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NOISE TRADER RISK: EVIDENCE FROM VIETNAM STOCK MARKET

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Abstract: This paper investigates the existence of noise trader risk in Vietnam's stock market and its effect on the daily returns of stock prices. The methodologies contain the estimation of GARCH (1,1) model to filter the residuals using the moving average method to calculate the impact of information traders. Noise trader risk or the risk that is caused by noise traders is derived by subtracting the residuals by the rational traders' impact. We find that the noise trader risk does exist in Vietnam's stock market and its impact on daily returns of stocks is unpredictable. Meanwhile, we find a positive impact of information traders on the stock returns. It increases the daily stock returns, and in turn, helps the market to correct itself because the stock prices move back to its fundamental value.

Keywords: noise trader risk, GARCH (1,1), Vietnam's stock market

1 Introduction

Vietnam's Stock Market (VSM) was officially established in 2000 with the first securities trading center known as Ho Chi Minh Stock Exchange. The second center was built in Ha Noi in 2005. The first five years of VSM witnessed a tranquil operation with small numbers of listed stocks and listed companies [19]. Later, thanks to the Vietnam's Securities Law, the market grew dramatically and reached its peak in 2007 with the total market capitalization accounting for approximately 40% of GDP before declining considerably to a level of about 18% of the GDP in 2008 due to the Global Financial Crisis (Figure 1) [18]. The stock market recovered rapidly afterward and became one of the best performers in Asia in 2016. As a young market that has undergone two steps of financial liberalization (removed interest rate ceiling in 2000 and issued foreign exchange ordinances in 2005), Vietnam's stock market has experienced a huge recession and a spectacular recovery, which implies a volatility cluster in stock returns. In this context, predicting return volatility is especially important in assets allocation, risks management, and portfolios selection [25].

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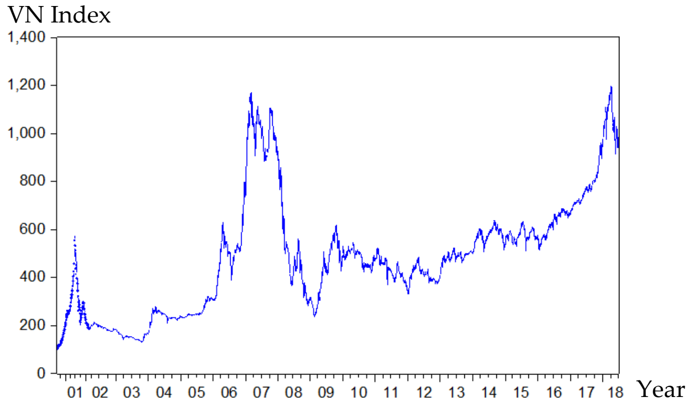

Figure 1. VN Index

Source: Ho Chi Minh stock exchange

However, the activities of individual investors can negatively affect the accuracy of volatility forecasting. According to Vietnam's Securities Depository in 2018, more than 99% of the participants in Vietnam's stock market are individual investors. According to De Long et al., individual investors may be good candidates for noise traders – investors, who have no access to inside information and basically trade on noises as if it were information [10]. In the stock market, the term "noises" implies the information that brings about the significant deviation of the assets prices from their fundamental value. Noise traders can also be considered as investors with unpredictable beliefs [20]. As a result, noise traders, who make noise trading, will cause the deviation of stock price or inefficiency of information [12]. Although some scholars state that noise traders play an important role by increasing the market liquidity [1–4], other authors believe that noise traders are the reason for market inefficiency because such investors are irrational [6]. In Vietnam, with a large proportion of individual investors in the market, the impact of noise traders on the market is inevitable.

However, the influence of noise traders on the VSM is not clear. This paper aims to investigate noise trader risk – the risk that noise traders cause to the market because they trade on noise – in VSM and how it affects the stock returns. In other words, do noise traders earn higher returns compared with information traders – investors that trade on information [24]? What is the effect of noise trader risk on stock returns? Analyzing this problem is essential in several aspects. Firstly, it provides implications for investors in managing risks, allocating assets, and selecting portfolios. Secondly, investors can adjust their behavior to obtain the highest returns on the basis of the results of this research. Finally, it helps regulators and policy-makers in controlling the financial system.

The literature of noise traders dated back in 1986 when Black first used the terms "noise traders". Since then, many other scholars have researched on this topic in various aspects. De Long et al. suggest a time-invariant model to test whether noise trader risk is priced [10]. The result shows that information arbitrageurs will require a risk premium for bearing such risk. Hence, the noise trader risk is priced. Sias et al. analyze closed-end-fund shares because they are subjected to noise trader risk and propose the opposite conclusion: noise traders do not receive higher returns for bearing higher risk compared with information traders [28]. Therefore, noise trader risk is not priced. On the other hand, Flynn examines the effects of arbitrage and the returns to arbitrage in closed-end funds and shows that arbitrageurs earn excess returns for bearing noise trader risk [13].

Other empirical research of noise trader risk focuses on the relationship between investor sentiments, stock returns, and volatility. Applying the noise trading model by De Long et al., Qiang and Shu-e analyze the mechanism of how investor sentiment affects stock prices using the OLS (Ordinary Least Squares) and GARCH-M (Generalized Autoregressive Conditional Heteroscedasticity - in the Mean) model [10, 23]. The results imply that investor sentiment is a systematic factor in creating stock prices. Koski et al. are the first to analyze the relationship between noise traders and daily volatility [14]. Using NASDAQ stocks and stock message board activities as a proxy for noise trading, the research team finds that noise trading increases volatility. Verma and Verma test the effects of fundamental and noise trading on conditional volatility and find that the investor sentiment positively affects stock returns but negatively stock volatility [30]. Podolski et al. have the opposite conclusion that noise traders' activities have a significant positive effect on stock price volatility in the case of the Australian Stock Exchange [22]. However, noise traders do not receive higher returns by bearing higher risk. This is also the conclusion by Scruggs when researching the Siamese twin shares: Royal Dutch/Shell and Unilever NV/PLC [26]. On the theoretical aspect, Campbell and Kyle develop a model of price formation process that forecasts that noise traders overreact to fundamental information and then excessively high volatility [8]. In the absence of information, noises will increase volatility in the short term. On the other hand, more information means less volatility as the rational traders are now at a better place to counter-react to the behavior of noise traders [9].

There are many research methods to investigate the existence and test the impacts of noise traders or to quantify the noise trader risk. One of the most common ways is to use the closed-end fund shares because such returns are exposed to more noise trader risks [13, 16, 28]. Investor sentiment is also used as noise trading in many papers [7, 15, 17]. Scruggs utilizes two pairs of twins shares to research about the magnitude and nature of noise trader risk [26]. Other authors use behavior error as a raw proxy for noise trader risk [24, 31]. According to Shefrin and Statman, the CAPM (capital asset pricing model) beta has a noise trader risk component and an efficient beta (BAPM – behavioral capital asset pricing model – beta) [27]. Therefore, the behavior error can be calculated as the difference between the CAPM beta and the BAPM beta. In the context of Vietnam's stock market, those methods are not applicable because of the lack of data (closed-end funds, twin shares) or conditions to use (the behavior error method needs the correct CAPM and BAPM beta). In our paper, we use the GARCH model and the moving average method to calculate the noise trader impact. The use of the GARCH model has been qualified by many previous authors [12, 22, 29].

Our paper contributes to the literature as the first research in Vietnam concerning this topic. As mentioned above, Vietnam's stock market is likely to be affected by noise traders. Therefore, it is essential to understand the nature and mechanism of noise trader risk. With that purpose, the rest of the paper will be structured as follows: Section 2 provides the methodologies, and Section 3 describes the data. Empirical results will be discussed in Section 4. Finally, some conclusions and future research will be mentioned in Section 5.

2 Methodologies

In this paper, we apply the GARCH (1,1) model given the evidence of kurtosis and volatility cluster in returns (will be mentioned in the next part). The selection of this model is justified because the GARCH model shows its efficiency in dealing with the characteristics of stock price dynamics, for example, volatility clustering, leptokurtic returns or serial correlation [5]. This model is estimated by applying the log likelihood procedures.

The estimation of noise trader impacts on stock returns consists of several steps. Firstly, we have to filter the returns to obtain residual returns [11]. We employ the model specification as follows:

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

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 on the basis 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 in different components (which will be mentioned later).

Next, we 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, we are able to measure the noise trader effect. According to Feng et al., the daily volatility of stock returns is the result of trading behavior [12]. This impact contains three parts: information volume that is generated by historical information and instant information; the non-information volume that results from other factors such as liquidity; and finally noise trading that is the activity of noise traders when they consider noise as information.

The residual of VN Index returns in equation (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. In order to capture the former part, we take the mean 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 noises. 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 we take $\Delta_t = \varepsilon_t - \varepsilon_{Kt}$, then Δ_t will explain the noise trader impact on the daily returns of VN Index.

In line with Feng et al., we choose K = 20 because we assume that there are 20 trading days only within a month. ε_{Kt} is calculated by applying the moving average method [12]. 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 on the basis of the GARCH (1,1) model.

Rearranging (3) yields:

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

Equation (4) shows that the real returns of VN Index comprises three parts: $\hat{r}_t$ is the influence of the historical information as 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 Δ_t means that noise traders increase the returns of stocks on day t and vice versa.

The relationship in equation (4) also enables us to test for the contribution of noise traders and information traders to the daily returns during the sample period. We take the average of ε_{Kt} and Δ_t and carry the one-sided t-test to check whether it is significantly larger or smaller than 0. We also calculate and check 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.

3 Data

The data in this research consist of daily prices of VN Index. The sample span is from 1 July 2013 to 2 July 2018 and has a total of 1247 observations. From the stock price index, we calculate the daily returns using formula (5):

$$r_t = lnP_t - ln\text{P}_{t-1} \quad (5)$$

Figure 2 shows the daily returns of VN Index. As can be seen from the graph, the period of May 2014 or August 2015 or at around March 2018 until July 2018 witnesses the turbulence in the market with large movement 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 appears to be non-normal, leptokurtic. This can be confirmed from the negative skewness coefficient and kurtosis coefficient, which are larger than 3.

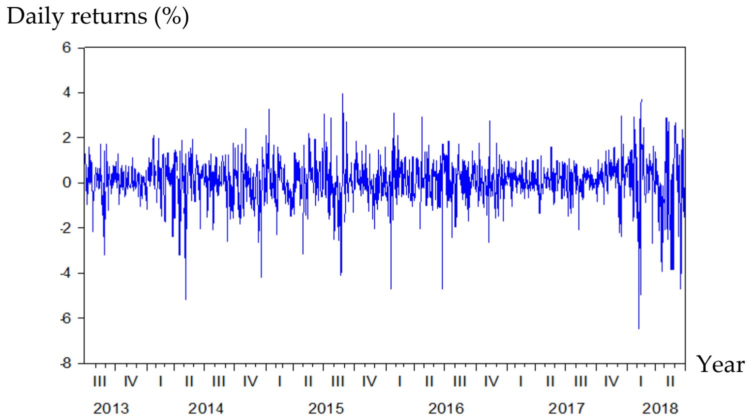

Figure 2. Daily returns of VN Index

Table 1. Descriptive statistics of daily returns

	Returns		
Mean	0.054107	Jarque-Bera	1074.678
Median	0.106446	Probability	0.000000
Maximum	3.956170		
Minimum	-6.464596	Sum	67.41787
Std. Dev.	1.045403	Sum Sq. Dev.	1360.619
Skewness	-0.825095		
Kurtosis	7.239920	Observations	1246

Source: Result from analysis

The result of optimal lag length determination shows that lag 1 is chosen because it provides minimum AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion). Next, we need to check the existence of heteroscedasticity in the residual. The ARCH LM test is used to verify the necessity to use the conditional heteroscedasticity model to modify the regression model. Table 2 shows the results of the test with a lag phase being 1. The results indicate that we should reject the null hypothesis, which literally means that the ARCH effect exists in the residuals.

Table 2. Test result of ARCH LM

F	97.76069	p-value	0.0000
$T \cdot R^2$	90.77315	p-value	0.0000

Source: Result from analysis

4 Empirical results

The existence of ARCH effect of the daily returns of VN Index in the previous section confirms the use of the GARCH (1,1) model. Table 3 reports the estimates of the returns and conditional variance equation. The AR(1) term in the mean equation is significant, which confirms the influence of historical information on the daily returns of VN Index. The coefficients of lagged variance and shock square terms are all significant at 1%, which means that the volatility of VN Index daily returns is time-varying. The sum of coefficients of lagged variance and shock square is less than 1. All of this confirms that the use of GARCH (1, 1) is appropriate.

Table 3. Estimation of GARCH model

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

Parameter	γ_o	γ_1	ω	α	β
VN Index	0.073742***	0.11461***	0.02987***	0.11691***	0.86192***
	(3.07668)	*(4.24032)*	*(2.64534)*	*(6.07968)*	*(34.44531)*

Note: Italic number in parentheses is t-statistics. ***, **, * represent the statistical significance at 1%, 5% and 10% (p-value) of the parameters.

Source: Result from analysis

The next step includes calculating the average residuals of 20 previous trading days (ε_{Kt}) using the moving average method and calculating the noise trader impacts (Δ_t).

Table 4. Descriptive statistics of ε_{Kt} and Δ_t

	$\boldsymbol{\varepsilon_{Kt}}$	$\boldsymbol{\Delta_t}$
Mean	-0.022933	-0.003838
Median	0.002553	0.004986
Maximum	0.652115	4.861493
Minimum	-1.025340	-6.168042
Std. Dev.	0.226451	1.063827
Skewness	-0.633592	-0.356057
Kurtosis	4.141036	6.937137
Jarque-Bera	148.4150	817.0829
Probability	0.000000	0.000000
Sum	-28.09340	-4.701514
Sum Sq. Dev.	62.76659	1385.235
Observations	1225	1225

Source: Result from analysis

Table 4 indicates that the mean of information traders and noise traders' impacts is both negative, which implies that, on average, the activities of information traders and noise traders reduce the daily returns of VN Index. However, we need to test for the statistical significance before making conclusions.

Figure 3 and 4 represent the information traders and noise traders' impacts on VSM. We can see that impact of the former is less volatile compared with that of the latter. This may indicate that the impacts of irrational investors are more unpredictable compared with that of rational investors. The impacts of rational investors fluctuate, but we can see a clear trend of the movement during a short time. Meanwhile, the impacts of irrational investors hover around zero, and there is no clear trend over the sample period.

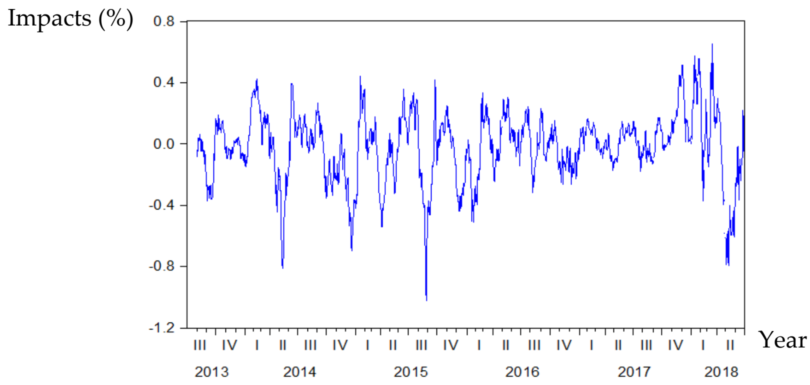

Figure 3. Information traders' impacts

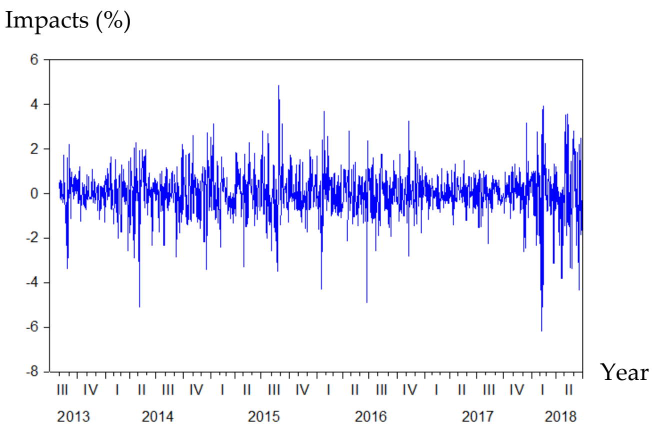

Figure 4. Noise traders' impacts

Source: Result from analysis

As mentioned before, we now carry the one-sided *t*-test of the mean of information traders' impact and noise traders' impact as well as calculating the correlation coefficient between them. The results are shown in Table 5.

Table 5. One-sided *t*-test

	Mean	Variance	N	t-Stat	P-value
ε_{Kt}	-0.022933	0.051280	1225	-3.544563	0.0002
Δ_t	-0.003838	1.131728	1225	-0.12627	0.44977
Correlation	-0.214				0.0000

Source: Result from analysis

According to Table 5, we reject the null hypothesis of $\varepsilon_{Kt} \leq 0$, which means that there is enough evidence to support the research hypothesis that $\varepsilon_{Kt} > 0$; in other words, the impacts of information traders on daily returns are positive on average. At the same time, we do not have enough evidence to reject the null hypothesis of $\Delta_t \leq 0$, which implies that the impacts of noise traders on daily returns are unpredictable. The correlation coefficient between the two impacts is –0.214, which indicates that information traders' activities are normally opposed to noise traders' activities. Irrational investors, who are trading on noises will cause the price deviation from the fundamental value (overpriced or underpriced). Rational investors with the information they have exploit the opportunities to do the arbitrage. Although the arbitrage has limitation, the activities of information traders – which are opposed to those of noise traders – will drive the stock prices toward its fundamental value. These findings play an important role for both investors and managers of the stock market. For investors, it implies that information traders usually experience positive returns when trading on the market because it helps to increase stock returns. On the other hand, noise traders' returns are unknown. Therefore, the findings encourage noise traders to be more rational in making their choices. If they want to earn positive returns on average, they should have better strategies in finding information and trading rules. For managers of the market, they should focus on increasing the transparency of the information. Once real information is more available, the market will have more information traders and it, in turn, will boost the performance of the stock market.

5 Conclusions

We analyze the daily returns of VN Index using the GARCH (1,1) model to investigate the existence of noise trader risk – the risk that irrational investors cause to the market because they trade on noises. The results indicate that noise trader risks do exist in Vietnam's stock market – where more than 99% of participants are individual investors. Noise traders' impacts are random, while information trader' activities help to increase the returns. Furthermore, those activities are proven to be in the opposite direction on average. This finding is important because noise traders occupy the majority proportion of the market. The government should focus on the increase in the efficiency of information to reduce the negative impacts of noise traders. Once investors receive more trustful information with less effort, they will make more rational choices in their trading. Moreover, individual investors, who often are noise traders, should make their investment via a professional fund. An investment fund is normally managed by experienced investors, and they can access more reliable sources of information. Another solution to help reduce the number of noise traders is to erect a technical barrier for those investors that want to trade on the stock market. For example, investors must participate in workshops or training courses and must obtain certification from the authorities, which allows them to trade. By this way, investors will be equipped with the necessary knowledge about the stock exchange, which could be useful in different situations.

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