,t}} \quad (9)$$

To check the robustness result, we use Eq. (10), $\varepsilon_{i,t}$ is the stock mispricing, $BULLR_{i,t}$ is bullish ratio as another proxy for investor sentiment, $BM_{i,t}$ is book-to-market, and $SIZE_{i,t}$ is firm size for stocks i at time t. We use the fixed effects in this model. R^2 is the adjusted R-square. "*" indicates significance at 10% level, "**" indicates significance at 5% level, "***" indicates significance at 1% level. Table 4 reports the robustness results for the mispricing and twitter sentiment.

$$\varepsilon_{i,t} = \alpha_{i,t} + \beta_1 BULLR_{i,t} + \beta_2 BM_{i,t} + \beta_3 SIZE_{i,t} + e_{i,t} \quad (10)$$

Table 4. Robustness Check for the Mispricing and Twitter Sentiment

	$\alpha_{i,t}$	$BULLR_{i,t}$	$BM_{i,t}$	$SIZE_{i,t}$	R^2
Coeff	0.914^{**}	-0.024^{*}	0.196^{***}	-0.058^{***}	97.05%
t-stat	1.969	-1.729	5.202	-2.948	

The result which is presented in Table 4 show that the relationship between twitter sentiment and stock mispricing are hold when using another proxy of investor sentiment. Although the level of significancy of the results are decreased, however, the relationship between stock mispricing and bull ratio (investor sentiment) remain negative with adjusted-R^2 of 97.05%.

3.5 Discussion

The findings of this study support the behavioral finance theory, which suggests that investor sentiment influences stock prices, causing them to deviate from their fundamental values. This theory posits that investors are subject to emotional influences and cognitive limitations in decision-making, leading to either excessive pessimism or optimism. As a result, stock prices become inaccurate, leading to mispricing (Lee et al., 1991).

Moreover, these findings align with W. Wang et al. (2021), who suggests that sentiment and stock return show negative relationship due to cultural dimensions, market integrity, also intelligence and education which in the end affect perception and behaviour of the investors. Consequently, prices are adjusted downward, and returns become lower than expected. Ultimately, stock prices fall below their intrinsic values.

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This study also highlights a strong correlation between Twitter sentiment and stock prices. Research by Kranthi Kumar et al. (2022) suggests that microblogging platforms like Twitter can serve as alternative tools for measuring investor sentiment, making them valuable for predicting capital market behaviour. Additionally, previous studies have demonstrated that stock price movements and future returns can be anticipated based on Twitter sentiment (Albahli et al., 2022; Duz Tan & Tas, 2021).

Furthermore, the relationship between BM and Eq_Misp exhibits a positive and significant correlation at the 1% significance level. This result aligns with (Y. Liu, 2024) which indicate that stock returns are negatively correlated with the component reflecting investor expectations, suggesting that high book-to-market ratios may result from excessive market reactions rather than fundamental factors, leading to stock mispricing.

Additionally, firm size (Ln_Size) demonstrates a significant negative relationship with Eq_Misp at a 5% significance level. This indicates that mispricing is more prevalent in smaller firms compared to larger ones. This relationship arises when investors receive limited analyst coverage about small-cap stocks, which lead to greater information asymmetry. As a result, investors tend to do speculative trading by overlooking the fundamental conditions of these stocks and overestimate their growth potential, causing stock prices to become overvalued (Quy Duong, 2024; Zhang, 2022).

4. CONCLUSION

This paper examined the impact of Twitter sentiment on market inefficiencies, proxied by stock mispricing, in Indonesia in 2017. The results of our study show that Indonesia stock price is undervalue of 19.5% during 2017, and dominantly affected by required return mispricing. It is argue that investors are not always rational and that their decisions are often influenced by emotions and cognitive biases, thus result in stock prices that deviate from their fundamental values. Beside that, our result also finds significant negative effect on Twitter sentiment to stock mispricing. These results concludes that investor sentiment, particularly as captured through Twitter activity, significantly contributes to stock mispricing in the Indonesian capital market which characterized by market inefficiencies. Therefore, investors and policymakers are advised to consider behavioral factors such as sentiment on social media when developing strategies and regulations to enhance market integrity and efficiency. However, this study has some limitations. First, we only use Twitter data to measure investor sentiment on social media, and also did not use number of followers, likes, and retweet in our analysis. Although Twitter is considered to be fairly representative social media in describing investor sentiment, however, the use of other social media such as Facebook and number of followers, likes, and retweet may allow us to get a more comprehensive understanding of sentiment and users behavior on social media as a whole. Second, we use quarterly sentiment as our proxy of investor sentiment since our estimation of stock mispricing is on quarterly basis. This may allow that our result did not respresent the daily effect of investor sentiment on stock price. Therefore, future research are suggest to use another proxy of stock mispricing that can be identified on daily basis.

REFERENCES

Albahli, S., Irtaza, A., Nazir, T., Mehmood, A., Alkhalifah, A., & Albattah, W. (2022). A Machine Learning Method for Prediction of Stock Market Using Real-Time Twitter Data. Electronics, 11(20), 3414. https://doi.org/10.3390/electronics11203414

Cam, H., Cam, A. V., Demirel, U., & Ahmed, S. (2024). Sentiment analysis of financial Twitter posts on Twitter with the machine learning classifiers. Heliyon, 10(1), e23784. https://doi.org/10.1016/j.heliyon.2023.e23784

Cheema, M. A., & Fianto, B. A. (2024). Investor sentiment and stock market anomalies: Evidence from Islamic countries. Pacific-Basin Finance Journal, 88, 102557. https://doi.org/10.1016/j.pacfin.2024.102557

Duz Tan, S., & Tas, O. (2021). Social Media Sentiment in International Stock Returns and Trading Activity. Journal of Behavioral Finance, 22(2), 221–234. https://doi.org/10.1080/15427560.2020.1772261

Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. The Journal of Finance, 25(2), 383–417.

Gong, X., Zhang, W., Wang, J., & Wang, C. (2022). Investor sentiment and stock volatility: New evidence. International Review of Financial Analysis, 80, 102028. https://doi.org/10.1016/j.irfa.2022.102028

Han, X., Sakkas, N., Danbolt, J., & Eshraghi, A. (2022). Persistence of investor sentiment and market mispricing. Financial Review, 57(3), 617–640. https://doi.org/10.1111/fire.12301

Kranthi Kumar, S., Alolo Abdul-Rasheed Akeji, A., Mithun, T., Ambika, M., Jabasheela, L., Walia, R., & Sakthi, U. (2022). Stock Price Prediction Using Optimal Network Based Twitter Sentiment Analysis. Intelligent Automation & Soft Computing, 33(2), 1217–1227. https://doi.org/10.32604/iasc.2022.024311

Lee, C. M. C., Shleifer, A., & Thaler, R. H. (1991). Investor Sentiment and the Closed-End Fund Puzzle. The Journal of Finance, 46(1), 75–109.

Leitch, D., & Sherif, M. (2017). Twitter mood, CEO succession announcements and stock returns. Journal of Computational Science, 21, 1–10. https://doi.org/10.1016/j.jocs.2017.04.002

Liu, D., Gu, H., & Lung, P. (2016). The equity mispricing: Evidence from China's stock market. Pacific Basin Finance Journal, 39, 211–223. https://doi.org/10.1016/j.pacfin.2016.06.007

Liu, Y. (2024). Explaining the Book-to-Market Ratio Effect from the Perspective of Behavioral Finance. Advances in Economics, Management and Political Sciences, 131(1), 20–26. https://doi.org/10.54254/2754-1169/2024.18412

Messaoud, D., Ben Amar, A., & Boujelbene, Y. (2023). Investor sentiment and liquidity in emerging stock markets. Journal of Economic and Administrative Sciences, 39(4), 867–891. https://doi.org/10.1108/JEAS-11-2020-0198

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DOI 10.47065/ekuitas.v6i4.7214

Mrad, S., Hamza, T., & Manita, R. (2024). Corporate investment sensitivity to equity market misvaluation. Review of Accounting and Finance, 23(1), 1–38. https://doi.org/10.1108/RAF-01-2023-0027

Nyakurukwa, K., & Seetharam, Y. (2023). Does online investor sentiment explain analyst recommendation changes? Evidence from an emerging market. Managerial Finance, 49(1), 187–204. https://doi.org/10.1108/MF-05-2022-0221

Oliveira, N., Cortez, P., & Areal, N. (2017). The impact of microblogging data for stock market prediction: Using Twitter to predict returns, volatility, trading volume and survey sentiment indices. Expert Systems with Applications, 73, 125–144. https://doi.org/10.1016/j.eswa.2016.12.036

Quy Duong, L. (2024). Stock Mispricing and Firm Innovation: Evidence from an Emerging Equity Market. Operations Research Forum, 5(4), 112. https://doi.org/10.1007/s43069-024-00394-w

Shiller, R. J. (1981). Do Stock Prices Move Too Much to be Justified by Subsequent Changes in Dividends? The American Economic Review, 71(3), 421–436.

Statista. (2018). Number of Twitter Users in Indonesia from 2014 to 2019 (in Millions). Https://Www.Statista.Com/Statistics/490548/Twitter-Users-Indonesia/.

Statista. (2024). Leading Countries Based on Number of Twitter Users as of April 2024 (in Millions). Https://Www.Statista.Com/Statistics/242606/Number-of-Active-Twitter-Users-in-Selected-Countries/.

Verma, R., & Verma, P. (2021). Investor sentiments and pricing errors. Review of Behavioral Finance, 13(4), 450–462. https://doi.org/10.1108/RBF-01-2020-0005

Wang, W., Su, C., & Duxbury, D. (2021). Investor sentiment and stock returns: Global evidence. Journal of Empirical Finance, 63, 365–391. https://doi.org/10.1016/j.jempfin.2021.07.010

Wang, Y., Guo, J., Yuan, C., & Li, B. (2022). Sentiment Analysis of Twitter Data. Applied Sciences, 12(22), 11775. https://doi.org/10.3390/app122211775

Zhang, T. (2022). Small Firm Effect in Stock Markets: An Assessment of the Chinese Listed Firm. https://doi.org/10.2991/aebmr.k.220307.281