

Print ISSN: 2288-4637 / Online ISSN 2288-4645
doi:10.13106/jafeb.2019.vol6.no3.19

Modeling Stock Price Volatility: Empirical Evidence from the Ho Chi Minh City Stock Exchange in Vietnam

Cuong Thanh NGUYEN¹, Manh Huu NGUYEN²

Received: June 2, 2019 Revised: June 10, 2019 Accepted: June 18, 2019

Abstract

The paper aims to measure stock price volatility on Ho Chi Minh stock exchange (HSX). We apply symmetric models (GARCH, GARCH-M) and asymmetry (EGARCH and TGARCH) to measure stock price volatility on HSX. We used time series data including the daily closed price of VN-Index during 1/03/2001–1/03/2019 with 4375 observations. The results show that GARCH (1,1) and EGARCH (1,1) models are the most suitable models to measure both symmetry and asymmetry volatility level of VN-Index. The study also provides evidence for the existence of asymmetric effects (leverage) through the parameters of TGARCH model (1,1), showing that positive shocks have a significant effect on the conditional variance (volatility). This result implies that the volatility of stock returns has a big impact on future market movements under the impact of shocks, while asymmetric volatility increase market risk, thus increase the attractiveness of the stock market. The research results are useful reference information to help investors in forecasting the expected profit rate of the HSX, and also the risks along with market fluctuations in order to take appropriate adjust to the portfolios. From this study's results, we can see risk prediction models such as GARCH can be better used in risk forecasting especially.

Keywords: Volatility, GARCH (1,1), EGARCH, GARCH-M, TGARCH, VN-index

JEL Classification Code: C22, C53, G10, G17

1. Introduction

Volatility is a statistical measure of profit distribution for a given market or stock index. In most cases, the higher the volatility, the greater the risk. Volatility can be measured by standard deviations or variances between returns of the same stock or market index. In the stock market, when stock prices rise or fall by more than 1% over an extended period of time, it is called an "unstable" market. In the US stock market, people use the VIX index to capture market

volatility (VIX was created by the Chicago Board Stock Exchange as a measure to assess the expected 30-day volatility of the US stock market derived from the real-time list price of the S & S index. P 500). This is really a measure of investors and traders to gamble on the future which will either follow the direction of the market or individual stocks. The higher the VIX index implies a risky market because of the high volatility.

In the financial market, modeling and forecasting volatility are essential for investors. For example, investors need to analyze the risks of holding an asset or a portfolio, besides, the expected confidence interval can change over time, so more accurate intervals can be obtained by modeling the variance of errors. On the other hand, more efficient estimation tools can be obtained if the heterogeneity in errors is handled correctly. Autoregressive Conditional Heteroskedasticity (ARCH) models are specifically designed to model and predict conditional variance. The variance of the dependent variable is modeled as a function by the past values of the dependent variable and the independent or exogenous variables. ARCH models were introduced by Engle (1982) and were generalized as GARCH or

1 First Author and Corresponding Author. Senior Lecturer, Dean, Faculty of Accounting and Finance, Nha Trang University, Vietnam [Postal Address: 2 Nguyen Dinh Chieu Street, Nha Trang City, Khanh Hoa Province, 650000, Vietnam].
Email: cuongnt@ntu.edu.vn

2 Lecturer, Faculty of Accounting and Finance, Nha Trang University, Vietnam; Ph.D. Candidate, Feng Chia University, Taiwan (R.O.C.). Email: manhnh@ntu.edu.vn

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(generalized ARCH) by Bollerslev (1986) and Taylor (2008). These models are widely used in various econometric studies, especially in financial time series analysis. Since developing GARCH models, some extensions and variants have been proposed. These variants can be divided into two groups: symmetric and asymmetric GARCH models.

This study uses GARCH (1,1), GARCH-M (1,1), EGARCH (1,1) and TGARCH (1,1) models to measure stock price fluctuations on the Ho Chi Minh stock exchange (HSX). The research results are useful reference information to help investors in forecasting the expected profit rate of the HSX, and also the risks along with market fluctuations in order to take appropriate adjust to the portfolios.

The paper includes five parts: Part 1 introduces research issues; Part 2 presents a theoretical overview and a research model; Part 3 presents research data and methods; Part 4 presents the results of empirical research; the final section summarizes the findings and implications.

2. Literature Reviews

There have been many studies using GARCH models in explaining the volatility of stock markets around the world, especially emerging markets. For example: French, Schwert, and Stambaugh (1987) examined the relationship between profitability and volatility in US stock market during the period 1928-1984. The authors have found that the expected market risk premium (expected return of the portfolio minus Treasury bills return) is positively related to the predictable volatility of the stock returns. In addition, the research results also show that extraordinary profits are negatively related to the abnormal change in the volatility of stock returns. This negative relationship provides indirect evidence of the positive relationship between risk premiums and expected fluctuations.

Chou (1988) used IGARCH and GARCH-M models to measure the sustainability of volatility and risk trade-off on the US stock market during period 1962-1985. Research results have found that the existence of shocks to stock profit fluctuations is very high. This finding also implies that identifying uncertain sources is important. Similarly, Baillie and DeGennaro (1990) used the GARCH-M model to check the relationship between the average return of the portfolios and the conditional variances or the standard deviations on a sample of 4542 observations from 1/01/1970 to 12/22/1987. After estimating a series of models from daily and monthly return data portfolios, authors suppose that the relationship between average profit and variance or standard deviation is weak. The results show that investors consider some other risk measures to be more important than the variance of portfolio returns.

Bekaert and Wu (2000) use market portfolios and portfolios with different leverage by the Nikkei 225 index, indicating that volatility in the stock market is asymmetric: profit and conditional volatility have an inverse relationship. McMillan, Speight, and Apgwilym (2000) analyzed the predicting performance of a series of statistical models and econometrics of FTA All and FTSE100 index volatility on daily, weekly and monthly data frequencies by both symmetric and asymmetric models. Research results show that GARCH models provide a relatively poor forecast, which may not be strong at higher frequencies.

Chiang and Doong (2001) studied daily stock index of 7 Asian stock markets (Hong Kong, Malaysia, Philippines, Singapore, Korea, Thailand, Taiwan) from January 1988 to June 1998. The Nikkei 225 (Japan) and the S&P 500 Index (US) are used for comparison with major developed markets. The authors have found evidence in most cases, higher average returns seem to be related to higher volatility and a deeper analysis of the relationship between stock returns and changed volatility. By using the GARCH-M (1,1) model, the author showed that the asymmetric effect hypothesis for conditional volatility was rejected for daily profit data but was not eligible to reject for monthly profit data.

Wei (2002) applied non-linear GARCH models to predict Chinese stock market volatility. As a result of forecasts for China, two weekly stock market index show that the QGARCH model can significantly improve the linear GARCH model and the random walk model. The results for the GJR model show that this is not a useful tool to forecast China's stock market volatility. Yu (2002) studied New Zealand stock market index volatility using the data sample consisting of 4741 daily profits during the period from 1/01/1980 to 12/31/1998. Research results show the efficiency of the GARCH(3,2) model, the best model in forecasting New Zealand stock price volatility compared to other models used in the study.

Farber, Nguyen, and Vuong (2006) found empirical evidence on the stock abnormal profit in the market, and the existence of a strong crowd effect on the extremely positive returns of the market portfolio in the period 2000-2006. The authors also assume that the ARMA-GARCH model is the best model in the case of serial correlation and the fat tail for the stable period. Alberg, Shalit, and Yosef (2008) used various GARCH models to analyze the average profit and conditional variance of Tel Aviv stock exchange (TASE) indicators. The results show that the asymmetric GARCH model with the density of the fat tail helps to improve the overall estimate to measure conditional variance. The EGARCH model uses the biased t-Student distribution to be the most successful for predicting TASE indicators. This result implies that the EGARCH model might be more useful

than the other three models in performing the Tel Aviv stock index's risk management strategies.

Do, McAleer, and Sriboonchitta (2009) used GARCH (1,1) and GJR-GARCH (1,1) models to describe profits and volatility in ASEAN emerging stock markets (Indonesia, Malaysia, Philippines, Thailand and Vietnam), combined with effects from international gold market. The GJR-GARCH (1,1) model seems to be effective in describing the daily stock returns of most markets, except Vietnam. Pati, Barai, and Rajib (2018) added volatility index (VX) to GARCH models when forecasting the volatility of 3 stock markets including India, Australia and Hong Kong. The results showed that the introduction of VX can improve the GARCH model efficiency. The significant and positive coefficients of VX in enhanced GARCH models show that VX contains relevant information in describing the volatility process.

In Vietnam there have been some studies on this topic. For example, the research of Tuyen (2011) suggests that the impact of shocks on volatility is symmetrical in Vietnam stock market. The author also explored the relevance of GARCH models in explaining the motives and volatility of stocks on Vietnam stock market during the period from January to October 2009. The research of Tran, Vo, and Pham (2017) estimated market risks for all industries in Vietnam from 2009 to May 2017 using the VaR and CvaR models. Experimental results from this study indicate that pharmaceuticals and energy are the least risky sectors, while oil and gas and securities are the most risky sectors among all industries in Vietnam. According to the study of Nguyen and Darné (2018) which used 10 GARCH models (GARCH, EGARCH, GJR-GARCH, IGARCH, RiskMetrics, APARCH, FIGARCH, FIAPARCH, FIEGARCH and HYGARCH) to test the characteristics of Vietnam market. Experimental results show that the FIAPARCH model is the most suitable model for VNindex and HNX index.

The above studies use different theoretical frameworks but all provide a scientific basis for a method to help investors and policy makers to determine the level of risk and volatility of market return and make appropriate decisions. Unlike previous studies, in this study, we used GARCH (1,1), GARCH-M (1,1), EGARCH (1,1) and TGARCH (1,1) models to measure volatility of stock prices in Ho Chi Minh stock exchange (HSX).

3. Data and Research Methodology

3.1. Data

The time series data used in this study is the daily closed price of the Ho Chi Minh City stock exchange index (VN-

Index) during the period from 1/03/2001–1/03/2019 with 4375 observations. The daily rate of return (R_t) of the closed index price is calculated as follows:

$$R_t = \text{Log}(P_t/P_{t-1})$$

In which: P_t is the index price at the end of the t trading day; P_{t-1} is the index price at the end of the $t-1$ trading day.

3.2. Research Models

The study uses GARCH (1,1) model and some variants include GARCH-M, EGARCH and TGARCH models.

3.2.1. GARCH (p, q) Model

The simplest GARCH model is described by GARCH (1,1), with the equations of mean and variance:

$$Y_t = X_t' \theta + \varepsilon_t \quad (1)$$

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (2)$$

In which the mean equation is given in (1) written as a function of exogenous variables with noise term. Since it is a predictive variance of a period based on past information, it is called a conditional variance. The equation of conditional variance specified in (2) is a function of three terms: Constant ω ; Information of the previous stage's volatility, measured by the lag of the residual square from the mean equation: ε_{t-1}^2 (ARCH effect); Predictive variance in the final stage σ_{t-1}^2 (GARCH effect).

Two values with 1 in parentheses of the simple model GARCH (1, 1) refer to the presence of the first-order automatic GARCH effect (the first term in parentheses) and the effect of ARCH on average sliding level one (second term in parentheses). A conventional ARCH model is a special case of the GARCH model, where there is no predictive variance delayed in the conditional variance equation, for example, the GARCH model (0, 1).

This is useful in finance, assuming an investor predicts the variance of this period by averaging the weighted average of the long-term average (constant), the forecast variance from the previous period (GARCH effect) and information of the previous stage's volatility (ARCH influence). If the asset returns unexpectedly increase or decrease, investors will increase the estimated variance for the next period. This model is also consistent with the dynamic clustering commonly found in financial profit data, in which large changes in profit are likely to be followed by further bigger changes.

From the simple model GARCH (1, 1), we can have the following GARCH model (p, q) as below:

$$\sigma_t^2 = \omega + \sum_{j=1}^q \beta_j \sigma_{t-j}^2 + \sum_{i=1}^p \alpha_i \varepsilon_{t-i}^2 \quad (3)$$

Equation (3) shows that the variance σ_t^2 depends on both past values by shocks, represented by the hysteresis variables of the squared disturbance class, and the past values of σ_t^2 itself, represented by the σ_{t-1}^2 variable.

3.2.2. GARCH-M Model

The GARCH model alone cannot explain the leverage effect, how to measure cluster dynamics in time series. Meanwhile, the GARCH model at the mean (GARCH-M) allows conditional mean to depend on its own conditional variance. In the financial sector, risk aversion is the behavior of investors, when encountering uncertainty, investors will try to lower that uncertainty. For example, the risk-averse investors may choose to put their money into a bank account with low interest rates but guaranteed, instead of investing in a stock that can bring high expected returns, but it is also contain the possibility of losing value. If you want these risk-averse investors to accept the risk of investing in higher risk assets (for example, stocks), they tend to require an additional risk premium for this action. Thus, the risk premium is a variable function with risk, the higher the risk, the greater the risk premium. If the risk is measured by the conditional variance, it becomes part of the mean equation of the variable Y_t .

Thus, the GARCH-M model (p, q) will look like this:

$$Y_t = X_t' \theta + \lambda \sigma_t^2 + \varepsilon_t \text{ or } Y_t = X_t' \theta + \lambda \log(\sigma_t^2) + \varepsilon_t \quad (4)$$

$$\sigma_t^2 = \omega + \sum_{j=1}^p \beta_j \sigma_{t-1}^2 + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2$$

3.2.3. EGARCH Model

The exponential GARCH model is proposed by Nelson (1991). The EGARCH model is based on a logarithmic expression of conditional variance. Nelson (1991) argues that EGARCH is a suitable model to test market leverage. Specifications for conditional variance are:

$$\log(\sigma_t^2) = \omega + \sum_{j=1}^q \beta_j \log(\sigma_{t-j}^2) + \sum_{i=1}^p \alpha_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| + \sum_{k=1}^r \gamma_k \frac{\varepsilon_{t-k}}{\sigma_{t-k}} \quad (5)$$

Note that the left side is the logarithm of the conditional variance. This implies that the leverage effect is exponential,

instead of quadratic and the forecast of the conditional variance is guaranteed to be non-negative. The presence of leverage can be tested by the hypothesis that $\gamma_i < 0$. The effect is asymmetric if $\gamma_i \neq 0$.

3.2.4. TGARCH Model

According to Gujarati (2003), GARCH model possesses many advantages, but it also has some limitations in estimating volatility. First, GARCH is assumed to be symmetric and the increase in volatility is greater when the previous profit is more negative compared to when they are the same magnitude but positive. Indeed, GARCH also rated good and bad information on the stock market. Asymmetric volatility attributes are explained in the document of leverage effect and the volatile feedback effect. When the story of volatile response takes place, the bad news brings higher volatility for current stock, causing the market participants to move up the variance since the volatility is persistent. The increase of the conditional variance leads to an immediate drop in market prices so that investors can be compensated in the form of additional expected profits. Therefore, in case of bad news, volatile feedback effects reinforce the leverage effect. Secondly, the binding of non-negative parameters involves the conditional variance, not negative. Therefore, a shock, regardless of its sign, always has a positive impact on volatility.

One of the common limitations of the GARCH model is that they are assumed to be symmetrical, which means that these models only care about the absolute value of the shocks, not the "sign" (negative or positive) - because noise or residuals are squared. According to Black (1976), Christie (1982), Schwert (1990), the leverage hypothesis that bad news (negative profit shock) increases financial leverage and makes stocks riskier, thereby increase the market volatility. So in a normal GARCH model, a strong shock with a positive or negative value has the same effect on the volatility of the data series. This conclusion does not reflect properly in the financial market. Experimental results show that negative shocks (affected by bad news) often have a stronger and longer impact than positive shocks (affected by good news). To be able to model and distinguish the effects of positive and negative shocks, Glosten, Jagannathan, and Runkle (1993) and Zakoian (1994) developed the TGARCH model. The main purpose of this model is to consider the asymmetry between positive and negative shocks. And this is also a way to test the effectiveness of the market. To do so, the authors propose to include a dummy variable into variance equation which interacts between the squared noise and dummy variable d_t , in which d_t is equal to 1 if $\varepsilon_{t-1} < 0$, and 0 if $\varepsilon_{t-1} > 0$. If the coefficient of this interaction variable is statistically significant, there will be

differences in different shocks. From this idea, the variance equation in the TGARCH model (1,1) will be as below:

$$\sigma_t^2 = \omega + \beta_1 \sigma_{t-1}^2 + \alpha_1 \varepsilon_{t-1}^2 + \gamma_1 \varepsilon_{t-1}^2 d_{t-1} \tag{6}$$

If the coefficient γ is statistically significant, good and bad news will have different effects on the variance. In particular, good news only has an effect on α_1 , while bad news will affect both α_1 and γ_1 . If the value $\gamma_1 > 0$, it indicates an asymmetry in the impact between the good and bad news. Conversely, if $\gamma_1 = 0$, the impact of news is symmetric.

4. Results

From Table 1, the R_t has a positive average value, the sharpness coefficient of the R_t distribution (Kurtosis index)

is more than twice of normal distribution coefficients, and Jarque-Bera test is significant statistics at 1%, this shows that R_t 's distribution does not follow the normal distribution rule.

As the test for stationarity of the sequence, Figure 1 shows the volatility clustering, especially in the period 2006-2010 and the profit margins fluctuate around the mean. Therefore, the R_t of the VN-Index may be a stationary sequence and might affect ARCH because R_t 's oscillations around the value of 0 are uneven. The autocorrelation diagram of R_t shows that R_t is a stationary sequence at lag 1 for AR and MA.

From Table 2, at the same time, the results of the two ADF and PP tests have rejected the hypothesis at 1% (P-value of ADF and PP is less than 1%). It can be concluded that the time series of data participating in this study is stationary.

Table 1: Diagram and Descriptive Statistics of daily rate of return - R_t

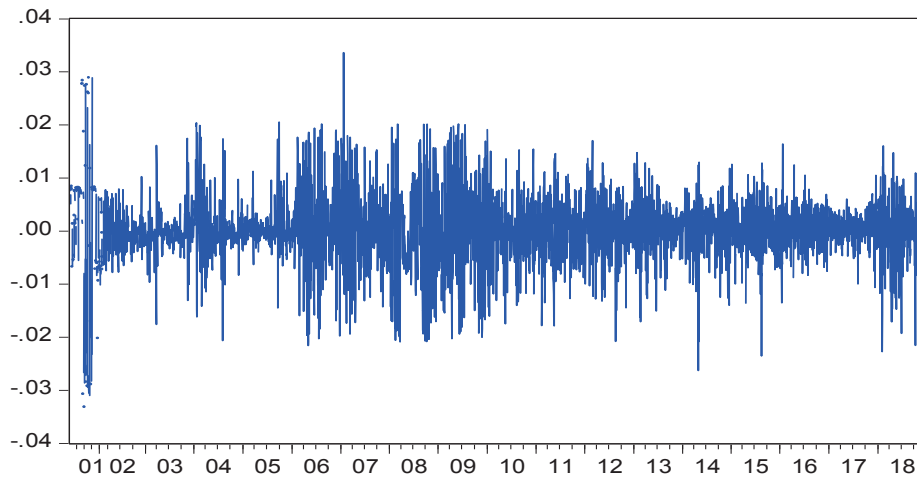
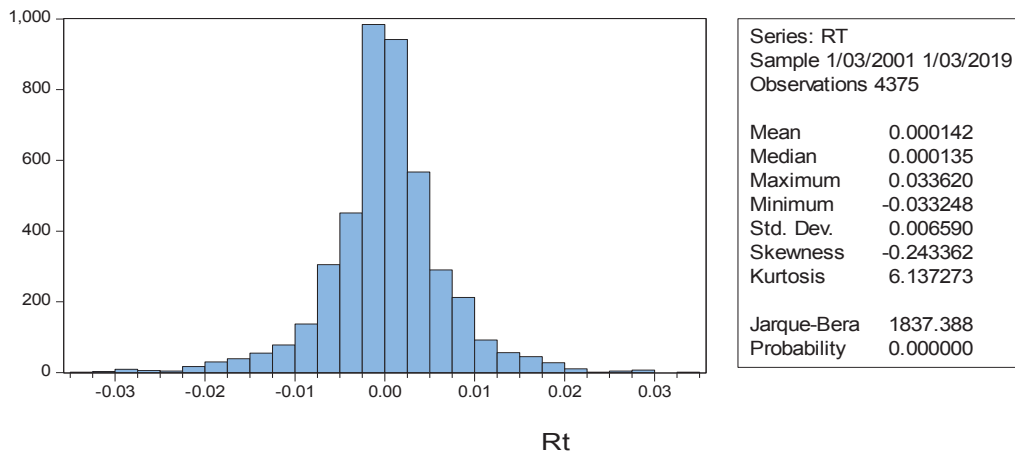


Figure 1: Volatility of rate of return - R_t

Table 2: Stationarity test for rate of return of VN-Index (Rt)

	ADF	PP
t-statistics	-22.33	-53.09
P-value	0.0000***	0.0000***
Test critical values		
1% level	-3.4316	-3.4316
5% level	-2.8620	-2.8620
10% level	-2.5670	-2.5670

***, ** and * indicates the meaning of 1%, 5% and 10% respectively

From Table 3, the results of ARCH effects (ARCH-LM test) of all 4 models used in the study were statistically significant. With the EGARCH model (1,1) has the highest statistical significance at 1%, two models of GARCH (1,1) and GARCH - M (1,1) are statistically significant at 5%, and TGARCH (1,1) model has a 10% significance level. Thus, the hypothesis H0: no ARCH effect in the models is rejected at the significance level of 1%, 5% and 10%. Thus, it can be concluded that the GARCH models used in the study are appropriate.

Table 3: Test of ARCH effects existence in the models

Heteroskedasticity Test: ARCH	GARCH (1,1)	GARCH- M (1,1)	EGARCH (1,1)	TGARCH (1,1)
F-statistic	6.372	3.961	6.936	3.782
Prob. F(1; 4372)	0.0116**	0.0466**	0.0085***	0.051*
Obs*R-squared	6.367	3.959	6.928	3.781
Prob. Chi-Square(1)	0.016**	0.0466**	0.0085***	0.051*
Akaike Info Criterion (AIC)	4.130	4.168	4.155	4.201
Schwarz criterion (SIC)	4.133	4.170	4.158	4.204

***, ** and * indicates the meaning of 1%, 5% and 10% respectively

As a result, estimating the GARCH (1,1) and GARCH-M (1,1) models are shown in Table 4, the GARCH variance model parameters (1,1) are statistically significant at the level of 1%. In the conditional variance equation, the estimate of the coefficient β (GARCH effect) is three times greater than the coefficient α (ARCH effect), which indicates the volatility of variance or risk with the return of Rt index is affected by past risks more than the value of past shocks.

The model GARCH - M (1,1) regression results show that the parameter λ (risk premium) has a positive value, statistically significant at less than 1%, which indicates that there is an influence of market volatility to profit, in other words, there is a trade-off between profit and market risk in the research sample.

Table 4: Regression results of GARCH (1,1) and GARCH-M (1,1)

Coefficient	GARCH (1,1)	GARCH-M (1,1)
Mean equation		
C – Constant	5.66E-05	2.67E-03***
λ – Risk premium	-	2.27E-04***
Variance equation		
ω (constant)	5.48E-07***	5.49E-07***
α (ARCH effect)	0.2135***	0.2288***
β (GARCH effect)	0.7917***	0.7852***
$\alpha + \beta$	1.0052	1.014
Log likelihood	16929.22	16982.72
Akaike Info Criterion (AIC)	-7.7372	-7.7607
Schwarz criterion (SIC)	-7.7314	-7.7520

***, ** and * indicates the meaning of 1%, 5% and 10% respectively

Table 5 compares the regression results of the asymmetry test for Rt by EGARCH (1,1) and the TGARCH (1,1) models. The parameter γ shows an asymmetric effect on two models of EGARCH (1,1) and TGARCH (1,1). The presence of the leverage effect can be checked by the hypothesis that $\gamma_i < 0$. With the EGARCH model (1,1), the leverage effect has a negative value but is not statistically significant, while TGARCH model (1,1) has $\gamma = 0.0253$ and is statistically significant at 10%. This proves that there is an asymmetry in the impact between good and bad news. In detailed, bad news increases the volatility of the profit variable (Rt), there are leverage effect at model TGARCH (1,1) and the negative shock or bad news has a stronger effect on the variance equation than positive shock or good news.

Table 5: Regression results of EGARCH (1,1) and TGARCH (1,1)

Coefficient	EGARCH (1,1)	TGARCH (1,1)
Variance equation		
ω (constant)	-0.6514***	5.62E-07***
α (ARCH effect)	0.4069***	0.2026***
β (GARCH effect)	0.9682***	0.7900***
$\alpha + \beta$	1.3751	0.9962
γ – Leverage effect	-0.0107	0.0253*
Log likelihood	17011.84	16930.29
Akaike Info Criterion (AIC)	-7.7736	-7.7372
Schwarz criterion (SIC)	-7.7634	-7.7347

***, ** and * indicates the meaning of 1%, 5% and 10% respectively

5. Conclusions

The study used symmetric models (GARCH, GARCH-M) and asymmetry (EGARCH and TGARCH) to measure the volatility of VN-Index profit from 1/03/2001 to 1/03/2019. The results show that there are clustering volatility and leverage effects on the VN-index's profitability index (Rt). Stationarity tests and ARCH effects were performed by the author to confirm the correctness of applying GARCH model in the study.

The research results show that the daily rate of return Rt has a strong volatility, especially in the period of 2006-2010 (see Figure 1), indicate a trade-off between profit and risk. During this period, strong volatility in the market could be attributed from the effects of the 2008 global financial crisis originating in the US. That means increasing profits also increase risks. Meanwhile, the EGARCH model (1,1) shows that the leverage effect has a negative value but is not statistically significant, while TGARCH model (1,1) has $\gamma = 0.0253$ and is statistically significant at 10%. This proves that there is an asymmetry in the impact between good and bad news. In detailed, bad news increases the volatility of the profit variable (Rt), there are leverage effect at model TGARCH (1,1) and the negative shock or bad news has a stronger effect on the variance equation than positive shock or good news. This result indicates that the volatility of stock returns has a big impact on future market movements under the impact of shocks, while asymmetric volatility increase market risk, thus increase the attractiveness of the stock market.

From this study's results, we can see the remarkable advantages of the regression model GARCH and the variations compared to the conventional OLS method (assuming constant variance) by determining the variance of the noise or the errors might have a relationship with each other. Therefore, risk prediction models such as GARCH can be better used in risk forecasting especially with financial time series data which are highly volatile and influenced by many exogenous factors such as foreign exchange, strong foreign currency prices, gold prices, oil prices ... This is an open research direction with subsequent research that can be used when analyzing other risk factors related to the yields of the stock market by putting other explanatory variables (or dummy variables) into the model. Therefore, the selection of suitable explanatory variables to include in the model considers exogenous variables that explain the volatility of Vietnam's stock market should be studied based on a theoretical basis and empirical results of reliable previous researches, and requires more investment in time and effort in order to build a model to predict the volatility of profits in accordance with the actual conditions of the Vietnam market in the future.

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