Estimating Value at Risk for Stock Exchange of Thailand Using GARCH Family Models

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Received 20 February 2023; received in revised form 4 April 2023; accepted 18 May 2023

Abstract
This study uses Value at Risk (VaR) technique to estimate the risk of investment in Stock Exchange of Thailand over a period of July 2, 2015 to December 27, 2019 for stock investment with a correlation to the performance of sector index, including Energy and Utilities (ENERG), Food and Beverage (FOOD), Banking (BANK), Commerce (COMM) and Information and Communication Technology (ICT). The VaR estimation result using parametric method shows that the GARCH (1,1) TARCH (1,1), and EGARCH (1,1) models are not radically different from each other in their outputs. However, the results show that parametric method using the model of EGARCH (1,1) is the best method for forecasting VaR. The results of VaR estimation at confidence level of 95% also report the lowest potential loss in stock investment with a correlation to the performance of COMM index, followed by stock investment with a correlation to the performance of FOOD, ENERG, BANK, and ICT index respectively.

Keywords: Value at risk, volatility, GARCH family, stock exchange of Thailand

1. Introduction

Since Thailand began recognizing the outbreak of the COVID-19 pandemic in 2020, Thai stock market experienced highly volatile. The Stock Exchange of Thailand (SET) index went down from 1,579.84 points on Dec 30, 2019 to the lowest drop to 1,024.46 points or decreased by 35.15% on March 23, 2020. After that the SET index bounced back to close at 1,589.51 points on September 30, 2022. Stock investment is risky so investors should be well-informed about information to confidently make decisions. It is important to examine the potential risk for future investment in the SET by estimating Value at Risk (VaR). VaR can indicate the worst possible expected loss for an examined time horizon and a specified confidence level.

Thus, this study aims to estimate the risk of stock investment with a correlation to the performance of sector index, including Energy and Utilities (ENERG), Food and Beverage (FOOD), Banking (BANK), Commerce (COMM) and Information and Communication Technology (ICT). The method used for risk measurement is VaR. The VaR is estimated by parametric method using the model of Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Family (GARCH, TARCH, and EGARCH) for estimating volatility.

2. Literature Review

Value at Risk (VaR) was introduced by J.P. Morgan in 1994 as the method of risk management. Previous study has examined the estimation of VaR by using three conventional methods, including non-parametric method, parametric method, and semi-parametric method. This paper focuses on parametric method, which measures risk by fitting probability curves to the examined data sample and then inferring the VaR from the fitted curve. To capture the various volatility effects observed in both the returns and prices of financial assets, the most popular models are the GARCH family volatility models. Jongadsayakul (2021) mentions the advantages and disadvantages of this method. Advantages include the model's ability to characterize the volatility clustering properties. Some models also capture the leverage effect. However, the performance of this approach strongly depends on the assumption concerning returns distribution and on the use of volatility model for estimating the conditional volatility of the returns. Studies undertaken by Angelidis, Benos, and Degiannakis (2004), So and Yu (2006), Carchano et al. (2010), Degiannakis, Floros, and Livada (2012), Restrepo Estrada. (2012), Abad and Benito (2013), Cera, Cera, and Lito (2013), Wong, Chin, and Tan (2016), Smolović, Lipovina-Božović, and Vujošević (2017), Gupta and Rajib (2018), Quang et al. (2018), and Wu (2018) have applied many variants of the GARCH model in VaR estimation. There are also some studies confirming the appropriateness of this method in estimating VaR for stock market indices and stock index futures contracts in Thailand. For example, Jongadsayakul (2020) estimates VaR in the Thailand Futures

Exchange (TFEX) for Sector Index Futures. Empirical results show that parametric method using the model of EGARCH (1,1) is the best method for forecasting VaR. The results of VaR estimation at confidence level of 95% using both non-parametric and parametric methods also report the lowest potential loss in Commerce Index Futures investment. Jongadsayakul (2021) estimates VaR for the assessment of risk exposure at the SET and TFEX. The 95% VaR using historical simulation and asymmetric GARCH models give solid results and outrank volatility-weight historical simulation with asymmetric GARCH models. A comparison of stock investments with a correlation to the performance of SET50 Index and SET50 Index Futures investment indicates that SET50 Index Futures investment carries higher risk.

Several studies use VaR as a tool for measuring risk during COVID-19 period. For example, Ahadiat and Kesumah (2021) use data during COVID-19 pandemic in 2020 to calculate the VaR of four state-owned banks in Indonesia. The AR (1, 1)-GARCH (1, 1) is found to be a good fit model for the measurement of the VaR. Using daily data of 17 major stock market and 27 world sector indices from January 2, 2017 to May 25, 2020, Castillo, León, and Ñíguez (2021) use EGARCH with Hansen's Skewed-t distribution augmented with a dummy variable to incorporate the COVID-19 effect on volatility. Their results show that there is a significant sudden shift up in the return distribution variance post the announcement of the pandemic, which must be explained properly to obtain reliable measures for financial risk management. However, Shaik and Padmakumari (2022) show that VaR models perform poorly during global financial crisis period (2008–2009) and COVID-19 period (2020–2021) compared to the overall period (2006–2021). On the other hand, Surowiec and Warowny (2021) redefine the concepts of assets and portfolio rates of return and describe the volatility in the numbers of deaths caused by Covid-19. They use VaR method to estimate the death rate from Covid-19 infection.

3. Data and Methodology

This research focuses on the following sectors: Energy and Utilities (ENERG), Food and Beverage (FOOD), Banking (BANK), Commerce (COMM) and Information and Communication Technology (ICT). These sectors are the underlying assets of Sector Index Futures traded in Thailand Futures Exchange. Daily data of closing prices are collected from SETSMART for a period starting from July 2, 2015 to December 27, 2019 due to sector reclassifications in 2015. The period of data collection is also chosen to exclude the impact of COVID-19 pandemic. VaR at 95% confidence interval is estimated by the parametric method using Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family models for estimating volatility.

The following GARCH family models are estimated to characterize the volatility clustering properties (Jongadsayakul, 2020).

Model 1: Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Model

The GARCH (1,1) model with constant mean can be written as follows:

Mean equation: $R_t = c_0 + \epsilon_t$; $\epsilon_t|I_{t-1} \sim N(0, \sigma_t^2)$

Variance equation: $\sigma_t^2 = \alpha_0 + \alpha_1\epsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2$

where R_t is the return, α_1 is the ARCH coefficient, β_1 is the GARCH coefficient.

Model 2: Threshold ARCH (TARCH) Model

To capture asymmetries in terms of negative and positive shocks, the TARCH (1,1) model is used as follows:

Mean equation: $R_t = c_0 + \epsilon_t$; $\epsilon_t|I_{t-1} \sim N(0, \sigma_t^2)$

Variance equation: $\sigma_t^2 = \alpha_0 + \alpha_1\epsilon_{t-1}^2 + \gamma\epsilon_{t-1}^2 d_{t-1} + \beta_1\sigma_{t-1}^2$

where $d_t = 1$ if $\epsilon_t < 0$, and 0 otherwise. If $\gamma > 0$, the leverage effect is observed as the impulse $\alpha_1 + \gamma$ of negative shocks is larger than the impulse α_1 of positive shocks.

Model 3: Exponential GARCH (EGARCH) Model

To capture asymmetries in terms of negative and positive shocks and to guarantee a positive conditional variance, the EGARCH (1,1) model is used as follows:

Mean equation: $R_t = c_0 + \epsilon_t$; $\epsilon_t|I_{t-1} \sim N(0, \sigma_t^2)$

Variance equation: $\ln(\sigma_t^2) = \alpha_0 + \alpha_1 |\epsilon_{t-1}/\sigma_{t-1}| + \gamma \epsilon_{t-1}/\sigma_{t-1} + \beta_1\ln(\sigma_{t-1}^2)$

where the negative sign of γ indicates the leverage effect.

The daily returns are computed as the natural logarithm of the current day's closing price divided by the previous day's closing price for a period of 1,100 days, between July 3, 2015 to December 27, 2019. The first 1,000 days of the return series are used to estimate the VaR models at significance level of 0.05, while the last 100 days are used to backtest VaR. Both unconditional coverage test (UC) and conditional coverage test (CC) developed by Kupiec (1995) and Christoffersen (1998) respectively are applied at the test significance level of 10% as recommended by Christoffersen (2012). The details of these tests are shown as follows (Jongadsayakul, 2021):

The unconditional coverage test, following a chi-squared distribution with one degree of freedom, is applied for the null hypothesis, H_0: $\pi = 0.05$, using the following likelihood ratio test statistic:

$$\mathrm{LR_{UC}} = 2[\ln((1-\pi)^{N_0}\pi^{N_1}) - \ln((1-\alpha)^{N_0}\alpha^{N_1})]$$

where

N_0 = the number of days in which VaR is not violated

N_1 = the number of days in which VaR is violated

π = the percentage of violation

The independence test checks, following a chi-squared distribution with one degree of freedom, is applied for the null hypothesis of serial independence, using the following likelihood ratio test statistic:

$$\mathrm{LR_{IND}} = 2[\ln((1-\pi_{01})^{N_{00}}\pi_{01}{}^{N_{01}}(1-\pi_{11})^{N_{10}}\pi_{11}{}^{N_{11}}) - \ln((1-\pi)^{N_0}\pi^{N_1})]$$

where N_{00} = the number of days in which VaR is not violated, following a non-violation in VaR

N_{01} = the number of days in which VaR is violated, following a non-violation in VaR

N_{10} = the number of days in which VaR is not violated, following a VaR violation

N_{11} = the number of consecutive VaR violations

$$\pi_{01} = \frac{N_{01}}{N_{00}+N_{01}}$$

$$\pi_{11} = \frac{N_{11}}{N_{10}+N_{11}}$$

However, with no consecutive VaR violations ($N_{11} = 0$), the test statistic is as follows:

$$\mathrm{LR_{IND}} = 2[\ln((1-\pi_{01})^{N_{00}}\pi_{01}{}^{N_{01}}) - \ln((1-\pi)^{N_0}\pi^{N_1})]$$

The conditional coverage test, following a chi-squared distribution with two degrees of freedom, examined the joint hypothesis of unconditional and independence tests. The test statistic can be described as $\mathrm{LR_{CC}} = \mathrm{LR_{UC}} + \mathrm{LR_{IND}}$.

4. Results

To estimate VaR at 95% confidence interval using parametric method, this study estimates the volatility of Sector Index returns using GARCH family. The estimation results of GARCH (1,1), TARCH (1,1), and EGARCH (1,1), including the estimated coefficients and their P-values, as well as diagnostics tests, are shown in Table 1, Table 2 and Table 3 respectively.

Before interpreting the results, it is important to assess the validity of the estimated models of GARCH family by employing Ljung–Box Q-test statistics up to lags 36 to check for serial correlation in the standardized residuals and Lagrange Multiplier test to examine for additional ARCH in the standardized squared residuals. The insignificant Ljung-Box Q statistics and LM ARCH statistics imply that the residuals of the estimated models are reasonably well behaved and adequately capture the persistence in the variance of returns.

Table 1 presenting the estimation result of GARCH(1,1) model shows that the coefficient for the previous shock (the ARCH coefficient: $\boldsymbol{\alpha_1}$) and that for its lagged conditional variance (the GARCH coefficient: $\boldsymbol{\beta_1}$) are highly statistically significant as their P-values equal 0.0000. For the estimation results of TARCH (1,1) model in Table 2, the value of γ in each sector is statistically significant and positive. Therefore, the leverage effect is observed as the impulse $\alpha_1 + \gamma$ of negative shocks is larger than the impulse α_1 of positive shocks. The EGARCH (1,1) model in Table 3 also shows the existence of leverage effect because of the negative sign of γ. Most of estimated coefficients in the variance equation are significant at the level of 0.01.

Table 1: Summary of GARCH (1,1) Model

Sector	c_0 (P-value)	α_0 (P-value)	α_1 (P-value)	β_1 (P-value)	Q-Stat (P-value)	LM ARCH (P-value)
BANK	7.73E-05	3.59E-07	0.031395	0.963125	35.166	0.9797
	(0.7748)	(0.0474)	(0.0000)	(0.0000)	(0.508)	(0.8062)
ICT	0.000277	1.93E-06	0.073853	0.91599	37.797	1.5922
	(0.3755)	(0.0003)	(0.0000)	(0.0000)	(0.387)	(0.6612)
ENERG	0.000579	7.61E-07	0.060209	0.935558	35.678	1.2019
	(0.0547)	(0.0344)	(0.0000)	(0.0000)	(0.484)	(0.7526)
COMM	0.000421	1.82E-06	0.080159	0.898932	26.384	0.0988
	(0.0996)	(0.0001)	(0.0000)	(0.0000)	(0.88)	(0.992)
FOOD	6.70E-05	2.10E-06	0.065296	0.90745	41.338	3.0451
	(0.7974)	(0.0007)	(0.0000)	(0.0000)	(0.249)	(0.3847)

Table 2: Summary of TARCH (1,1) Model

Sector	c_0 (P-value)	α_0 (P-value)	α_1 (P-value)	γ (P-value)	β_1 (P-value)	Q-Stat (P-value)	LM ARCH (P-value)
BANK	-3.37E-05	5.90E-07	0.013829	0.044311	0.956523	36.479	0.7508
	(0.8979)	(0.0059)	(0.1176)	(0.0001)	(0.0000)	(0.446)	(0.8612)
ICT	0.000119	2.07E-06	0.039209	0.054152	0.920049	38.244	1.2271
	(0.7056)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.368)	(0.7465)
ENERG	0.000362	1.52E-06	0.023863	0.069295	0.928747	35.556	1.1761
	(0.2374)	(0.0012)	(0.0388)	(0.0000)	(0.0000)	(0.49)	(0.7587)

Sector	c_0 (P-value)	α_0 (P-value)	α_1 (P-value)	γ (P-value)	β_1 (P-value)	Q-Stat (P-value)	LM ARCH (P-value)
COMM	0.000363	2.00E-06	0.061748	0.032191	0.898526	26.456	0.221
	(0.1735)	(0.0000)	(0.0005)	(0.0765)	(0.0000)	(0.877)	(0.9741)
FOOD	-4.54E-05	2.81E-06	0.03592	0.077357	0.888748	46.278	2.147
	(0.8622)	(0.0000)	(0.0237)	(0.0016)	(0.0000)	(0.117)	(0.5425)

Table 3: Summary of EGARCH (1,1) Model

Sector	c_0 (P-value)	α_0 (P-value)	α_1 (P-value)	γ (P-value)	β_1 (P-value)	Q-Stat (P-value)	LM ARCH (P-value)
BANK	-3.39E-05	-0.12955	0.078277	-0.041791	0.992749	35.785	0.9694
	(0.8965)	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.479)	(0.8087)
ICT	-4.54E-05	-0.18598	0.12832	-0.049532	0.9897	39.615	0.6055
	(0.8838)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.312)	(0.8952)
ENERG	0.000408	-0.23412	0.119328	-0.054639	0.984398	36.347	1.1722
	(0.1704)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.453)	(0.7597)
COMM	0.000357	-0.40305	0.161654	-0.030532	0.970552	25.604	0.255
	(0.1603)	(0.0000)	(0.0000)	(0.0086)	(0.0000)	(0.901)	(0.9683)
FOOD	-4.06E-05	-0.51338	0.14431	-0.073504	0.957908	45.811	2.3865
	(0.8771)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.127)	(0.4961)

After the parameters are estimated, the volatility of the daily returns is forecasted using GARCH family models that cater for volatility clustering. Table 4, 5 and 6 show the results of VaR modelling using GARCH (1,1), TARCH (1,1) and EGARCH (1,1) respectively.

The results of parametric method show that the VaR estimations at 95% confidence interval using GARCH family models easily pass independence test and conditional coverage test at a significance level of 10%, as well as unconditional coverage test at a significance level of 5%. As a result, the model accuracy is accepted. Empirical results show that parametric method using the model of EGARCH (1,1) is the best method for forecasting VaR since the model findings based on EGARCH (1,1) has the lowest numbers of VaR exceptions. By comparison, the results of VaR estimation at confidence level of 95% report the lowest potential loss in COMM, followed by FOOD, ENERG, BANK, and ICT respectively. COMM sector has a lowest average VaR value so it provides a lowest risk investment compared to other sectors.

Table 4: Results of VaR Modelling Using GARCH (1,1) and Model Evaluation

Sector	Avg. VaR (α = 0.05)	π (π_{11})	LR_{UC} (P-value)	LR_{IND} (P-value)	LR_{CC} (P-value)
BANK	-1.6438%	0.06	0.1984	0.9190	1.1174
		(0.17)	(0.6560)	(0.3377)	(0.5720)
ICT	-2.0293%	0.09	2.7510	0.0508	2.8018
		(0.11)	(0.0972)	(0.8217)	(0.2464)
ENERG	-1.5677%	0.05	0.0000	0.5266	0.5266
		(0.00)	(1.0000)	(0.4680)	(0.7685)
COMM	-1.3748%	0.06	0.1984	0.7665	0.9649
		(0.00)	(0.6560)	(0.3813)	(0.6173)
FOOD	-1.4046%	0.05	0.0000	0.5266	0.5266
		(0.00)	(1.0000)	(0.4680)	(0.7685)

Table 5: Results of VaR Modelling Using TARCH (1,1) and Model Evaluation

Sector	Avg. VaR (α = 0.05)	π (π_{11})	LR_{UC} (P-value)	LR_{IND} (P-value)	LR_{CC} (P-value)
BANK	-1.7782%	0.05	0.0000	0.5266	0.5266
		(0.00)	(1.0000)	(0.4680)	(0.7685)
ICT	-2.0645%	0.09	2.7510	0.0508	2.8018
		(0.11)	(0.0972)	(0.8217)	(0.2464)
ENERG	-1.5870%	0.05	0.0000	0.5266	0.5266
		(0.00)	(1.0000)	(0.4680)	(0.7685)
COMM	-1.4087%	0.06	0.1984	0.7665	0.9649
		(0.00)	(0.6560)	(0.3813)	(0.6173)
FOOD	-1.4479%	0.04	0.2253	0.3334	0.5588
		(0.00)	(0.6350)	(0.5637)	(0.7562)

Table 6: Results of VaR Modelling Using EGARCH (1,1) and Model Evaluation

Sector	Avg. VaR ($\alpha = 0.05$)	π (π_{11})	LR_{UC} (P-value)	LR_{IND} (P-value)	LR_{CC} (P-value)
BANK	-1.7427%	0.05	0.0000	0.5266	0.5266
		(0.00)	(1.0000)	(0.4680)	(0.7685)
ICT	-2.1642%	0.09	2.7510	0.0508	2.8018
		(0.11)	(0.0972)	(0.8217)	(0.2464)
ENERG	-1.6567%	0.05	0.0000	0.5266	0.5266
		(0.00)	(1.0000)	(0.4680)	(0.7685)
COMM	-1.4442%	0.05	0.0000	0.5266	0.5266
		(0.00)	(1.0000)	(0.4680)	(0.7685)
FOOD	-1.4822%	0.04	0.2253	0.3334	0.5588
		(0.00)	(0.6350)	(0.5637)	(0.7562)

5. Conclusion

This research uses the daily data of closing prices for a period starting from July 2, 2015 to December 27, 2019 to estimate VaR of Sector Index at 95% confidence interval using parametric method. The selected sectors include Energy and Utilities (ENERG), Food and Beverage (FOOD), Banking (BANK), Commerce (COMM) and Information and Communication Technology (ICT). The GARCH family models, including GARCH (1,1), TARCH (1,1), and EGARCH (1,1) models, are used for volatility modeling.

The empirical results show that the VaR estimations at 95% confidence interval using GARCH family models easily pass unconditional coverage test, independence test, and conditional coverage test. They provide the lowest VaR value in COMM Index. Moreover, VaR model based on EGARCH (1,1) tends to be more accurate than others due to the lowest numbers of VaR exceptions.

The VaR estimation in this paper can provide investors valuable information for examining the potential risk for their future investment in Stock Exchange of Thailand. Based on the VaR measure, the low risk investment is stock investment with a correlation to the performance of COMM Index, followed by stock investment with a correlation to the performance of FOOD, ENERG, BANK, and ICT Index respectively.

Acknowledgement

The author is thankful to Department of Economics, Faculty of Economics, Kasetsart University for financial support to carry out this research.

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