Asset Price Volatility of Listed Companies in the Vietnam Stock Market

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Abstract: This study aims to measure the volatility in asset prices of listed companies in the Vietnam stock market. The authors use models such as AR, MA and ARIMA combined with ARCH and GARCH to estimate value at risk (VaR) and the results generate relatively accurate estimates. In Vietnam, the stock market has been through periods of wild fluctuations in security prices and abnormal fluctuations cause many risks in investment activities. Based on this empirical result, investors can approach the method to determine asset price volatility to make proper investment decisions.

Keywords: Asset price volatility, VaR, ARIMA - GARCH (1,1), risks.

JEL Classification: C58 . G12 . G17.

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1. Introduction

Since financial instabilities in the 1990s (Jorion, 1997; Dowd, 1998; Crouhy et al., 2001), financial institutions have focused on modifying and conducting studies through complex models to estimate market risks. The increased volatility in the capital market encouraged research and field surveys to recommend and develop proper risk management models. Managing risks in capital markets based on VaR models have become academic topics receiving special attentions. VaR provides answers to the questions of what the maximum value an investment portfolio can lose under normal market conditions over a time horizon and with a certain degree of confidence (RiskMetrics Group, 1996).

In an attempt to measure the accuracy of estimates of risk management models, this study used a two-stage process to check each volatility estimation technique. In the first stage, backtesting was conducted to examine the model's accurate statistics. In the second stage, this study used a forecasting assessment technique to examine differences between the models. This study focused on out-of-sample as an assessment criterion since one model, which might be incomplete to certain assessment criteria, can still produce better forecasts for the out-of-sample examples than predetermined models. This study shows that the GARCH model is more agile, generates more complete volatility estimations, while providing all coefficients, distribution assumptions and confidence degrees. Moreover, although the utilisation of all available data represents a common practice in estimating the volatility, the authors find that at least in some cases, a limited sample size can generate more accurate estimates than VaR because it combines changes in the business behaviour more effectively. The next section describes ARCH, GARCH models, and assessment frameworks for VaR estimates. The authors also provide preliminary statistics, explain procedures and present the result of empirical surveys of estimation models for daily stock returns.

2. Literature Review

2. 1. Value at Risk

The volatility of a company's asset prices is an important financial variable because it measures risk levels of the company's assets. Profits always come with risks. The greater the risk is, the higher the profit is. Thus, the estimation of asset price volatility of a company assists investors in measuring risk levels of the company's asset, producing estimations of the profit returned from investing in the company to formulate investment strategies.

According to Hilton (2003), VaR was first used for stock companies listed in the New York stock exchange (NYSE). Hendricks (1996) claims that VaR is the maximum amount of money that an investment portfolio can lose over a given time horizon with a certain confidence degree. Therefore, VaR describes a loss that can happen due to the exposure to market risks over a given period at a certain confidence level.

In the late 1990s, the US Securities and Exchange Commission dictated that companies must report a quantitative proclamation about market risks in their financial reports in order to provide investors with convenience. Since then VaR has become a primary tool. At the same time, the Basel Committee on Banking Supervision said that companies and banks can rely on internal VaR calculations to establish their capital requirements. Therefore, if their VaR is relatively low, the amount of money that they have to spend on risks that can be worse, can also be low.

In Vietnam, the State Securities Commission issued a regulation on the establishment and operation of the risking management system for fund management companies in 2013. In this regulation, the State Securities Commission referred to VaR and basic VaR calculations to help fund management companies manage risk more efficiently. VaR is typically calculated for each day of the asset holding period with a confidence of 95% or 99%. VaR can be applied to all liquid categories, whose values are adjusted according to the market. All high liquidity assets that have unstable values are adjusted according to the market with a certain probability distribution rule. The most significant limitation of VaR is that assumptions about market factors which do not change substantially during the VaR period. This is a significant limitation because it caused the bankruptcy of a series of investment banks in the world in 2007 and 2008 due to sudden changes in the market conditions that exceeded extrapolated trends.

For investors, VaR of a financial asset portfolio is based on three key variables: confidence degree, the period in which VaR is measured, and profit and loss distribution during this period. Different companies have different demands for the degree of confidence depending on their risk appetite. Investors with low-risk appetite would like to have a high degree of confidence. Additionally, the degree of confidence selected should not be too high when verifying the validity of VaR estimates because if the degree of confidence is too high, e.g. 99%, VaR will be higher. In other words, VaR is lower when loss probability is higher, requiring a longer period to collect data to determine the validity of the test.

The period over which VaR is measured: one of the important factors for applying VaR is the time period. In different timeframes, a portfolio's rate of return fluctuates at different degrees. The volatility of a portfolio is greater when the period is longer.

Profit/loss distribution during the VaR period: the profit/loss distribution line represents the most important variable, which is also the most difficult to be defined. Since the degree of confidence depends on risk tolerance of the investors, VaR is higher when the degree of confidence is high. Investors with low risk acceptance will formulate a strategy that can reduce the probability of worst scenarios.

The idea of Hendricks (1996) and Hilton (2003) is to calculate VaR of the market asset price by indicating the maximum amount of money a portfolio can lose due to the exposure to market risks over a certain period and with a given degree of confidence. In this study, the left fractile of the return rate of the market asset price is used to measure downside risks while the right fractile describes upside risks, indicating that with the volatility of the return rate, investors may suffer losses. Therefore, this method focuses on reducing highest risks that can be seen in financial markets. This will help to generates more accurate estimates of market risks.

2.2. Empirical Studies

Bao et al. (2006) examined the RiskMetrics model, the conditional autoregressive VaR and the GARCH model with different distributions: normal distribution, the historically simulated distribution, Monte Carlo simulated distribution, the non-parametrically estimated distribution, and the EVT-based (Extreme Value Theory) distributions for such markets as Indonesia, Korea, Malaysia, Taiwan, and Thailand. Their results indicate that RiskMetric and GARCH models with distributions such as normal distribution, t-student distribution, and the generalised error distribution (GED) can be accepted before and after the crisis while the EVT-GARCH behaves better during the 1997-1998 financial crisis in Asia.

Mokni et al. (2009) examined GARCH family models such as GARCH. IGARCH and GJR-GARCH were adjusted with normal distribution assumptions, t-students and skewed t-students to estimate VaR of NASDAQ index during a stable period of the US stock market from 01/01/2003 until 16/07/2008. The results show that GJR-GARCH models perform better than GARCH and IGARCH models in two stages.

Koksal & Orhan (2012) compared a list of 16 GARCH models in risk measure VaR. Daily return data were collected from emerging markets (Brazil, Turkey) and developed markets (Germany, USA) during the period from 2006 until the end of

August 2009. Applying both unconditional tests of Kupiec and conditional tests of Christoffersen, the study shows that, on average, ARCH model performs the best, followed by the GARCH model (1,1) while t-students distribution generates better results than standard distribution.

Zikovic & Filer (2009) compared the VaR estimation between developed and emerging countries before the 2008 - 2009 global financial crisis. Models used in this study include moving average model, RiskMetric, historical simulation, GARCH, filtered historical simulation, EVT using GPD and EVT-GARCH distribution. Data include stock indexes in five developed markets (USA, Japan, Germany, France, and England) and eight emerging markets (Brazil, Russia, India, South Africa, Malaysia, Mexico, Hong Kong and Taiwan) from 01/01/2000 until 01/07/2010. The results show that the best performing models were EVT-GARCH and historically simulated models with updated market fluctuations.

Kamil (2012) used logarithm of rate of return WIG-20 in period 1999-2011 with different types of ARIMA-GARCH(1,1) to calculate VaR in short and long term. The author concludes that the calculation of VaR is impacted by distribution (normal distribution, t-student distribution, generalised error distribution-GED) with the condition of rate of return and find the best model to calculate VaR with chosen data.

Vo Hong Duc & Huynh Phi Long (2015) test the suitability of risk measure VaR in Vietnam. The study uses 12 different models to estimate one-day VaR for stock indexes in the VN-Index and HNX-Index exchanges during the period 2006 – 2014 at different risk levels. The results show that at the risk level of 5%, many estimation models do not satisfy test conditions. In addition, Hoang Duong Viet Anh & Dang Huu Man (2011), Vo Thi Thuy Anh and Nguyen Anh Tung(2011) studied risk acceptance models with data collected from the stock market in Vietnam. These studies were conducted by referring to parameters through such economic models as AR, MA, combined with ARCH and GARCH.

Generally, in these studies, VaR is calculated by the parametric approach with a main focus on GARCH models and its sub models. These studies show that financial data series are complex and hardly follow standard distribution rules. The estimation of financial time series data is suitable for ARIMA models ranging from the original ARIMA model to extended models such as ARCH, GARCH, and GARCH-M, GR-GARCH variants. ARCH models change in the conditional variance, therefore making it possible to predict the risk level of an asset's rate of return. However, ARCH has some limitations. If ARCH effects have too many lags, they will significantly reduce the degrees of freedom in the model and this become increasingly serious for short time series, which negatively affects estimation results. Models assuming positive and negative shocks have the same level of effect on risks. In practice, the price of a financial asset reacts differently to negative and positive shocks. GARCH model was developed to partially overcome these limitations.

3. Methodology and Data

There are many approaches to VaR calculation which include nonparametric and parametric approaches. The nonparametric approach was known for the historically simulated model. However, one limitation of this method is that the distribution of historical data will overlap in the future. The parametric approach contains RiskMetrics and GARCH models. Within the scope of this article, the authors use parametric approach through time series econometric models: AR, MA and ARIMA combined with ARCH and GARCH.

3.1. Methodology

Methods used in this study included Box-Jenkins ARIMA and GARCH. First, this study investigates the stabilisation of time series data by ADF method. The next step is to examine the autocorrelation of the data. LB method is used to test ARCH effects of financial data series. If the original data series do not stabilise, the difference method is used to test whether the series are stationary. In this study, in order to select a model, AIC standard is adopted. The results of GARCH model estimates is used to predict the volatility of stock prices by VAR and post-test VAR procedures via backtesting. Research data is the daily closing data of companies listed on the Vietnamese stock market.

To apply Box-Jenkins ARIMA procedures to the stabilised time series, the stabilised series is obtained by taking an appropriate degree of error. This leads to the ARIMA (p, d, q) model where p is the autoregressive level, q stands for the moving average order, and d represents the order of the stabilised series.

The ARIMA (p, d, q) is given as:

$$\phi_p(B)(1-B)^d y_t = \delta + \theta_q(B)u_t$$

where $\phi_p(B) = 1-\phi_1 B -\ldots\phi_p B^p$ is the process of pth autoregressive process; $\theta_q(B) = 1-\theta_1 B -\ldots\theta_q B^q$ is the qth moving average process; $(1-B)^d$ is the dth difference, B is the backward shift operator of the differencing order and u_t is white noise.

Previous studies have tested the effectiveness of GARCH model in explaining the volatility in financial markets. These studies indicate that GARCH models can identify and quantify volatility levels with long and fat tail distribution, and volatility clustering often appearing in the financial data series.

The ARCH model is specifically developed to model and forecast conditional variances. ARCH model was introduced by Engle (1982) while GARCH model was proposed by Bollerslev (1986). These models have been widely used in economically mathematic models, especially in the analysis of financial time series as in the studies of Bollerslev et al. (1992, 1994). GARCH model is more general than ARCH model. GARCH (p, q) model is given as:

$$\begin{cases} r_t = \mu + \varepsilon_t \sigma_t \\ \sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \end{cases}$$

in which p is the order of GARCH model; q is the order of ARCH model; (p, q) is the number of lags.

The ε_t error is assumed to follow a specific distribution rules with a mean value of 0 and the conditional variance σ_t^2. r_t and μ reflect the average value and return. μ is positive and quite small. ω, β_j, α_i are parameters of the model and also the proportion of the coefficients whose lags are assumed to be non-negative. According to Floros (2008), ω value will be quite small and $\alpha + \beta$ are forecasted to be smaller than 1 and to be relatively identical, in which $\beta > \alpha$. This explains for the fact that news about the volatility in the previous period can be measured based on ARCH coefficient . Also, the estimate clearly indicates the sustainability of the volatility when experiencing economic shocks or the impact of events on the volatility.

One important point of GARCH models is estimating these parameters using an appropriate maximum estimation method. According to many studies, among sub-models of the general GARCH (p,q) model, GARCH (1,1) is the most effect model because it generates most accurate estimates (Floros, 2008).

The simplest form of GARCH model is GARCH (1,1) and it is given as follow:

$$\begin{cases} r_t = \mu + \varepsilon_t \sigma_t \\ \sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \end{cases}$$

in which ε_{t-1}^2 and σ_{t-1}^2 are respectively the squared return and the conditional variance of the day before.

The most obvious advantage of GARCH model compared to ARCH is that

ARCH(q) is infinite equals to GARCH(1,1) (Engle, 1982; Bollerslev, 1986). If ARCH model has too many lags (q is large), it can affect results of the estimate given a significant decrease in the degree of freedom in the model.

In the study of Dmitriy (2009), to calculate VaR, formulas of upside VaR and downside VaR on the stock exchanges are given as follows:

- VaR formula: $VaR_t = \alpha\sigma_t$
- Upside VaR formula: $VaR_t^{upside} = \mu_t + \alpha\sigma_t$
- Dowside VaR formula: $VaR_t^{dowside} = -\mu_t - \alpha\sigma_t$

in which μ_t is the expected rate of return with conditions of the stock; α is the quantile for normal distribution which is often used for residuals of the GARCH model on the stock exchange; and σ_t is the conditional variance series of the asset.

Many researchers show their interest in accurate estimates of future risks. In an attempt to evaluate the quality of VaR estimates, models should be rechecked by appropriate methods. Backtesting is a statistical process for comparing actual profits and losses with corresponding VaR estimates. For example, if the degree of confidence is used to calculate the complete VaR of VaR methods, especially when a few methods are compared. Two alternative methods to VaR methods that are often used in studies include: the basis of accuracy tests and loss functions.

VaR backtesting model is implemented by calculating the number of losses which are greater than VaR estimates. The number of VaR violations can be defined as follows:

$$I_{t+1} \begin{cases} 1 & \text{loss} > \text{VaR} \\ 0 & \text{loss} \leq \text{VaR} \end{cases}$$

A risk model should be enhanced to estimate the probability (p) of VaR violations. VaR violation probability relies on the VaR coverage ratio. Processes of a risk model determine exactly as a series of random coin tosses (Christoffersen & Jacobs, 2004).

3.2. Data

We randomly selected two companies listed on the Ho Chi Minh City stock exchange (HOSE): a financial company and a non-financial company for the test. This helped us to simplify the research process and not to affect the scientific nature of the research. Collected data are daily closing prices of listed companies on the market. Closing price data were collected from 21/11/2006 until 04/12/2015. Specifically, closing prices of ACB were collected from 21/11/2006 and closing prices of AAA were gathered from 15/07/2010. ACB is the stock code of the Asia commercial bank and AAA is the stock code of An Phat plastic and green environment company. Daily rates of return of closing prices were calculated as follows:

$$r_t = ln(P_t/P_{t-1})$$

in which: P_t is the stock price at the closing time on the tth exchange date; P_{t-1} is the closing price of the stock on the t-1th date.

Figure 1 shows that the return rate of AAA and ACB stocks fluctuated over time with prices going up and down. There is volatility clustering in the series.

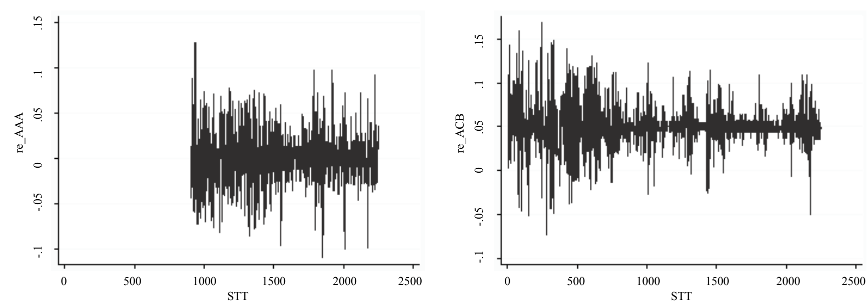

Figure 1. Daily rates of return of AAA and ACB (21/11/2006-04/12/2015)

Analysis results of the basic statistical values show significant fluctuations in the series. Kurtosis measures peaked or flat degrees of a distribution in comparison with a normal distribution whose kurtosis is 0. A distribution has a peaked shape when the kurtosis is positive and a flat shape when the kurtosis is negative. A kurtosis of more than 3 show that the "peakedness" of the peaked distribution is greater than a normal distribution. Stationary test reveals that both AAA and ACB series stabilised at the significant level of 1%. Jarque-Bera test shows that the averages of the two series have non-normal distributions. ARCH effect tests uses Ljung-Box Q test lags (10) for the squared residuals of the return rate with a significant level of 1%. This indicates that GARCH (1,1) can be applied to these data series.

Table 1. Descriptive Statistics

	RE_AAA	RE_ACB
Avarage	-0.0005	-0.0001
Standard Deviation	0.0294	0.0233

	RE_AAA	RE_ACB
Skewness	0.0391	0.1088
Kurtosis	3.9788	6.7684
JB test	53.9525 (0.000)	1333.414 (0.000)
Sample	1.343	2.246
ADF test	-34.2351 (0.000)	-41.0204 (0.000)
LB-Q (10)	19.9636 (0.000)	52.6971 (0.000)

4. Empirical Results

• ***GARCH model estimation***

A GARCH model includes two equations. The first one is an average equation while the second one is a variance equation. The estimate results obtained from the research data are represented in Figure 2.

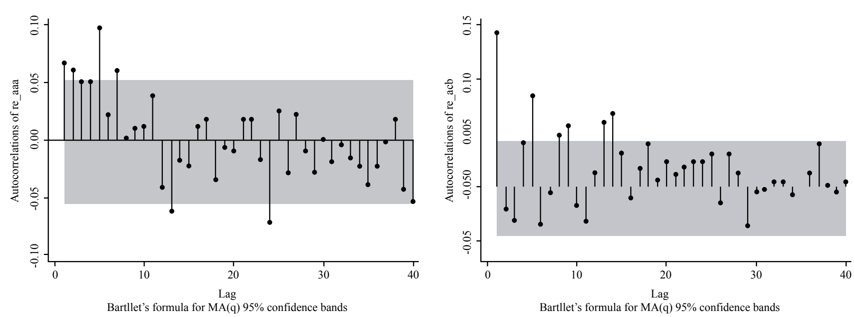

Figure 2. Autocorrelation results of AAA and ACB stocks

Results obtained from the Box-Jenkins method show that AAA and ACB data series are significant (Figure 2). Therefore, in this study, ARIMA can be applied in the mean equation for ARCH effects. Data experiment allow us to select lags of AR (1) and MA (1). Outlier observations have null values, suddenly falling to 0. d is obtained through Jarque-Bera and ADF methods, indicating that the series stabilises at level 1.

The comparison between the values of AIC and Log likelihood from GARCH (1,1), GARCH (2,2), GARCH (1,2) và GARCH (2,1) in Table 2 show that GARCH (1,1) provides the smallest AIC and the largest Log likelihood.

Table 2. Results of GARCH model of AAA

Parameter	GARCH (1,1)	GARCH (2,2)	GARCH (2,1)	GARCH (1,2)
AR (1)	0.8650*** (4.10)	0.8380*** (4.65)	0.8630*** (4.81)	0.9080*** (5.23)
MA (1)	-0.8470*** (-3.77)	-0.8150*** (-4.27)	-0.8440*** (-4.44)	-0.8960*** (-4.86)
α_1	0,1460*** (6.77)			0.2520*** (7.190)
α_2		0.1330*** (5.94)	0.1100*** (6.95)	
β_1	0.7990*** (30.63)		0.840*** (37.65)	
β_2		0.7760*** (22.37)		0.6630*** (16.83)
α_0	0.00005*** (5,24)	0.0001*** (4.96)	0.00004*** (4.76)	0.0001*** (5.75)
N	1.343	1.343	1.343	1.343
AIC value	-5876.8000	-5806.0000	-5841.2000	-5872.9000
BIC	-5845.5000	-5774.8000	-5810	-5841.7000
Log likelihood	2944.3800	2909.0250	2926.6120	2942.4610
t statistics in parentheses				

** p<0.05, ** p<0.01, *** p<0.001.*

Standardised results of AIC and Log likelihood of Table 3 show that the selected model for estimations in this research is GARCH (1,1). Selection criteria of the model are the smallest AIC and the largest Log likelihood.

Table 3. Results of GARCH model of ACB

Parameter	GARCH (1,1)	GARCH (2,2)	GARCH (2,1)	GARCH (1,2)
AR (1)	-0.9650*** (-54.49)	0.9270*** (34.78)	0.2490 (1.12)	-0.7880*** (-5.43)
MA (1)	0.9780*** (71.56)	-0.8710*** (-27.73)	-0.1490 (-0.66)	0.8180*** (6.04)
α_1	0.2950*** (14.51)			0.249*** (17.18)
α_2		0.31700*** (13.84)	0.2080*** (12.21)	

Parameter	GARCH (1,1)	GARCH (2,2)	GARCH (2,1)	GARCH (1,2)
β_1	0.7290*** (59.08)		0.7810*** (56.97)	
β_2		0.6860*** (41.52)		0.7560*** (107.06)
α_0	0.00001*** (18.94)	0.00002*** (16.69)	0.00002*** (14.24)	0.00001*** (25.41)
N	2.246	2.246	2.246	2.246
AIC value	-11805.2000	-11572.4000	-11590.3000	-11708.9000
BIC	-11770.9000	-11538.1000	-11556.0000	-11674.6000
Log likelihood	5908.59000	5792.2150	5801.1640	5860.4490
t statistics in parentheses				

** p<0.05, ** p<0.01, *** p<0.001.*

Figure 3 describes trends of the conditional variance of the return rate series of AAA and ACB, representing the volatility degree of corresponding data series. The volatility degrees of the two series are different and the series fluctuate significantly, in which the volatility in the return rate of AAA is greater. Volatility scale not only represents highest risks during each period but can also help us predict market volatility and relevant risks.

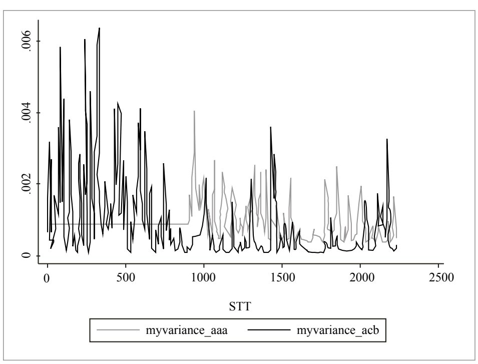

Figure 3. Conditional variance of the return rates of AAA and ACB

• ***Upside and downside VaR calculation***

Figure 4 reveals that VaR estimates at the confidence degrees of 95% and 99% creates series of return rate of AAA and ACB. Asset fluctuations are relatively significant, and this indicates that with strong volatility, investors holding the asset will face very high risks.

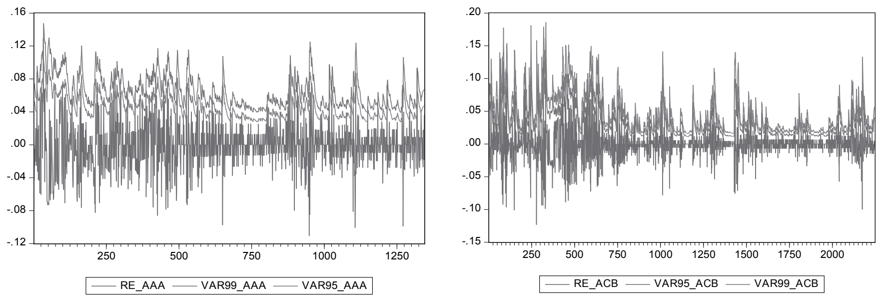

Figure 4. Calculation of VaR (95%) và VaR (99%)

Results in Figure 5 shows that the confidence degree of 99% provides more accurate estimates than 95% with fewer violations. Next, we consider the estimation period of 10 days and the degrees of confidence of 95% and 99%, generating accurate results. The results indicate that volatility in AAA's asset is more complex and larger than those of ACB during the observed period.

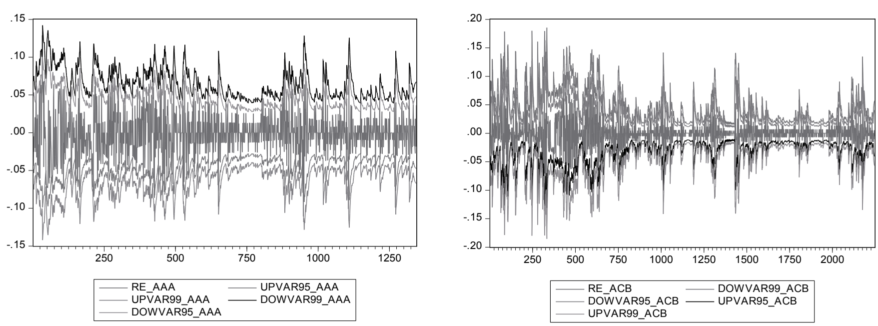

Figure 5. VaR 95% and VaR 99% (Upside/Downside)

• ***Analysis of the estimation process***

Figure 6 show that VaR estimation during a period of 10 days is accurate at the degrees of confidence of 95% and 99% for both AAA and ACB. Violation rate is 0% during this period and this result has been confirmed since the post test results.

• ***Backtesting***

Backtesting was conducted on ACB's data series with 2.247 samples. Tests within the sample was completed with 2.237 samples during the period from 21/11/2006 until 20/11/2015. Out of sample tests were performed for the 10 remaining samples during the period from 23/11/2015 until 04/12/2015 (Table 4).

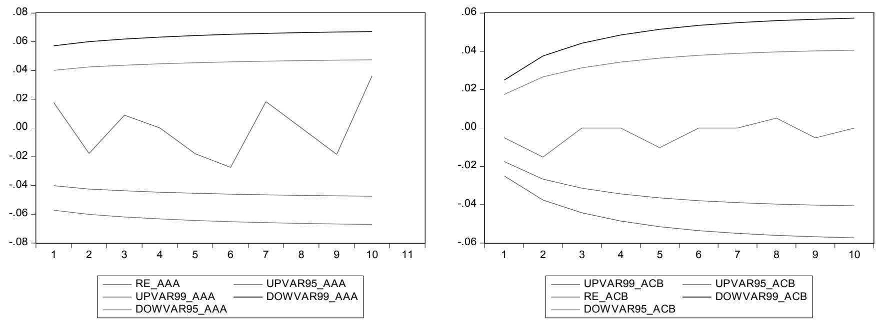

Figure 6. Actual rates of return and 10-day VaR with the confidence degrees of 95% and 99%

Table 4. Post test results

ACB (21/11/2006-20/11/2015)	
VaR 95%	VaR 99%
170 violations (7.57%)	73 violations (3.25%)
AAA (15/07/2010-20/11/2015)	
125 violations (9.33%)	38 violations (2.83%)

Similarly, AAA's data series with 1.344 sample were divided into two periods. Within sample tests were conducted on 1.334 samples from 15/7/2010 until 04/12/2015. Out of sample test were conducted on the 10 remaining samples from 23/11/2015 until 04/12/2015.

Backtesting results within the sample show that the numbers of violations at different degrees of confidence are different. In contrast, out of sample backtesting results (during the period from 23/11/2015 until 04/12/2015) provide a violation rate of 0% for both AAA and ACB's series.

5. Conclusion

The results of this study indicate that given the volatile nature of the financial data series, it is necessary to select an appropriate measuring tool. Experimental studies on AR, MA, and ARIMA models in combination with ARCH and GARCH allow us to estimate VaR. Post-test procedures show that estimate results are reliable. VaR provides predictions of maximum losses on the stock during a certain period and at a predetermined degree of confidence. In other words, VaR provides a scientific basis for us to determine whether risks facing investors are within allowable limits. This allows investors to recognise the safety of holding assets on the market. In addition, investors can use available data and GARCH economic model to determine VaR for their assets. Investors will be able to decide whether to continue holding current assets or not.

This study was conducted in an attempt to measure the volatility degrees in assets of listed companies on the stock exchange in Vietnam. Estimate results of the GARCH model show that the two data series of AAA and ACB is significant for GARCH (1,1). This result is consistent with requirements from AIC and Log likelihood standards of econometric models. Post-test results indicate that GARCH (1,1) can recognise and quantify fluctuations with long-tailed and thick-tailed distributions which fluctuate according to clusters in the financial data series. Post-test results of the 10-day estimates generates perfectly accurate results at the two degrees of confidence in comparison with the actual results. Upside and downside cases of the model is influenced by the selection of the estimated period. One important factor of the financial data series is that the distribution of data leads to the accuracy of the model estimate. Most financial data have long-tailed and thick-tailed distributions. From the above-mentioned experimental results, the authors hope to support risk managers in making decisions and solutions to minimize risks.

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