Jongadsayakul, W. (2021). Value at risk estimation of the SET50 index: Comparison between stock exchange of Thailand and Thailand futures exchange. *Journal of International Studies, 14*(1), 227-240. doi:10.14254/2071-8330.2021/14-1/16

Journal of International Studies

Scientific Papers

Value at risk estimation of the SET50 index: Comparison between stock exchange of Thailand and Thailand futures exchange

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Abstract. Value at Risk (VaR) is the most widely used measure of risk. This study uses SET50 daily returns from the period from July 3, 2015 to December 27, 2019 to estimate VaR for the assessment of risk exposure at the Stock Exchange of Thailand and Thailand Futures Exchange using the three following methods: non-parametric method with the historical simulation approach, parametric method with GARCH family models, and semi-parametric method with volatility-weight historical simulation of the GARCH family models. Accuracy of the estimated models is also assessed by performing the VaR backtests of unconditional coverage, independence, and conditional coverage. In forecasting VaR with the confidence level of 95%, historical simulation and asymmetric GARCH models (TARCH and EGARCH models) give solid results and outrank volatility weight historical simulation. Moreover, 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. Therefore, investment decisions on SET50 Index Futures should be taken more carefully since this market is more volatile than the underlying spot market.

Received: June, 2020
1st Revision: February, 2021
Accepted: March, 2021

DOI: 10.14254/2071-8330.2021/14-1/16

Keywords: value at risk, risk management, volatility, Thailand

JEL Classification: G17, G32

1. INTRODUCTION

Value at Risk (VaR) is the most widely used measure of risk exposure. It is a summary of possible losses due to normal market conditions. Investors can suffer losses greater than VaR but only with a specified small probability. Therefore, VaR provides investors valuable information for examining potential risks of their future investments. There are numerous papers dealing with the proper and correct estimation of VaR. Previous studies have examined the estimation of VaR using three conventional methods, namely, non-parametric method, parametric method, and semi-parametric method. These three methods are based on different assumptions. Without making strong assumptions about returns distribution, the non-parametric method believes that the near future will be sufficient like the recent past so that recent returns can be used to estimate VaR. There are numerous non-parametric approaches, and the most popular of them is historical simulation. It is simple, easy to implement, and widely used in VaR calculations. The parametric method, on the other hand, measures risk by firstly fitting probability curves to the examined data sample and next conjecturing VaR from the fitted curve. Previous studies used the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family models to estimate the conditional volatility of financial returns. The semi-parametric method is the combination of the non-parametric and the parametric methods. Hull & White (1998) provided one way of bridging the gap between the model building and the historical simulation approaches. They allow volatility updating schemes, such as GARCH, to be incorporated into the historical simulation for calculating VaR.

Determining what is the best method for calculating VaR has been one of the main research areas in financial risk management. Unlike the literature dealing with VaR calculations in developed financial markets, appropriate estimation and forecasting of VaR for emerging financial markets are not very extensive. The Stock Exchange of Thailand (SET) is one of the most developed and liquid markets in Asia. It began its operations on April 30, 1975. Its total market capitalisation as of December 30, 2019 was 559 billion USD, thus making it the second largest in terms of market capitalization among the ASEAN exchanges. Moreover, Thailand has become the most liquid capital market in the ASEAN since 2012. It reached average daily trading value of 1,478 million USD in 2019, with Singapore going second (with the average daily trading value of 781 million USD). Thai stock market is also the largest fundraising venue in the ASEAN since 2014 and till present. In 2019, the size of the initial public offering issued at Thai stock market was 2,714 million USD, which is a 12.8 percent increase from the previous year. Moreover, Thai capital market has been recognized internationally as a leader in capital market corporate governance. Out of 35 global stock exchanges, the SET was the only Asian exchange to reach the top 10 stock exchanges on sustainability disclosure. Thailand Futures Exchange (TFEX), a subsidiary of the SET, was established on May 17, 2004 as the only organized derivative exchange market in Thailand, hosting all derivative trading such as index futures and options, stock futures, gold futures, interest rate futures, currency futures, and rubber futures. Futures Industry Association's global list of the top derivatives exchanges ranked TFEX as the 26th among the world derivatives exchanges in 2019. Its average trading volume was 428,369 contracts per day in 2019, 0.5 percent up from the previous year. Its current trading value was also equal to the SET's trading value. However, there is potential for growth in TFEX's trading value to become higher than that of the SET. This study therefore aims to measure risk exposure at SET and TFEX by using three methods of VaR estimation, namely, non-parametric method using historical simulation approach, parametric method using GARCH family models, and semi-parametric method using volatility-weight historical simulation. The VaR backtests of unconditional coverage, independence, and conditional coverage are also implemented to test the statistical accuracy of the models.

The results show that asymmetric GARCH models, TARCH and EGARCH models perform better than the symmetric GARCH model when forecasting volatility of SET50 Index and SET50 Index Futures returns. The 95% VaR using historical simulation and asymmetric GARCH models give solid results and outrank volatility-weight historical simulation with the asymmetric GARCH models. Both methods easily pass all the backtests at the significance level of 10%. The results contradict the study by Hull & White (1998) which shows that the volatility-weight historical simulation approach is superior to the historical simulation approach. Although VaR concept has been widely studied in the literature on risk management, this is the first study on the comparison of the SET and TFEX investment using VaR calculations. Similar to the findings of some previous studies (see Carchano et al., 2010; Wu, 2018), futures are riskier than their corresponding spot markets. Therefore, investors should choose the right investment avenue for their savings according to their risk preference.

The rest of the paper is organized as follows. The next section presents a brief literature review. The sources of data and the methodology used for calculating VaR are described in the third section. The fourth section presents the results of VaR estimation and backtesting. Finally, we conclude the paper in section 5.

2. LITERATURE REVIEW

Value at Risk (VaR) is a measure of the maximum potential change in value of a portfolio of financial instruments with a given probability over a pre-set horizon (J.P. Morgan & Reuters, 1996). Previous study has examined the estimation of VaR by using three conventional methods as follows:

1. Non-parametric method: The non-parametric method is based on the use of historical data. The most popular non-parametric approach is historical simulation, which makes use of historical data by constructing the cumulative distribution function of financial returns over time for predicting VaR. This method requires a large data set to produce a reliable VaR estimate. Moreover, it gives equal weights to all observations. This means that the VaR estimate does not react fast enough to recent market condition.

2. Parametric method: The parametric method is based on statistical parameters of the return distribution. Since there is evidence of volatility clustering in financial returns, this method consists of the econometric modelling of conditional volatility derived from Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family models.

3. Semi-parametric method: The semi-parametric method is the combination of the non-parametric method and the parametric method.

Abad et al. (2014) review some of the most important VaR methodologies and show their advantages and disadvantages. Table 1 concludes these advantages and disadvantages of the approaches adopted to calculate VaR in this paper, including historical simulation approach, GARCH family approach, and volatility-weight historical simulation approach. Examples of papers that report the estimation of VaR using these approaches are also included.

Based on Table 1, several studies estimate VaR for stock market indices. For example, Angelidis et al. (2004) implement several volatility models (GARCH, TARCH, and EGARCH) under three distributional assumptions (normal, student-t and generalized error distribution) and four historical sample sizes (500, 1000, 1500 and 2000 observations) in order to estimate the 95% and 99% one-day VaR for five completely diversified equity index portfolios (S&P 500, Nikkei 225, FTSE 100, CAC 40 and DAX 30). Wong et al. (2016) provide extensive comparison of conditional volatility and VaR forecasts on S&P500, FTSE100, and DAX30 market indices among 13 risk models that involve GARCH and realized volatility specifications. Smolović et al. (2017) also use both asymmetric and symmetric GARCH type models with four different distributions (normal, student-t, skewed student-t, and a reparameterised Johnson distribution) in estimating VaR for the Montenegro MONEX index before and during the global financial crisis. Some studies calculate VaR for stock index futures contracts. Tang & Shieh (2006) calculate VaR for S&P 500, Nasdaq 100, and Dow Jones stock index futures using FIGARCH (1, d, 1) and HYGARCH (1, d, 1) models with normal, student-t, and skewed student-t distributions. Kasman (2009) also calculates VaR for ISE-30 index futures contract in Turkish Derivatives Exchange using the FIGARCH(1,d,1) model with three different distributions (normal, student-t, and skewed student-t). However, only few studies estimate VaR for stock market indices and stock index futures contracts. For example, Carchano et al. (2010) estimate one-day-ahead VaR in the spot and futures markets for S&P 500, DAX 30, and Nikkei 225 using ARMA-GARCH model. They also calculate the number of violations to determine the accuracy of VaR. A comparison of spot and futures markets indicates that spot data provide less than or the same number of violations than futures data. The minimum return and the 1%-percentile return are also lower for futures data than spot data. A possible reason is that futures markets demonstrate extra volatility or an overreaction when the market falls with respect to their corresponding spot markets. Wu (2018) presents the empirical study on the performance of GARCH and CARR VaR models for CSI-300 spot and futures index.

Table 1

Advantages and Disadvantages of VaR Approaches

Methods	Advantages	Disadvantages	Examples of papers
Non-parametric approach - Historical simulation approach without making any assumptions of normality or other fixed form distribution.	No assumptions about the return distribution and the volatility and covariance of returns are made with this approach. This approach can handle non-normal features.	The results completely depend on the examined data set. It requires a large sample of past historical data to ensure a reliable result. It also does not take any recent changes in volatility into account. This means that the VaR estimate does not react fast enough to recent market condition.	Beder (1995); Hendricks (1996); Richardson et al. (1997); Raaji & Raunig (1998); Chen et al. (2009); Chen & Chen (2013); Abad & Benito (2013); Mentel (2013)
Parametric approach with the assumption of normal distribution and the use of GARCH family models for estimating volatility.	This approach characterizes the volatility clustering properties. Some models also capture the leverage effect.	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. With the assumption of normal distribution for financial returns, it ignores leptokurtosis and skewness.	Angelidis et al. (2004); So & Yu (2006); Carchano et al. (2010); Degiannakis et al. (2012); Restrepo E. (2012); Abad & Benito (2013); Cera et al. (2013); Wong et al. (2016); Smolović et al. (2017); Gupta & Rajib (2018); Quang et al. (2018); Wu (2018)
Semi-parametric approach (the combination of the non-parametric method and the parametric method) - Volatility-weight historical simulation, a link between the historical return and volatility changes	This approach directly takes into account the volatility changes by updating the return information to take into account the recent changes in volatility.	The results slightly depend on the data set.	Hull & White (1998)

Source: own compilation

Although VaR have been extensively discussed in literature, this study aims to apply various VaR techniques in the Stock Exchange of Thailand (SET) and Thailand Futures Exchange (TFEX), the top stock and derivatives exchanges in ASEAN. It is the first study to conduct a comparison of the SET and TFEX in terms of VaR estimation as a measure of risk exposure.

3. DATA AND METHODOLOGY

The Stock Exchange of Thailand (SET) launched SET50 Index on August 16, 1995 as a benchmark of investment in the SET. It is calculated from the stock prices of the top 50 listed companies on the SET in terms of large market capitalization, high liquidity and compliance with requirements regarding the distribution of shares to minor shareholders. SET50 Index was also introduced to accommodate the issuing of index futures and options. SET50 Index Futures, on the other hand, was launched by Thailand Futures Exchange (TFEX) as the first derivatives product on April 28, 2006. The contract was modified to have a smaller contract size on May 6, 2014. The contract size of SET50 Index Futures now matches that of SET50 Index Options. Therefore, investors can develop strategies using SET50 Index Futures and Options more easily. To measure risk exposure in the SET and TFEX, this study collects daily closing prices of SET50 Index spot and futures series from SETSMART for a period starting from July 2, 2015 to December 27, 2019 to estimates VaR for SET50 Index and SET50 Index Futures at 95% confidence interval. 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. The first 1,000 days of the return series are used to estimate the VaR models, while the last 100 days of the return series are used to backtest VaR at the test significance level of 10% as recommended by Christoffersen (2012).

3.1. Models of VaR estimation

This paper uses three different methods for calculating VaR.

1. The non-parametric method using historical simulation approach.

$\mathrm{VaR}(\alpha = 0.05)$ is the 0.05 quantile of the historical return distribution.

2. The parametric method using Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family models for estimating volatility (σ).

At a 5% significance level, the VaR estimation is computed as $\mathrm{VaR}(\alpha = 0.05) = c_0 + Z\sigma$, where Z corresponding to the 5th percentile of the standard normal distribution is - 1.64485.

3. The semi-parametric method using volatility-weight historical simulation.

This method updates return data to take into account the recent changes in volatility as given by $r_t^* = \frac{\sigma_T r_t}{\sigma_t}$, where r_t^* is the volatility adjusted return at time t, σ_T is the most recent forecast of return volatility, and σ_t is the forecast of return volatility for day t. According to this approach, the GARCH family models are used to estimate return volatility. Therefore, $\mathrm{VaR}(\alpha = 0.05)$ is the 0.05 quantile of empirical distribution of the volatility adjusted return.

3.2. GARCH family models

Bollerslev (1986) proposed the GARCH model as a generalization of the Autoregressive Conditional Heteroscedasticity (ARCH) model, which was introduced by Engle (1982). In practice, the GARCH (1,1) model often proves to be quite adequate and is not beaten easily by other model specification (see for example, Carnot et al., 2011; Javed & Mantalos, 2013; Jongadsayakul, 2020). This study therefore employs the GARCH (1,1) model for modelling the conditional variance of returns, σ_t^2, to characterize the volatility clustering properties in financial data. The GARCH (1,1) model with constant mean can be presented as:

$$r_t = c_0 + \varepsilon_t \tag{1}$$

$$\varepsilon_t = \sigma_t Z_t \tag{2}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{3}$$

where r_t is the asset return at time t, Z_t is a sequence of iid random variables with mean zero and unit variance, α_1 is the ARCH coefficient, and β_1 is the GARCH coefficient.

The GARCH (1,1) model assumes that positive and negative error terms have a symmetric effect on the volatility. However, this assumption is frequently violated in practice. Several extensions of the GARCH models have been developed to capture the leverage effect. Two models of asymmetric volatility include Threshold ARCH (TARCH) model developed by Zakoian (1990) and Glosten et al. (1993) and Exponential GARCH (EGARCH) model developed by Nelson (1991). They are represented by the following expressions.

TARCH (1,1) model:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 d_{t-1} + \beta_1 \sigma_{t-1}^2 \tag{4}$$

where d_t is a dummy variable that takes on the value of 1 if $\varepsilon_t < 0$, 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.

EGARCH (1,1) model:

$$\ln\left(\sigma_t^{\,2}\right) = \alpha_0 + \alpha_1 \left|\varepsilon_{t-1} / \sigma_{t-1}\right| + \gamma \varepsilon_{t-1} / \sigma_{t-1} + \beta_1 \ln\left(\sigma_{t-1}^2\right) \tag{5}$$

where the γ coefficient captures the asymmetric effect of previous shocks. The negative sign of γ indicates the leverage effect.

3.3. Evaluation framework

It is important to check the reliability and accuracy of VaR calculation. A way of testing if a model's predictions are in line with realized data is called backtesting. The earliest statistical technique for backtesting is the unconditional coverage test proposed by Kupiec (1995). The unconditional coverage test checks whether the fraction of violations (π) are in accordance with the chosen significance level (α).

Following a chi-squared distribution with one degree of freedom, the likelihood ratio test statistic for the unconditional coverage test $(\mathrm{LR_{UC}})$ can be written as follows:

$$\mathrm{LR_{UC}} = 2\left[\ln\left((1-\pi)^{\mathrm{N_0}} \pi^{\mathrm{N_1}}\right) - \ln\left((1-\alpha)^{\mathrm{N_0}} \alpha^{\mathrm{N_1}}\right)\right] \tag{6}$$

where $\mathrm{N_0}$ = the number of days in which VaR is not violated;

$\mathrm{N_1}$ = the number of days in which VaR is violated;

$\pi = \dfrac{\mathrm{N_1}}{\mathrm{N_0} + \mathrm{N_1}}$;

α = the probability level of 5%.

The independence test checks whether the VaR violations are clustered. It has a chi-square distribution, asymptotically, with one degree of freedom. The likelihood ratio test statistic for the independence test $(\mathrm{LR_{IND}})$ can be written as follows:

$$\mathrm{LR_{IND}} = 2\left[\ln\left((1-\pi_{01})^{\mathrm{N_{00}}} \pi_{01}^{\mathrm{N_{01}}} (1-\pi_{11})^{\mathrm{N_{10}}} \pi_{11}^{\mathrm{N_{11}}}\right) - \ln\left((1-\pi)^{\mathrm{N_0}} \pi^{\mathrm{N_1}}\right)\right] \tag{7}$$

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

$\mathrm{N_{01}}$ = 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;

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

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

If there is no consecutive VaR violations (N_{11} = 0), the following test statistic is applied:

$$LR_{IND} = 2\left[\ln\left(\left(1-\pi_{01}\right)^{N_{00}} \pi_{01}{}^{N_{01}}\right) - \ln\left(\left(1-\pi\right)^{N_0} \pi^{N_1}\right)\right] \tag{8}$$

The conditional coverage test proposed by Christoffersen (1998) is the combination of the unconditional coverage test and the independence test. This test is asymptotically distributed as a chi-squared distribution with two degrees of freedom. It examines the joint hypothesis of unconditional and independence tests. The likelihood ratio test of conditional coverage test $\left(LR_{CC}\right)$ can be calculated as $LR_{CC} = LR_{UC} + LR_{IND}$.

4. EMPIRICAL RESULTS AND DISCUSSION

This section states and discusses the results of the daily VaR estimation from all three main VaR estimation techniques, namely non-parametric method (historical simulation), parametric method (GARCH family models), and semi-parametric method (volatility-weight historical simulation). In addition, the accuracy of the estimated models is assessed by performing the VaR backtests of unconditional coverage, independence, and conditional coverage.

Table 2 shows the 95% VaR estimation for SET50 Index and SET50 Index Futures using historical simulation approach. To calculate VaR with a confidence level of 95%, the returns are ranked into percentiles. The 5th percentile return of SET50 Index is -1.3051% and that of SET50 Index Futures is -1.4153%. The recorded percentage of violations is 6% in case of SET50 Index and 3% in case of SET50 Index Futures. There is no consecutive VaR violations observed in SET50 Index and SET50 Index Futures. The statistical tests of unconditional coverage, independence, and conditional coverage along with the p-values show that the historical simulation method provides the accurate VaR estimator for SET50 Index and SET50 Index Futures at a significance level of 10%. By comparison in terms of VaR, SET50 Index Futures investment carries higher risk than stock investment with a correlation to the performance of SET50 index.

Table 2

Results of the Estimated Historical Simulation VaR and Model Evaluation

Types of asset	**VaR$\left(\alpha = 0.05\right)$**	**π [π_{11}]**	**LR_{UC} [P-value]**	**LR_{IND} [P-value]**	**LR_{CC} [P-value]**
SET50 Index	-1.3051%	0.06 [0.00]	0.1984 [0.6560]	0.7665 [0.3813]	0.9649 [0.6173]
SET50 Index Futures	-1.4153%	0.03 [0.00]	0.9769 [0.3230]	0.1856 [0.6666]	1.1625 [0.9220]

Source: own calculation

Assuming the standard normal distribution assumption, this study estimates the return volatility of SET50 Index and SET50 Index Futures using GARCH family models. Stationarity of the series is tested first with Augmented Dickey-Fuller unit root test. The test result rejects null hypothesis of the unit root and that means SET50 Index and SET50 Index Futures return series are stationary in the period under study. The estimation results of the GARCH (1,1), TARCH (1,1), and EGARCH (1,1) models for in-sample data (the first 1,000 days) are shown in Table 3. It reports the estimated coefficients and their P-values, as well as diagnostics tests. To test the validity of the estimated GARCH family models, a Ljung–Box Q statistic is employed to check for serial correlation in the standardized residuals. Then a Lagrange Multiplier (LM) test is employed to make sure that the models capture all ARCH effect. The statistically insignificant Ljung-Box and LM test statistics indicate a failure to detect the presence of any serial correlation or autoregressive conditional heteroscedasticity in the residuals of the estimated models.

Table 3

Summary of GARCH Family Models

Types of asset	c_0 **[P-value]**	α_0 **[P-value]**	α_1 **[P-value]**	β_1 **[P-value]**	γ **[P-value]**	**Q-Stat [P-value]**	**LM ARCH [P-value]**
Panel A: GARCH (1,1) model							
SET50 Index	0.000346 [0.1379]	6.87E-07 [0.0000]	0.080507 [0.0000]	0.913501 [0.0000]		23.392 [0.948]	1.0684 [0.7847]
SET50 Index Futures	0.000407 [0.0838]	4.24E-07 [0.0004]	0.084501 [0.0000]	0.916516 [0.0000]		26.078 [0.888]	5.6291 [0.1311]
Panel B: TARCH (1,1) model							
SET50 Index	0.000133 [0.5738]	1.29E-06 [0.0000]	0.010488 [0.3594]	0.914208 [0.0000]	0.112230 [0.0000]	25.067 [0.914]	0.7782 [0.8547]
SET50 Index Futures	0.000257 [0.2901]	7.30E-07 [0.0001]	0.049688 [0.0000]	0.906023 [0.0000]	0.082317 [0.0000]	27.160 [0.856]	2.7724 [0.4281]
Panel C: EGARCH (1,1) model							
SET50 Index	0.000239 [0.2808]	-0.393199 [0.0000]	0.146157 [0.0000]	0.970996 [0.0000]	-0.079139 [0.0000]	24.258 [0.932]	0.2741 [0.9648]
SET50 Index Futures	0.000205 [0.3897]	-0.460291 [0.0000]	0.220771 [0.0000]	0.969288 [0.0000]	-0.079802 [0.0000]	26.406 [0.879]	1.5698 [0.6663]

Source: own calculation

From Table 3, Panel A reports the estimation result of the GARCH(1,1) model. The coefficient for the previous shock (the ARCH coefficient: α_1) and that for its lagged conditional variance (the GARCH coefficient: β_1) are positive and are highly statistically significant as their P-values less than 0.01. $\alpha_1 + \beta_1$ is equal to 0.994 for SET50 Index. The value of this sum is less but close to unity, suggesting that the volatility is highly persistent. Although the return volatility has a very long memory, the volatility process returns to its mean. For SET50 Index Futures, the summation of the ARCH and GARCH estimates slightly higher than 1 means the shock has explosive effect. One possible answer of the misspecification of the GARCH (1,1) model is the ignorance of asymmetric behavior. The asymmetric GARCH models (the TARCH (1,1) and EGARCH (1,1) models) are estimated to overcome this problem.

As shown at the Panel B of the Table 3, the estimation result of the TARCH(1,1) model shows that the leverage coefficients (γ) are 0.112230 and 0.082317 for SET50 Index and SET50 Index Futures respectively. They are positive and highly significant at 99% level, indicating the presence of an asymmetric behavior. In case of SET50 Index, the ARCH effect of 0.010488 for positive residuals is smaller than one of 0.122718 for negative residuals. The increase in volatility due to bad news is also greater than that for good news in SET50 Index Futures market. Bad news has an impact of 0.132005 while good news has an impact of 0.049688.

In the EGARCH specification (Panel C), conditional variance is an exponential function, thus there is no need for nonnegativity restrictions, as in earlier GARCH and TARCH specifications. All estimates are statistically significant at 99% level. γ is the asymmetry parameter measuring a leverage effect equal -0.079139 and -0.079802 for SET50 Index and SET50 Index Futures respectively. They are negative and highly significant, indicating the existence of the leverage effect for the SET50 Index and SET50 Index Futures returns. In case of SET50 Index, the reaction to positive shocks is 0.067018 and 0.225296 on negative shocks. The effect of 0.300573 for negative shocks is also larger than the effect of 0.140969 for positive shocks in SET50 Index Futures market.

The results contained in Table 3 suggest that the TARCH (1,1) and EGARCH (1,1) models are more appropriate for modelling volatility of SET50 Index and SET50 Index Futures returns. As for volatility forecasts, the results confirm the findings of previous studies in literature showing that capturing the asymmetric behavior of volatility is essential for accurate volatility.

Since there is evidence that the TARCH (1,1) and EGARCH (1,1) models produce better forecasts than the GARCH (1,1) model, the VaR numbers are calculated at the 95% confidence level using the TARCH (1,1) model and the EGARCH (1,1) model as shown in Panels A and B of Figure 1. Table 4 reports the statistical tests of unconditional coverage, independence, and conditional coverage along with the p-values.

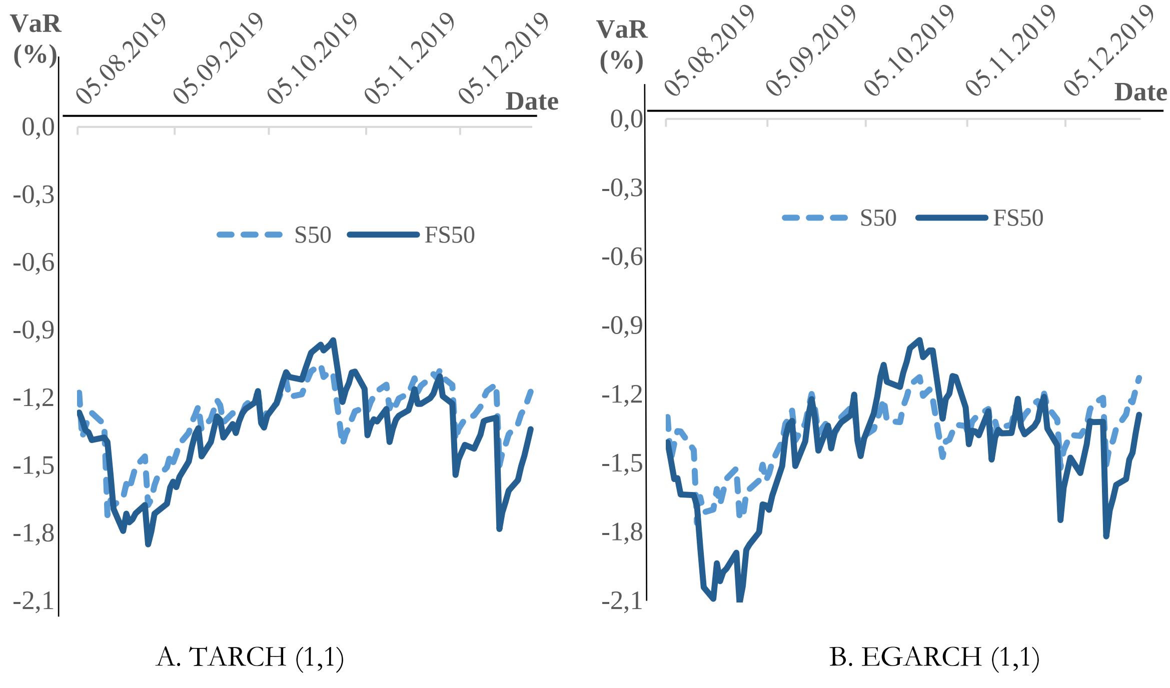

Figure 1. Forecasting VaR at 95% Confidence Interval

Source: own calculation

Table 4

Results of VaR Modelling Using Asymmetric GARCH models and Model Evaluation

Types of assets	VaR $(\alpha = 0.05)$ [Avg.]	π [π_{11}]	LR_{UC} [P-value]	LR_{IND} [P-value]	LR_{CC} [P-value]
Panel A: TARCH (1,1) model					
SET50 Index	-1.7210% to- 1.0548% [-1.2939%]	0.06 [0.00]	0.1984 [0.6560]	0.7665 [0.3813]	0.9649 [0.6173]
SET50 Index Futures	-1.8506% to- 0.9456% [-1.3550%]	0.03 [0.00]	0.9769 [0.3230]	0.1856 [0.6666]	1.1625 [0.5592]
Panel B: EGARCH (1,1) model					
SET50 Index	-1.7614% to- 1.1256% [-1.3716%]	0.06 [0.00]	0.1984 [0.6560]	0.7665 [0.3813]	0.9649 [0.6173]
SET50 Index Futures	-2.1109% to- 0.9640% [-1.4447%]	0.03 [0.00]	0.9769 [0.3230]	0.1856 [0.6666]	1.1625 [0.5592]

Source: own calculation

According to Figure 1, most of the time VaR numbers for SET50 Index Futures (FS50) are slightly below the numbers for SET50 Index (S50). Using the TARCH (1,1) model, the average VaR estimates for the SET50 Index and SET50 Index Futures are -1.2939% and -1.3550% respectively. By comparison, stock investment with a correlation to the performance of SET50 Index is considered lower risk investment than SET50 Index Futures investment. This result is also confirmed by the VaR estimation at 95% confidence interval using the EGARCH (1,1) model. The results of the EGARCH (1,1) model show that the average VaR estimate for the SET50 Index is -1.3716% while that for SET50 Index Futures is -1.4447%. To evaluate their accuracy with respect to the 90% confidence interval, Table 4 shows that the results of VaR estimation at 95% confidence interval using the TARCH (1,1) and EGARCH (1,1) models in SET50 Index spot and futures markets easily pass all tests at a significance level of 10%. The recorded percentage of violations is 6% in case of SET50 Index and 3% in case of SET50 Index Futures. There is no consecutive VaR violations observed in SET50 Index and SET50 Index Futures. As a result, the model accuracy is accepted. With a focus on the performance of historical simulation and asymmetric GARCH-based VaR methodologies, they give very reliable and similar results in SET50 Index spot and futures markets.

Combining the non-parametric method with the parametric method, this study estimates the historical simulation VaR from the SET50 Index and SET50 Index Futures returns that have been adjusted to the current state of the market volatility with asymmetric GARCH models. The estimation results of volatility-adjusted historical simulation VaR with TARCH (1,1), and EGARCH (1,1) are presented in Table 5.

To calculate the 95% VaR, the volatility adjusted returns are ranked into percentiles. By using the TARCH (1,1) model for estimating volatility, the 5th percentile volatility adjusted return of SET50 Index is -1.0737% and that of SET50 Index Futures is -1.0022%. The number of violations of the estimated VaR is greater for futures than in spot market. The recorded percentage of violations is 6% in case of SET50 Index and 10% in case of SET50 Index Futures. There is no consecutive VaR violations observed in SET50 Index while there is an evidence of clustering issue in SET50 Index Futures. The percentage of consecutive VaR violations in SET50 Index Futures is 10%. Therefore, the VaR estimation in SET50 Index is able to pass all tests at a significance level of 10%. On the other hand, the VaR estimation in SET50 Index Futures passes independence test and conditional coverage test at a significance level of 10% while it is able to pass unconditional coverage test for a poor significance level of 1%.

Table 5

Results of the Estimated Volatility-Adjusted Historical Simulation VaR with Asymmetric GARCH models and Model Evaluation

Types of assets	**VaR** $(\alpha = 0.05)$	π [π_{11}]	LR_{UC} **[P-value]**	LR_{IND} **[P-value]**	LR_{CC} **[P-value]**
Panel A: TARCH (1,1) model					
SET50 Index	-1.0737%	0.06 [0.00]	0.1984 [0.6560]	0.7665 [0.3813]	0.9649 [0.6173]
SET50 Index Futures	-1.0022%	0.10 [0.10]	4.1308 [0.0421]	0.0000 [1.0000]	4.1308 [0.1268]
Panel B: EGARCH (1,1) model					
SET50 Index	-1.1934%	0.06 [0.00]	0.1984 [0.6560]	0.7665 [0.3813]	0.9649 [0.6173]
SET50 Index Futures	-1.1488%	0.08 [0.13]	1.6158 [0.2037]	0.2099 [0.6468]	1.8257 [0.4014]

Source: own calculation

By using the EGARCH (1,1) model for estimating volatility, the results of the estimated volatility-adjusted historical simulation VaR show that the 95% VaR estimates for SET50 Index and SET50 Index Futures are -1.1934% and -1.1488% respectively. The number of violations of the estimated VaR is greater for futures than in spot market. The recorded percentage of violations is 6% in case of SET50 Index and 8% in case of SET50 Index Futures. There is no consecutive VaR violations observed in SET50 Index while there is an evidence of clustering issue in SET50 Index Futures. The percentage of consecutive VaR violations in SET50 Index Futures is 13%. However, the 95% VaR estimates for SET50 Index and SET50 Index Futures are able to pass all tests at a significance level of 10%.

Although volatility-weight historical simulation approach indicates that stock investment with a correlation to the performance of SET50 Index has a higher level of risk than SET50 Index Futures investment, it has a poor performance in estimating VaR for SET50 Index Futures compared to other methods. This finding contradicts the empirical evidence presented by Hull & White (1998) which shows volatility-weight historical simulation VaR superior to that of the historical simulation approach.

5. CONCLUSION

The financial risk modeling has become a major area of research in last decades. Value at Risk (VaR) has been used to estimate the risk of investment in developed financial markets. However, determining the appropriate estimation and forecasting VaR in emerging financial market is not very extensive. This study therefore aims to calculate VaR for the assessment of risk exposure in the Stock Exchange of Thailand (SET) and Thailand Futures Exchange (TFEX) by using SET50 daily returns from the period July 3, 2015 to December 27, 2019. Three conventional methods are employed for VaR estimation with the 95% confidence interval, including non-parametric method using historical simulation approach, parametric method using Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family models, and semi-parametric method using volatility-weight historical simulation with GARCH family models. The VaR estimates are thereafter evaluated through the VaR backtests of unconditional coverage, independence, and conditional coverage in order to find the best model.

To estimate the volatility of returns for SET50 spot and futures index, this paper employs the GARCH (1,1), TARCH (1,1), and EGARCH (1,1) models assuming normal distribution. The results point out that two representative asymmetric GARCH models, TARCH and EGARCH models, are found to fit the data better than symmetric GARCH model. The 95% VaR using historical simulation and asymmetric GARCH models give solid results and outrank volatility-weight historical simulation with asymmetric GARCH models. They are able to pass all tests at a significance level of 10%. However, the combination of historical simulation and asymmetric GARCH models does not guarantee in any way the success of VaR model.

The VaR estimation in this paper can provide investors valuable information for examining the potential risk for their future investment in the SET and TFEX. Using historical simulation and asymmetric GARCH-based VaR methodologies, SET50 Index Futures is riskier than stock investment with a correlation to the performance of SET50 Index. Therefore, investment decision in SET50 Index Futures should be taken more carefully since SET50 Index Futures market is more volatile than the underlying spot market.

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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