THE INFLUENCE OF NOISE TRADERS ON THE VIETNAMESE STOCK MARKET

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Abstract

The study examines the impact of noise trading on stock returns. The investor sentiment index is constructed as a representative of noise trading. This index is extracted from the social network Facebook and the mainstream online newspapers. Based on data collected using the text language analysis method, the author tests a regression model to explain the impact of investor sentiment on the stock returns in the Vietnamese stock market. The result is that sentiment extracted from newspapers positively impacts stock returns over the same period, while sentiment extracted from social networks has no impact. Therefore, investors can use the online newspapers-based investor sentiment index as a tool in technical analysis when making decisions.

Keywords: Sentiment, Behavioral Finance, Stock returns, Noise trading, Individual, investors.

1. INTRODUCTION

According to the effective market hypothesis of Fama (1970), investors are rational, making decisions based on information about a security's intrinsic value or fundamental data. However, according to Black (1986), investors sometimes trade based on noise signals rather than information. Noise signals are false or irrelevant information for securities valuation (Ackert & Deaves, 2009). Noise trading is the buying and selling of securities based on sentiment or random signals rather than on intrinsic value or underlying data. Noise traders are investors who make decisions based on noise signals (Shleifer & Summers, 1990). Noise trading can cause the market to fluctuate sharply, risking bubbles and collapses (Dow & Gorton, 1997).

Sentiment affects the decision-making of a noise trader by influencing their perception (Hua & Wang, 2018). "Investor sentiment, defined broadly, is a belief about future cash flows and investment risks that is not justified by the facts at

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hand" (Baker & Wurgler, 2007). Investors are subject to sentiment (Long et al., 1990). Sentiment is a proxy for noise trading because it reflects the irrationality and emotion in the investor's behavior, causing their decision to deviate from the fundamental values of securities (Berardi, 2022). Empirical studies have proven that investor sentiment can better explain short-term fluctuations in asset prices than fundamental factors (Uygur & Taş, 2014), (Alfano et al., 2020). Emotional factors such as optimism and pessimism play an essential role, as noise traders often trade based on emotions rather than fundamental information (Schneider & Nunez, 2024). In conclusion, investor sentiment is a suitable proxy for noise trading.

This paper aims to verify the impact of noise trading on the stock returns of public corporations listed on the Ho Chi Minh City Stock Exchange (HOSE) in the five years from 2018 to 2022. The first reason is that this study is suitable for the context of Vietnam's stock market – a frontier market where most investors are individuals (State Securities Commission of Vietnam, 2022). Many studies have noted that the majority of noise traders are individual investors (Long et al., 1990; Sanders et al., 1997; Shleifer & Summers, 1990). However, research on this topic for the Vietnamese market is still limited. Secondly, during the research period, the Vietnamese stock market faced many impacts from macroeconomic events. The US-China trade war that started in 2018 took away most of the previous stock market growth while also causing confusion among investors, making other investment channels safer, such as the bond and precious metals sectors. During the COVID-19 pandemic, the VN index witnessed a significant **decline** in the first three months of 2020, with market capitalization dropping by as much as 28%. Despite the initial decline, the lockdown period in Vietnam positively influenced the stock market because of the Vietnamese government's effective stimulus packages and sectoral shifts in healthcare and e-commerce, leading to a rise in stock prices. Taking effect in August 2020, the European-Vietnam Free Trade Agreement (EVFTA) fosters deeper integration with the global economy, particularly the EU market. This integration can bring about greater transparency in the Vietnamese stock market, attracting more investors and raising the market's profile internationally.

This study provides further empirical evidence of noise trading and confirms the role of investor sentiment as a proxy of noise trading in the stock market. The research has the same interest as the studies of Cuong et al., (2019) and Phan et al., (2023). The study has two new points. First, research builds sentiment indices directly from textual language analysis at the corporate level. Second, the paper shows that the impact of social networks like Facebook and mainstream online newspapers is different on the stock returns. As a result, sentiment extracted from mainstream online newspapers positively impacts the stock returns. Meanwhile, social networks do not affect stock returns.

The rest of the paper is structured as follows: part 2 is the literature review, part 3 is the research methods, part 4 is the results and discussion, Part 5 is the conclusion, and section 6 is for reference.

2. THEORETICAL FRAMEWORK AND LITERATURE REVIEW

2.1 Theoretical framework

Noise trading refers to the practice of making investment decisions based on erroneous or irrelevant information, rather than on fundamental data about the asset's intrinsic value. This concept was first introduced by Black (1986), who defined noise trading as trading on noise as if it were valuable information, thereby providing liquidity to the market but also making stock prices more volatile and less efficient. Noise traders, often characterized by their unpredictable beliefs and irrational behavior, can cause significant deviations in stock prices from their fundamental values, at least in the short term, due to the limited willingness of risk-averse arbitrageurs to bet against them (Cuong et al., 2019). Long et al., (1990) identifies four key effects of noise trading on financial markets: the "create space" effect, which increases volatility and expected returns for noise traders; the "Friedman" effect, where noise traders' poor market timing leads to buying high and selling low; the "hold more" effect, which results in higher expected returns if noise traders are generally bullish; and the "price pressure" effect, where increased demand from noise traders pushes up asset prices, ultimately lowering their expected returns.

Since noise trading is not quantifiable, representations for noise trading are necessary to identify and analyze the behavior of noise traders in the financial markets. In the study of Sanders et al., (1997), the trading experience was used by individual investors who believe in technical signals despite the absence of significant unusual profits. Unexplained trading volume based on fundamental information shows that it contributes significantly to the volatility of the Turkish stock market (Baklaci et al., 2011). The variance of the residual from asset valuation models reflects the role of the noise trader and their connection to misvaluation (Aabo et al., 2017). These different proxies help researchers and policymakers understand the impact of disruptive trading on the market and develop strategies to mitigate its impact.

Investor sentiment is a multifaceted concept in behavioral finance that encapsulates the collective mood, optimism, or pessimism of investors towards securities and financial markets, often leading to irrational trading behaviors and market volatility (Hua & Wang, 2018; Kamath et al., 2022). It is defined as investors' beliefs about future cash flows and investment risks that are not justified by the facts at hand, influencing their judgment and risk assessment (Khuu et al., 2017; Siganos et al., 2017). Sentiment can be shaped by various factors, including psychological states, weather, sports outcomes, and macroeconomic variables, which can lead to significant market impacts such as mispricing and high volatility (Hua & Wang, 2018; Khuu et al., 2017). The measurement of investor sentiment is complex and can be approached through different methodologies, including macroeconomic and market variables, survey-based indices, and text-based sentiment analysis (Chan et al., 2017; Khuu et al., 2017). Understanding investor sentiment is essential for comprehending market behaviors and making informed investment decisions, as it integrates both rational and emotional processing in decision-making (Hua & Wang, 2018).

The sentiment is a fitting proxy for noise trading because investors' decision-making is driven by emotions such as optimism and pessimism (Schneider & Nunez, 2024). Psychological shocks, often caused by exogenous factors and amplified by uncertainty, cause them to misvalue and make the market more volatile (Berardi, 2022). The more optimistic, the more the noise trader misjudges the variance of profits (Uygur & Taş, 2014). Sentiment causes the stock market to fluctuate, and the positive sentiment induces trading volume and profitability (Siganos et al., 2014).

Measuring investor sentiment is a multifaceted task that involves various approaches, each with its own strengths and limitations. One common method is using survey-based indices, such as the European Economic Sentiment Indicator (ESI) and the University of Michigan Consumer Sentiment Index, which directly gauge investor and consumer confidence through polls and surveys (Simoes Vieira, 2011) . These surveys can provide insights into investor attitudes but may suffer from biases and inaccuracies due to the subjective nature of responses (Nguyen & Pham, 2018). Another approach is market-based measures, which rely on financial data such as closed-end fund discounts, IPO first-day returns, trading volumes, and volatility indices like the VIX. These measures are advantageous due to their high-frequency availability but can be confounded by other economic forces, making it difficult to isolate sentiment effects (Baker & Wurgler, 2007; Nguyen & Pham, 2018). Additionally, textual analysis of media content, including financial news and social media posts, has emerged as a valuable tool for capturing sentiment. Studies have shown that negative words in news articles and tweets can predict stock market movements, although this method can be time-consuming and complex due to the vast amount of data (Gu & Kurov, 2020; Nguyen & Pham, 2018). More recently, internet search behavior has been utilized to measure sentiment, with tools like Google's Search Volume Index (SVI) providing real-time data on investor concerns and interests. This method is considered superior for its ability to capture genuine sentiment without the biases inherent in surveys (Nguyen & Pham, 2018). Combining these various measures into a composite index can help mitigate the limitations of individual proxies and provide a more robust indicator of investor sentiment (Baker & Wurgler, 2007). Overall, while no single method is perfect, a multi-faceted approach that incorporates survey data, market-based measures, textual analysis, non-economic factors, and internet search behavior offers a comprehensive way to gauge investor sentiment.

The original framework for researching the effect of investor sentiment on stock returns has evolved significantly since its inception, drawing from various theoretical and empirical studies. The behavioral models of asset pricing, particularly those by Long et al., (1990) demonstrated the relationship between noise trader sentiment and asset prices. This framework was further expanded by Baker and Wurgler (2007). Their research highlighted that investor sentiment significantly affects stock prices, leading to anomalies that traditional finance theories, such as the efficient market hypothesis of Fama (1970), struggle to explain.

2.2. Literature review

Sentiment extracted from online newspapers significantly impacts stock returns by influencing investor behavior and market dynamics. Hagenau et al., (2013) increased the accuracy of predictions by using the "two-word combination" feature to extract the emotional state of the post. They enhanced existing text mining methods by using more expressive features to represent text and employing market feedback as part of their feature selection process. Li et al., (2014) used the Harvard Psychological Dictionary and Loughran–McDonald Financial Sentiment Dictionary to construct a sentiment space. A topic modeling framework applied to Russian financial news showed that sentiment could detect return-predictive signals, outperforming existing models in terms of Sharpe ratio and annual return and demonstrating a Granger causal relationship for over 70% of portfolio stocks (Riabykh et al., 2022). Similarly, sentiment analysis of news articles from the Common Crawl archives revealed a statistically and economically significant impact on U.S. stock market events, supporting the notion that public news sentiment affects financial markets (Jazbec et al., 2021).

Researchers used the FGNHI (Facebook Gross National Happiness Index) to predict stock returns in the stock market. The results show that FGNHI can predict the stock market's performance in the short term (Karabulut, 2013). Pessimism causes trading volumes and stock returns to increase (Siganos et al., 2017). However, FGNHI data is no longer available due to privacy concerns (Bukovina, 2016), so little research has been done in this direction.

Like FGNHI, Refinitiv's Marketpsych Indices (RMI) attempts to gauge emotional states with different targets and approaches. While FGNHI relied solely on the analysis of words in Facebook posts to measure the general happiness of Facebook users in a specific country, RMI utilizes a broader net, encompassing news articles, social media commentary (including platforms beyond Facebook), and potentially other sources to generate the investor sentiment towards stocks, currencies, commodities, and even entire markets. Some authors exploited RMI and asserted that investor sentiment on social media and online newspapers influences stock market volatility. However, the overall effect is faint (Chan et al., 2017). Social networks promote market efficiency by adding relevant and meaningful information to basic financial information officially published by joint stock companies (Eierle et al., 2022; Gu & Kurov, 2020). Impacts of sentiments obtained from Twitter and online newspapers show opposite results (Dunham & Garcia, 2021; Nyakurukwa & Seetharam, 2023).

Research by Widoatmodjo and Siswanto (2017) tested the impact of gossip that spread out through social media as a particular factor and all trading days in a week to a stock return in the Indonesian stock market. They used the gossip in social media to respond to the massive use of the internet in stock investment. The existence of noise traders strengthens the existence of gossip. Using a multivariate statistical technique and combined with an event study with five windows (five days before and after a gossip has been posted), this research analyzes the stock return that gets the most gossip posted by investors. The result suggests that gossip on social media does not significantly influence stock return, and automatically, no persistence exists.

Follow Baker and Wurgler (2007), some studies explore the relationship between investor sentiment and stock return in the Vietnamese stock exchange using a sentiment index created through principal components analysis (PCA). To and Dinh (2022) built the market sentiment index based on five components: initial public offering, the yield on the initial shares issued, the number of shares traded, dividend premium, and additional shares. Similarly, Phan et al., (2023) use five components of the sentiment index but replace the number of traded shares and additional shares with stock turnover, Closed-end fund, and ETF discount. Van (2022) also utilized the initial public offering, the yield on the initial shares issued, and supplemented market liquidity, market breadth, and transaction volume of foreign investors. The common point of these studies is to build a sentiment index indirectly from market indices. In the Vietnamese stock market, the majority of investors are individuals with limited knowledge and time to research information. It is unlikely that the overall market indexes can influence their sentiment.

Other research also built sentiment factors indirectly. Cuong et al., (2019) applied the GARCH (1,1) model to estimate noise trader impacts on stock returns by filtering residuals and employing moving average methods to calculate noise trader impact. Nguyen and Pham (2018) utilized the Google Trends' Search Volume Index of financial and economic terms that Vietnamese searched from January 2011 to June 2018 to construct the sentiment index. The limitations mentioned in the paper include the time-consuming nature of collecting data from Google Trends due to restrictions on data downloads and the challenge of obtaining control variables at comparable frequencies to match the high-frequency nature of sentiment effects.

Studies in the Vietnamese stock market context also have different results on the influence of sentiment. The research of Cuong et al., (2019) indicates noise trader risk in Vietnam's stock market, impacting daily stock returns unpredictably. To and Dinh (2022) focus on analyzing the impact of psychological and economic factors on stock returns of listed companies in Vietnam across different stock market cycles and find significant short-term reversals in stock indices driven by pessimism. While Van (2022) and Nguyen and Pham (2018) reveal an inverse correlation between market sentiment and future stock returns, Phan et al., (2023) highlight a significant positive correlation between stock return and investor sentiment. These studies build general sentiment indexes at the market level, not the company level. This way may limit the market forecasting ability of these indices.

From the analysis of the limitations of current research in the context of the Vietnamese stock market, the author finds a research gap. This study builds investor sentiment indices directly from the text language analysis technique at the company level. Language is the code system by which humans can communicate their ideas and feelings. Therefore, measuring sentiment through language will have more accurate results. Using sentiment as a proxy of noise transactions, the author builds a regression model to clarify the impact of noise traders on the stock returns of securities in the Vietnamese market.

3. RESEARCH METHODS

3.1 Data collection

Investor sentiment data

Regarding investors' emotional data, the author exploited it from the website SMCC.vn of Information Selection Technology Joint Stock Company (InfoRe). SMCC allows users to enter search keywords into the system and will return results that are the level of emotion expressed in news posts, and comments on official press sites and social network Facebook. Keywords used for this research target are stock tickers of companies listed on the HOSE.

By using advanced deep-learning techniques to process Vietnamese text, SMCC's AIs will assess whether the news stories' emotional state is positive, negative, or neutral. The AI (Artificial Intelligence) system specialized in classifying emotional nuances in SMCC's texts, built from a data set of more than 100,000 Vietnamese sentences that have been analyzed for sentence structure and labeled. Sentences were randomly selected across all different social domains, and content containing adjectives was prioritized. These sample data are continuously supplemented from data relabeled by SMCC users during use to update the classification model. In total, more than one million stickers are applied by SMCC personnel and users in the dataset. SMCC's AI used deep learning to extract semantic vectors of sentences and paragraphs and classify them using vector space rather than dictionaries.

SMCC's classification model has two parts: (1) a large language model and (2) a nuanced classification model. Large language models represent the relationship of words that frequently appear together in a sentence or a text and help extract the feature vector of any Vietnamese sentence. The large language model is based on about 10 billion unlabeled texts. The nuance classification model is based on feature vectors of the data labeled with nuances for classification. Therefore, the model can also classify content that needs to be labeled correctly. In particular, SMCC can handle emoticons, such as emojis, because SMCC's large language model is trained on unlabeled data, including emojis and teen codes. The computer automatically classifies trained and quality-tested data. Verification is performed using the n-fold validation method. One hundred thousand training sentences are divided into two parts: 90% for training and 10% for testing on a model. SMCC engineers test many times with different n-folds on similar training parameters to find a way to train an AI model with the most stable quality.

In addition, AI also evaluates the reach level of any article based on the characteristics of the article author, such as the number of friends and followers the post has, the average number of interactions and comments the post has, and the internal metrics of the post, such as likes, shares, and comments. This reach level is classified into 11 levels, from 0 to 10.

Stock Data

Stock market data is collected from the websites vietstock.vn and investing.com.

After cleaning the data, the authors obtained 20.947 observations of 85 listed companies, weekly frequency, during the 5-year study period from 2018 to 2022.

3.2 Research model

The study is based on the Capital Asset Pricing Model (CAPM). CAPM is the most popular asset pricing theory in Sharpe (1964) and Lintner (1965). It is often called Sharpe-Lintner-CAPM. By now, the application of CAPM has become widespread. It is considered limited to estimating a company's cost of capital and evaluating the performance of a managed portfolio. CAPM is built on the portfolio theory of Markowitz (1952). CAPM has been proven to be suitable to explain fluctuations in stock returns in the context of the Vietnamese stock market (Dung & Duyen, 2020). To and Dinh (2022) concluded that the extended CAPM with the Vietnamese market sentiment index is statistically significant. This research follows To and Dinh (2022) and adds investor sentiment variables into CAPM as proxies of noise trading to test their impact on stock returns.

Banz (1981), for the first time, evaluated the relationship between the total market value of the common stock of a firm and its return and showed that the common stock of small firms had higher risk-adjusted returns than the common stock of large firms. Smaller firms, in general, are much more risky than larger firms, leading to lower prices and higher returns. Market capitalization, which represents the total market value of a company's outstanding shares, has been shown to significantly affect stock returns across various studies and contexts (Crain, 2011). According to Nguyen et al., (2020), since the Vietnamese stock market is small and not well-established, individual investors might be attracted more by larger companies that are commonly believed to be more profitable and less risky. Therefore, the authors add the market capitalization variable as a controlling variable in the model. The model is developed as follows:

$$R_{i,t} - R_{f,t} = \alpha + \beta_1 * (R_{m,t} - R_{f,t}) - \beta_2 * SI\_Fb_{i,t} + \beta_3 * SI\_News_{i,t} + \beta_4 * Ln\_MK_{i,t} + Ui + \varepsilon_{i,t} \quad (1)$$

Table 1: Explanation of variables in the model

STT	Variable name	Symbol	Variable Measurement
1	The rate of return of securities i at the time t	Ri,t	The weekly rate of return of securities i is calculated in % and determined by the formula: $R_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}} x\ 100$ In which: - Ri,t: The rate of return of securities i in week t - $P_{i,t}$: The closing price of securities in week t - $P_{i,t-1}$: The closing price of securities i in week t-1
2	The risk-free interest rate at t	Rf,t	The risk-free interest rate is the interest yield of 10-year Government bonds of the State Bank of Vietnam.
3	The market's rate of return at the time of t	Rm,t	The market profitability is calculated in % and determined by the formula: $R_m = \frac{\text{VnIndex}_t - \text{VnIndex}_{t-1}}{\text{VnIndex}_{t-1}} x\ 100$ In which: - Rm: The market's rate of return in week t. - Vn-Indext: The Vn-Index closed the week - Vn-Indext-1: Vn-Index closes week 1
4	Investor sentiment	$SI\_Fb_{i,t}$	Posts and comments with positive sentiment are assigned a score of 1, a negative is -1, and a

	extracted from Facebook		neutral is 0. The reach level (R) is used as a weight. The formula calculates the average weekly sentiment for each stock: $SI\_Fb = \frac{\sum(1).R + \sum(-1).R}{\sum R}$
5	Investor sentiment extracted from mainstream online newspapers	$SI\_News_{i,t}$	News with positive sentiment is assigned a score of 1, a negative is -1, and a neutral is 0. The reach level (R) is used as a weight. The average weekly sentiment for each stock is calculated by the formula: $SI\_News = \frac{\sum(1).R + \sum(-1).R}{\sum R}$
6	The market capitalization of securities i at the time t	$Ln\_MK_{i,t}$	Market capitalization _MK is the product of the number of shares outstanding and the weekly closing price of stock i. The authors use Ln_MK instead of MK to reduce the error when estimating the model.

Source: Author's Proposal

3.3 Research hypothesis

In the regression model (1), beta factors 2 and 3 of the investor sentiment are the main interested factors. According to Phan et al., (2023), if investors become more positive, they will trade more, leading to higher profitability. Siganos et al., (2014) also affirmed that positive sentiment helps increase the number of stocks traded in the market and their profitability. Therefore, the study tested the following two hypotheses.

Hypothesis 1: Investor sentiment extracted from social media sources positively impacts the stock returns.

Hypothesis 2: Investor sentiment extracted from online news sources positively impacts the stock returns.

4. Results and discussion

4.1 The impact of investor sentiment on the stock returns

Table 1: ***Summary statistics***

Variable	Number of observations	Mean	Standard deviation	Min	Max
R_i-R_f	20,947	0.3375	5.7729	-37.9306	40.0585
R_m-R_f	20,947	0.2051	2.6001	-14.5919	7.9374
SI_Fb	20,947	0.2312	0.3753	-1.0000	1.0000
SI_News	20,947	0.1062	0.2707	-1.0000	1.0000
Ln_MK	20,947	0.4805	1.7023	-3.2189	5.7384

Source: Author's estimation

From 2018 to 2022, Vietnam's stock market had growth momentum thanks to the Vietnam-EU Free Trade Agreement, causing the VN-Index to peak at 1,393 points in January 2020. However, the market was also heavily affected by the COVID-19 pandemic, causing the VN-Index to drop to 574 points in March 2020. In the context of such strong market fluctuations, the overall profitability of the market and each stock has a significant standard deviation. According to the descriptive statistical results, the mean of the stock returns is 0.3375% with a standard deviation of 5.7729. The lowest rate of return was negative, 37.9306%, and the highest rate of return was 40.0585%.

The SI_Fb and SI_News variables have positive mean values, indicating that investor sentiment in the market is generally optimistic. Both the average value and the standard deviation of SI_Fb are larger than SI_News, which means that investor sentiment extracted from social networks has more substantial volatility than the data obtained from mainstream online newspapers. The smallest values of the variables SI_Fb and SI_News are both -1, and the most significant value is 1 because the sentiment has been quantified, as shown in Table 1.

The results of the multi-collinear test with the model (1) show that the VIF coefficients are all approximately equal to 1, proving that there is no multi-collinear phenomenon between the independent variables of the model.

Table 2: *Multi-collinear test results*

Variable	VIF	1/VIF
SI_News	1.11	0.903126
SI_Fb	1.10	0.913184
Ln_MK	1.01	0.987288
R_m-R_f	1.00	0.999793
Mean VIF	1.05	

Source: Author's estimation

The research data is panel data, including sentiment index, market capitalization, and returns of different stocks in weeks during the five years 2018 - 2022. Therefore, to estimate the coefficient of the model (1), the study uses Pooled OLS (POLS), fixed-effect model (FEM), and random-effect model (REM) because these models are suitable for panel data analysis.

To select the model POLS or FEM, the authors estimated FEM. P value = 0.0000 < 0.05, so FEM is selected. The authors continue to estimate REM and use the Hausman test to choose between REM and FEM. P value = 0.000 means that FEM is better than REM, so FEM is ultimately chosen. Because FEM has autocorrelation and heteroscedasticity, a robust option is included to address this issue. The result obtained is FEM_Adjusted.

Table 3: Results of panel data analysis

Regression Variables	POLS	FEM	REM	FEM_Adjuted
R_m-R_f	0.280***	0.277***	0.280***	0.277***
	(0.015)	(0.015)	(0.015)	(0.025)
SI_Fb	(0.107)	(0.066)	(0.107)	(0.066)
	(0.110)	(0.114)	(0.110)	(0.123)
SI_News	1.520***	1.556***	1.520***	1.556***
	(0.153)	(0.154)	(0.153)	(0.160)
Ln_MK	0.028	1.282***	0.028	1.282***
	(0.023)	(0.097)	(0.023)	(0.208)
	0.130***	- 0.485***	0.130***	-0.485***
_Cons	(0.048)	(0.067)	(0.048)	(0.106)
Number of observations	20,947	20,947	20,947	20,947
Adjusted R-squared	0.0209	0.0291	0.0214	0.0291
Hausman test	Prob>chi2 = 0.0000			
Note: *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels. Values in parentheses () are standard errors				

Source: Author's estimation

From the results of regression analysis and theoretical model of the impact of noise trading on stock returns in the Vietnamese stock market, the linear regression equation is formulated as follows:

$$R_{i,t} - R_{f,t} = -0.106 + 0.277 * \left(R_{m,t} - R_{f,t}\right) - 0.066 * SI\_Fb_{i,t} + 1.556 * SI\_News_{i,t} + 1.282 * Ln\_MK_{i,t} + Ui + \varepsilon_{i,t}$$

The regression results show that the model's R_m-R_f, SI_News, and Ln_MK variables all positively impact the stock returns at a statistically significant level of 1%. However, the beta coefficient of the SI_Fb variable is not statistically significant.

The beta factor 1 is 0.277, indicating that when the overall market rate of return increases by 1%, the average stock returns increase by 0.277%. The beta coefficient 3 is 1.556, indicating that when investor sentiment extracted from online newspaper sources changes from pessimistic to neutral or from neutral to optimistic, the average stock returns increase by 1.556%. The beta coefficient 3 is

positive, and the largest of the four coefficients means that investor sentiment extracted from online newspaper sources has a solid and positive impact on stock returns. This result reinforces the observation of Phan et al., (2023) about the positive influence of sentiment factors on stock returns. During the research period, Vietnam's stock market is affected by many international events with significant potential risks, such as the US-China trade war and the Vietnam-EU free trade agreement. However, Vietnamese investors often engage in irrational behaviors, such as seeking risks in risky situations and avoiding risks in safe circumstances (Cao et al., 2021). In other words, this psychological factor induces them to invest more and forms a going-up market trend.

Consequently, the profitability of the market in general and of the securities of each company in particular increase. On the other hand, the regulations on social distancing during the Covid period also caused a large amount of capital to flow from other sectors into the stock market. The Vietnamese government's stimulus policies, interest rate reductions, and social subsidies have also contributed to this.

The beta coefficient 4 is 1,282, which means when the market capitalization increases by 1%, the stock returns also increase by 1,282%. This result contrasts Banz (1981)'s conclusion that small-sized companies have higher stock returns due to their higher risk premium. Barber and Odean (2008)'s attention theory can explain this fact. The number of large companies is negligible because the Vietnamese stock market is a frontier market. Large companies often broadcast more news in the mass media and attract the attention of investors. As a result, investors tend to buy more large stocks, increasing their prices and affecting the stock returns in the short term.

While the beta 3 of the SI_News variable was statistically significant at 1%, the beta 2 of the SI_Fb variable was not statistically significant. In other words, investor sentiment extracted from social media sources does not impact the stock returns. This result is similar to the conclusion of Widoatmodjo and Siswanto (2017) for the Indonesian stock market. First, most Facebook users or groups are closed, small groups, or personal pages, so the reach levels are much lower than that of mainstream online newspapers. Second, while the language of mainstream newspapers is formal and transparent in terms of spelling and style, the language used in social networks is often informal, abbreviated, and misspelled, which can confuse the readers and challenge the language processing system of Infore company.

5. CONCLUSION

Noise trading is the challenge to an efficient market. Studying the impact of noise trading in the context of a frontier stock market like Vietnam is of practical significance because the number of individual investors in this market type is overwhelming. The transparency of information in the market could be higher. The proportion of foreign investors and the information disclosed for this group of investors is still limited. With these characteristics, the market can not be efficient because investors can access information differently. Most investors are individuals whose decision-making is affected a lot by sentiment.

Since noise trading cannot be measured, the author chooses investor sentiment as a proxy to study the impact of noise trading. Sentiment impacts cognition, which in turn influences the trader's decision-making (Hua & Wang, 2018). The study has several key findings. First, the research introduces a novel approach by constructing sentiment indices derived directly from textual language analysis at the corporate level. Second, the impact of social networks and mainstream online newspapers is different. Sentiment extracted from mainstream online newspapers is found to have a positive impact on stock returns. However, the study finds no impact of sentiment from social networks on stock returns. Third, due to the limited size and development, the Vietnamese stock market tends to draw individual investors towards larger, more established companies perceived as safer and more profitable. This concentrated investor interest creates higher demand for shares in these companies, making their stock prices more sensitive to public opinion and news compared to smaller stocks. This finding similar with the conclusion of Nguyen et al., (2020). The results of this study provide valuable information for investors in assessing risks and making investment decisions. Investors should pay attention to both information from online newspapers and social networks but should be cautious with information from social networks due to higher volatility and unreliability. In addition, investors should also consider the market capitalization factor when choosing investment stocks.

This research only focuses on the relationship between stock returns and noise trading in a given period. The analysis uses investor sentiment data as a proxy for noise trading. Future studies may supplement the impact of other macroeconomic factors on stock profitability or compare the impact of investor sentiment from online newspapers and social media in different countries.

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