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Noise trader risk and its effect on market volatility: Evidence from Vietnam's stock market

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ABSTRACT

This study examines the presence of noise trader risk in Vietnam's stock market and its impact on daily stock returns. The research employs GARCH (1,1), EGARCH, and PGARCH models to filter residuals, followed by a moving average approach to measure the effect of informed traders. Noise trader risk, defined as the risk arising from irrational traders, is calculated by subtracting the influence of rational traders from the residuals. The results show that noise trader risk exists in Vietnam's stock market, but its effect on daily returns is unpredictable. In contrast, informed traders have a positive impact on stock returns, helping to correct market prices toward their fundamental values.

1. Introduction

Vietnam's Stock Market (VSM) was officially established in 2000 with the launch of the Ho Chi Minh Stock Exchange, followed by the Hanoi Stock Exchange in 2005. The initial years were marked by modest activity, with a limited number of listed stocks and companies. However, developments under Vietnam's Securities Law led to significant growth, peaking in 2007 when total market capitalization reached approximately 40% of GDP. This growth was indicative of the market's increasing maturity and the successful implementation of financial reforms. Notably, Vietnam's GDP grew at an average rate of 6% annually from 2010 to 2022, reflecting the country's ongoing economic progress and reform efforts (Ryan et al., 2021). Following a considerable decline to about 18% of GDP in 2008 due to the Global Financial Crisis, the market rebounded quickly and became one of Asia's best performers by 2016 (Truong et al., 2022). VSM has continued to evolve, experiencing robust growth and increased foreign investment, driven by ongoing economic reforms and a young, dynamic population. Vietnam's stock market has undergone two major phases of financial liberalization: the removal of the interest rate ceiling in 2000 and the introduction of foreign exchange regulations in 2005. Over the years, it has faced a substantial downturn and remarkable recoveries, reflecting volatility clustering in stock returns. As of 2023, the market continues to attract both domestic and international investors, supported by improved regulatory frameworks and a growing number of listed companies. This development positions Vietnam as a significant player in the Southeast Asian financial landscape. In this context, predicting return volatility is crucial for asset allocation, risk management, and portfolio selection. However, the actions of individual investors can adversely affect the accuracy of volatility forecasting. In 2023, Eight percent of Vietnam's population or 7.76 million people are investing in stocks, according to Vietnam Securities Depository (VSD). Following De Long et al. (1990), individual investors often function as noise traders—investors who lack access to inside information and trade based on noise, treating it as information. In stock markets, "noise" refers to information that causes significant deviations in asset prices from their fundamental values. Noise traders are often characterized by unpredictable beliefs, leading to stock price deviations and market inefficiencies. While some scholars argue that noise traders enhance market liquidity, others contend that their irrational behavior contributes to market inefficiency. Given the high proportion of individual investors in Vietnam, the influence of noise traders on the market is significant. The impact of noise traders on the VSM, however, remains ambiguous. This paper aims to investigate the risk of noise trader risk—the risk introduced by noise traders

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through their trading activities—and its effects on stock returns. Specifically, the authors explore whether noise traders achieve higher returns compared to information traders and the overall effect of noise trader risk on stock returns. Analyzing this issue is vital for several reasons. First, it provides insights for investors regarding risk management, asset allocation, and portfolio selection. Second, it enables investors to adjust their strategies for optimal returns based on research findings. Finally, it assists regulators and policymakers in overseeing the financial system.

2. Literature review

The literature on noise traders dates back to 1986 when Black (1986) first introduced the term "noise traders." Since then, numerous scholars have explored this topic from various perspectives. De Long et al. (1990) proposed a time-invariant model to test whether noise trader risk is priced, concluding that information arbitrageurs demand a risk premium for bearing such risk. Conversely, Sias et al. (2001) analyzed closed-end fund shares exposed to noise trader risk and argued that noise traders do not receive higher returns than information traders. Flynn (2012) examined arbitrage effects in closed-end funds, demonstrating that arbitrageurs earn excess returns for bearing noise trader risk.

Other empirical research on noise trader risk has focused on the relationships among investor sentiment, stock returns, and volatility. Qiang and Shu-e (2009) utilized the noise trading model by De Long et al. (1990) to analyze how investor sentiment influences stock prices, employing OLS and GARCH-M models. Their findings suggest that investor sentiment is a systematic factor affecting stock prices. Dhameja (2019) and Koski et al. (2004) were the first to study the relationship between noise traders and daily volatility, finding that noise trading increases volatility. Verma and Verma (2007) and Schneider and Nunez (2024) explored the effects of fundamental versus noise trading on conditional volatility, concluding that investor sentiment positively impacts stock returns but negatively affects stock volatility. Conversely, Podolski–Boczar et al. (2009) found that noise trader activities significantly increase stock price volatility on the Australian Stock Exchange, yet these traders do not achieve higher returns for bearing this risk. Scruggs's (2007) research examined noise trader risk in financial markets, using a comparative analysis of two similar markets. The study shows how the presence of non-professional investors (noise traders) can lead to abnormal price fluctuations that deviate from intrinsic asset values. By analyzing real data, the author highlights the significant impact of investor psychology and behavior on market stability. The findings suggest that noise trader risk can create volatility, providing insights for investors and regulators on adjusting investment strategies in turbulent market conditions. On a theoretical level, Campbell and Kyle (1993) developed a model predicting that noise traders overreact to fundamental information, resulting in excessively high volatility in the absence of information. With more information, volatility decreases as rational traders counteract noise traders' behaviors. Sinha (2015) examined the dynamics of noise traders' risk in the Indian stock markets, specifically NSE and BSE. The study analyzes how noise traders impact stock prices and market stability, revealing that their activity can lead to short-term price volatility, influencing the decisions of informed investors. Using quantitative methods, the research highlights the relationship between noise traders and market fluctuations, noting that their presence can result in price bubbles and crashes. The findings emphasize the importance of understanding noise traders' risks for effective investment and risk management strategies. Various research methods have been employed to investigate noise traders' existence and quantify noise trader risk. Closed-end fund shares are commonly used due to their heightened exposure to noise trade risks. Additionally, investor sentiment has been applied as a proxy for noise trading in numerous studies. Scruggs (2007) utilized twin shares to analyze the magnitude and nature of noise trader risk. Other authors have employed behavioral errors as proxies for noise trader risk. Shefrin and Statman (1994) posited that the CAPM beta comprises a noise trader risk component and an efficient beta (BAPM—behavioral capital asset pricing model beta). Therefore, behavioral error can be calculated as the difference between the CAPM beta and the BAPM beta. However, in the context of Vietnam's stock market, these methods are limited by data availability (e.g., closed-end funds, twin shares) or the necessary conditions for implementation (e.g., the behavioral error method requires accurate CAPM and BAPM betas). In this paper, the authors employ the GARCH model and moving average method to assess noise trader impacts. The use of the GARCH model has been validated by previous research.

This study contributes to the literature as the first research focusing on noise trader risk in Vietnam. Given that Vietnam's stock market is influenced by noise traders, understanding the nature and mechanisms of noise trader risk is essential. The remainder of the paper is structured as follows: Section 3 outlines the methodologies, Section 4 details the data, Section 5 discusses empirical results, and Section 6 presents conclusions and suggestions for future research.

3. Methodologies

This paper applies to the GARCH (1,1) model due to evidence of kurtosis and volatility clustering in returns, which will be elaborated upon in the next section. The selection of this model is justified, as the GARCH model effectively addresses the characteristics of stock price dynamics, such as volatility clustering, leptokurtic returns, and serial correlation. This model is estimated to use log-likelihood procedures. Estimating the impact of noise traders on stock returns involves several steps. Firstly, the returns are filtered to obtain residual returns. The following model specification is employed:

$$r_t = \gamma_0 + \gamma_1 r_{t-1} + \varepsilon_t \tag{1}$$

where, r_t is the returns of VN-Index of day *t*. An AR (1) process is used to explain the autocorrelation of stock returns. The optimal lag length of VN-Index returns is determined because of the AIC and BIC criteria. Furthermore, it captures the effects of historical information on stock returns today. It helps to separate the residual or returns into different components (which will be mentioned later).

Next, the authors apply the ARCH LM (Autoregressive Conditional Heteroscedasticity Lagrange Multiplier) test to verify the ARCH effect of the series. The parameters in the variance model are estimated using the residual returns (ε_t) from the previous step.

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{i,t-1} \tag{2}$$

At this point, the noise trading effect can be measured. According to Feng et al. (2014), the daily volatility of stock returns results from trading behavior, which includes three components: the volume of information generated by historical and current data; the non-information volume stemming from factors such as liquidity; and noise trading, which arises when noise traders treat noise as information.

The residual of the VN Index returns in Eq. 1 (ε_t) contains the part that cannot be explained by past information because the AR (1) specification already accounts for the historical information. Hence, it represents the impacts of recent information and irrational trading of investors. To capture the former part, this research takes the meaning of residuals in K previous trading days (ε_{Kt}) as it includes the impact of temporary good or bad news on stock returns. Over the period of K days before day t, there is information and noise that can affect the stock returns in different directions. Noise traders would work on that information and noise. Taking the average value of the residuals will filter out the effects of noise traders as the activities of noise traders will cancel each other. ε_{Kt} now contains only the effect of good or bad news because it will be used by rational investors to trade; then, it changes the fundamental value of stocks.

As a result, if $\Delta_t = \varepsilon_t - \varepsilon_{Kt}$, then Δ_t will explain the noise trader impact on the daily returns of the VN Index. In line with Feng et al. (2014); this research chooses K = 20 based on the assumption that there are 20 trading days in a month. ε_{Kt} is calculated by applying the moving average method. The relationship between variables can be rewritten as follows:

$$r_t - \hat{r}_t = \varepsilon_t = \varepsilon_{Kt} + \Delta_t \tag{3}$$

where, $\hat{r}_t$ is the estimated returns of the VN Index based on the GARCH (1,1) model. Rearranging (3) yields:

$$r_t = \hat{r}_t + \varepsilon_{Kt} + \Delta_t \tag{4}$$

Eq. 4 shows that the real returns of the VN Index comprise three parts: $\hat{r}_t$ is the influence of the historical information the AR(1) already captures; ε_{Kt} is the activities of rational investors, which affects the daily returns; Δ_t is the noise trader impacts. A positive means that noise traders increase the returns of stocks on day t and vice versa.

The relationship in Eq. 4 also enables us to test the contribution of noise traders and information traders to the daily returns during the sample period. The authors take the average of and carry the one-sided t-test to check whether it is significantly larger or smaller than zero. This research also calculates and checks the statistical significance of the correlation coefficient between Δ_t and ε_{Kt} as it shows the co-movement between the activities of information traders and those of noise traders.

4. Data

The data in this research consists of daily prices of the VN Index. The sample period spans from July 1, 2013, to July 1, 2024, encompassing a total of 2,747 observations. Daily returns are calculated from the stock price index using the following formula:

$$r_t = \ln(P_t) - \ln(P_{t-1}) \tag{5}$$

Fig. 1 shows the daily returns of the VN Index. As can be seen from the graph, the period of May 2014 or August 2015 or around March 2018 until July 2018 witnessed turbulence in the market with large movements of returns followed by further large movements, known as volatility clustering. According to Table 1, the mean return of this sample period is positive, at 0.054%, which is unsurprising because this period experiences the recovery of Vietnam's stock market. The time series of daily returns is non-normal, leptokurtic. This can be confirmed by the negative skewness coefficient and kurtosis coefficient, which are larger than 3.

The result of optimal lag length determination shows that lag one is chosen because it provides minimum AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion). Next, this research needs to check the existence of heteroscedasticity in the residual. The ARCH LM test is used to verify the necessity of using the conditional heteroscedasticity model to modify the regression model. Table 2 shows the results of the test with a lag phase being one. The results indicate that the null hypothesis should be rejected, which means that the ARCH effect exists in the residuals.

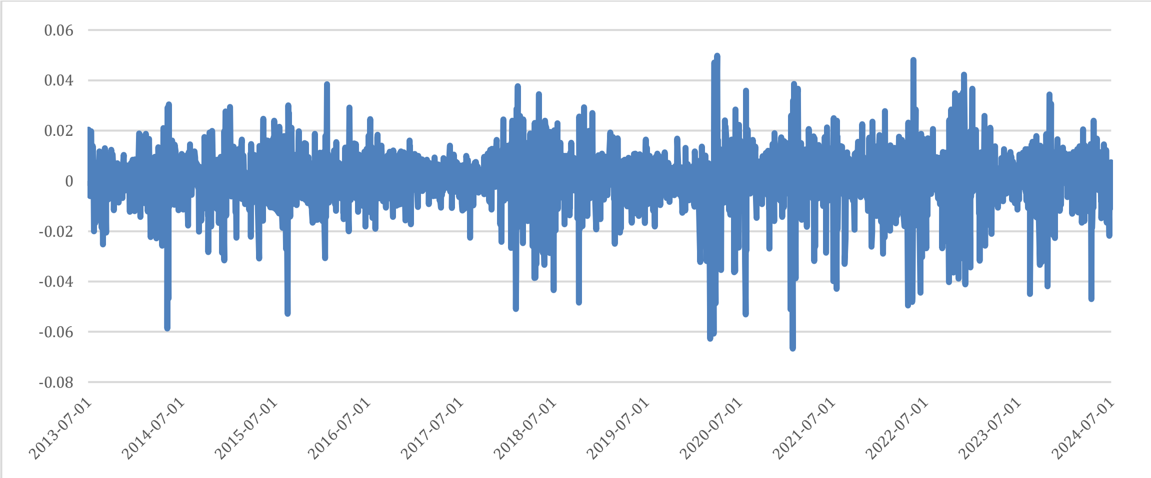

Fig. 1: Daily returns of the VN index

Table 1: Descriptive statistics of daily returns

Mean	0.000413
Median	0.001200
Maximum	0.049800
Minimum	-0.066700
Std. Dev.	0.011299
Skewness	-0.869468
Kurtosis	7.299204
Jarque-Bera	2461.661
Probability	0.000000
Sum	1.135400
Sum Sq. Dev.	0.350593
Observations	2747

Table 2: Test result of ARCH LM

F-statistic	5.844929	Prob. F (1,2743)	0.0029
Obs*R-squared	11.65722	Prob. Chi-square (1)	0.0029

5. Empirical results

The analysis of the daily returns of the VN-Index reveals the presence of the ARCH effect, which supports the application of the GARCH (1,1) model. Table 3 provides the estimates for both the returns and the conditional variance equation. The significance of the AR (1) term in the mean equation underscores the influence of historical information on the daily returns of the VN-Index. This finding indicates that past price movements play a crucial role in predicting future returns.

To ensure the robustness of our results, the authors conducted additional checks by estimating alternative models, including EGARCH and PGARCH specifications. The results remained consistent with these models, confirming the robustness of our findings. Furthermore, the authors performed a subsample analysis, dividing the data into pre-crisis and post-crisis periods. The estimated coefficients were stable across these sub-periods, suggesting that our conclusions are not sensitive to specific time frames.

Moreover, the coefficients for both the lagged variance and the squared shock terms are significant at the 1% level, confirming that the volatility of the VN-Index's daily returns is indeed time-varying. The sum of the coefficients of the lagged variance and shock square is less than 1, reinforcing the suitability of the GARCH (1,1) model for capturing the dynamics of the data.

$$r_t = \gamma_0 + \gamma_1 r_{t-1} + \varepsilon_t$$
$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{i,t-1}$$

Table 3: Estimation of the GARCH (1,1) model

Parameter	γ_0	γ_1	ω	α	β
VN index	0.051913**	0.209051***	0.021209**	-0.146541*	0.871238***
		EGARCH model			
VN index	0.599884***	-0.616505**	0.217569*	-0.087602*	0.950708**
		PGARCH model			
VN index	0.00362*	0.121161**	0.452231**	0.855528*	0.091450*

***, **, * represent the statistical significance at 1%, 5%, and 10% (*p*-value) of the parameters

The next step includes calculating the average residuals of twenty previous trading days (ε_{Kt}) using the moving average method and calculating the noise trading impacts (Δ_t). The authors applied the moving average method to analyze volatility trends, chosen for its ability to smooth volatility and capture short-term fluctuations, which is particularly relevant for financial time series. The selection of K=20 for the moving average was based on empirical optimization, where this value minimized forecast errors. Sensitivity analysis with alternative window sizes (K=10 and K=30) yielded similar results, reinforcing the robustness of the conclusions. This approach aligns with previous research, such as Feng et al. (2014), which suggests that a 20-period window is optimal for modeling short-term volatility. Table 4 presents descriptive statistics indicating that the mean impacts of both information traders and noise traders are negative. This suggests that, on average, the activities of both groups tend to decrease the daily returns of the VN-Index. However, it is crucial to perform statistical tests to ascertain the significance of these findings before reaching any firm conclusions.

Table 4: Descriptive statistics of (ε_{Kt}) and (Δ_t)

	ε_{Kt}	Δ_t
Mean	-0.000944	-0.000784
Median	-0.000164	-0.000421
Maximum	0.045489	0.006574
Minimum	-0.067740	-0.018015
Std. Dev.	0.011281	0.002907
Skewness	-0.946807	-1.165452
Kurtosis	7.342243	6.315164
Jarque-Bera	2567.606	1879.798
Probability	0.000000	0.000000

Figs. 2 and 3 visualize the impacts of information traders and noise traders on the VN-Index, highlighting key differences between the two. The impact of information traders appears to be less volatile compared to that of noise traders, suggesting that the behavior of irrational investors is more unpredictable. While the impacts of rational investors fluctuate, they exhibit a discernible trend over shorter time frames, reflecting more systematic trading behavior based on available information. In contrast, the impacts from irrational investors seem to hover around zero, lacking any clear trend throughout the observed sample period.

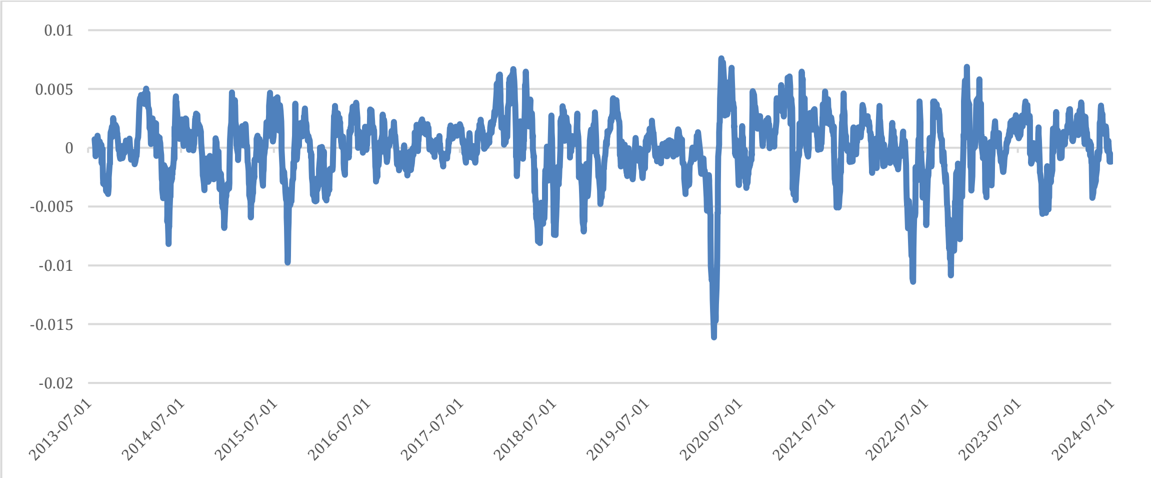

Fig. 2: Information traders' impacts

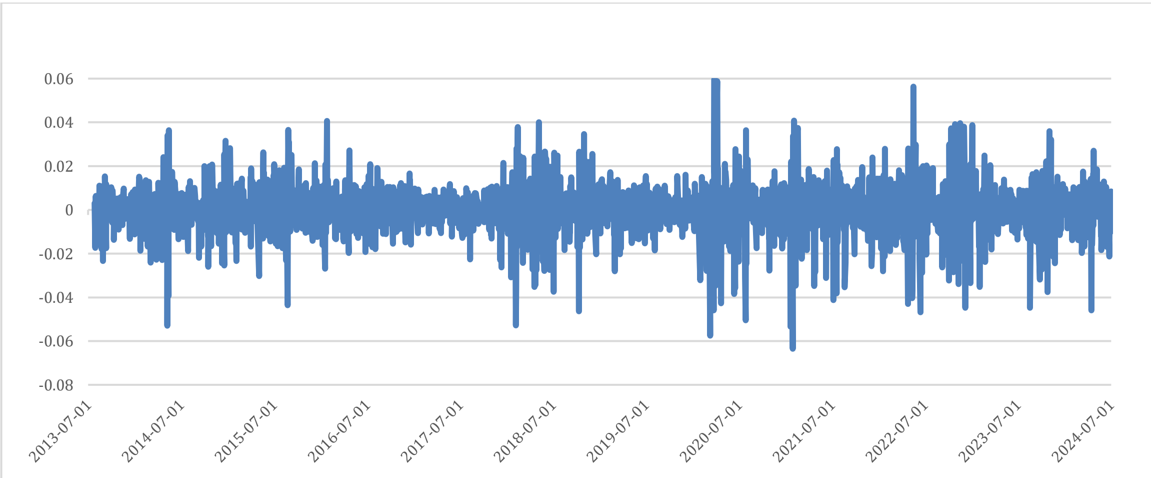

Fig. 3: Noise traders' impacts

As noted earlier, the authors proceed with a one-sided t-test to evaluate the mean impacts from both information traders and noise traders, alongside calculating the correlation coefficient between these two groups. The results are detailed in Table 5.

Table 5: One-sided t-test

	Mean	Variance	N	t-stat	P-value
ε_{Kt}	-0.000944	0.000008	2728	-3.909241	0.00004
Δ_t	0.008017	0.000128	2728	-0.645348	0.960731
Correlation	-0.223				0.0000

The findings in Table 5 indicate a rejection of the null hypothesis that the mean impact of information traders is less than or equal to zero (<=0). This result provides substantial evidence to support the hypothesis that the impact of information traders on daily returns is, on average, positive. In contrast, the authors do not find sufficient evidence to reject the null hypothesis that the mean impact of noise traders is less than or equal to zero, suggesting that the effects of noise traders on daily returns remain unpredictable and erratic. The calculated correlation coefficient of -0.223 between the impacts of information traders and noise traders indicates an inverse relationship. This suggests that the activities of information traders typically counteract those of noise traders. When irrational investors engage in trading based on noise, they can create price deviations from fundamental values, leading to potential overpricing or underpricing of stocks. Conversely, rational investors leverage their information to exploit these mispricing, engaging in arbitrage activities.

Despite the inherent limitations of arbitrage, the opposing behaviors of information traders and noise traders drive stock prices closer to their fundamental values over time. This dynamic underscores important practical implications for both investors and stock market managers. For investors, the results suggest that information traders, who base their decisions on reliable data, are more likely to realize positive returns, contributing to overall stock performance. This highlights the advantage of adopting informed strategies and leveraging accurate information in making investment decisions. On the other hand, the uncertain nature of noise traders' returns driven by irrational behaviors exposes them to higher risks and potential losses. Therefore, the findings encourage noise traders to reconsider their strategies and adopt more rational decision-making approaches. To achieve consistent positive returns, they must focus on improving their information-gathering techniques and developing structured trading rules that minimize emotional or speculative trading decisions. However, a key limitation in this context is that not all investors have equal access to information, which can hinder the effectiveness of rational decision-making. While institutional investors and professional funds generally have better access to credible information, individual investors may struggle to make well-informed decisions, especially in markets with information asymmetry. This reinforces the need for more equitable access to market data, which can be a challenge in many emerging markets.

For market managers, the findings emphasize the importance of fostering greater transparency of information. By improving the availability of accurate, timely, and comprehensive information, market authorities can create an environment where informed trading strategies thrive. Attracting more information traders to the market can enhance its overall efficiency and performance, ensuring more accurate price discovery and better resource allocation. However, the practical challenge lies in creating systems that effectively reduce misinformation and provide equal access to all market participants, particularly given the rapid rise of alternative information channels like social media, which may further complicate information dissemination. In this respect, regulatory measures should not only focus on increasing transparency but also on ensuring that information is reliable and that all investors, regardless of their sophistication, can interpret it effectively.

6. Conclusions

This study analyzed the daily returns of the VN-Index using the GARCH (1,1) model to investigate the phenomenon of noise trader risks specifically, the risks posed by irrational investors who trade based on noise rather than fundamental information. The results provide compelling evidence that noise trader risks are indeed present in Vietnam's stock market, where individual investors comprise more than 80% of participants.

Our findings reveal that the impacts of noise traders are random, whereas the activities of information traders tend to contribute positively to market returns. Notably, these two groups operate in opposing directions on average. This insight is particularly significant given the dominant presence of noise traders in the market, which underscores the potential for their trading behaviors to introduce volatility and inefficiencies. In a similar vein, a study by Inuduka et al. (2024) highlighted that noise traders can introduce volatility in other markets, such as Bitcoin, where information flows through platforms like Telegram and X, further exacerbating market instability. This is consistent with the challenges posed by irrational trading behaviors in traditional stock markets.

To mitigate the adverse effects of noise traders, it is essential for the government to prioritize enhancing the efficiency and transparency of information dissemination in the market. Providing investors with reliable and easily accessible information will enable them to make more informed and rational trading decisions. This can be achieved through regulatory measures aimed at improving the flow of accurate financial data and reducing misinformation.

Additionally, individual investors, who often function as noise traders, should be encouraged to consider investment through professional funds. Such funds are typically managed by experienced professionals who have access to credible sources of information and possess the expertise necessary to navigate the complexities of the market. By doing so, individual investors can mitigate their risks and enhance their potential for positive returns.

Another initiative-taking approach to reduce the prevalence of noise traders is to implement technical barriers for those seeking to participate in the stock market. For instance, prospective investors could be required to attend workshops or training courses that provide foundational knowledge about stock trading and the workings of financial markets. Obtaining certification from regulatory authorities could then serve as a prerequisite for trading. This educational framework would equip investors with essential knowledge, enabling them to engage more competently and responsibly in trading activities.

In summary, addressing the challenges posed by noise trader risks in Vietnam's stock market requires a multifaceted approach. Enhancing information transparency, encouraging investment through professional funds, and implementing educational prerequisites for traders can collectively foster a more rational trading environment. By taking these steps, a more efficient market that benefits all participants can be cultivated.

List of abbreviations

VSM	Vietnam's stock market
GDP	Gross domestic product
VSD	Vietnam Securities Depository
GARCH	Generalized autoregressive conditional heteroskedasticity
EGARCH	Exponential generalized autoregressive conditional heteroskedasticity
PGARCH	Power generalized autoregressive conditional heteroskedasticity
AR (1)	Autoregressive model of order 1
AIC	Akaike information criterion
BIC	Bayesian information criterion
ARCH LM	Autoregressive conditional heteroskedasticity Lagrange multiplier
VN Index	Vietnam Index
CAPM	Capital asset pricing model
BAPM	Behavioral asset pricing model
Std. Dev.	Standard deviation
Sum Sq. Dev.	Sum of squared deviations
Obs	Observations
Prob.	Probability
t-stat	t-statistic
N	Number of observations

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Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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