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VALUE AT RISK ANALYSIS FOR EQUITYINVESTMENT AT THAI MARKET

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Abstract: *Representing one of the key measurements of risk management, Value-at-Risk turns to be the influencing tool,which usually interprets the strength of financial institution and indications for the portfolio management. The study explores two fundamental methodologies for Value-at-Risk calculations, i.e. Historical Simulation and Monte Carlo Simulation, in conjunction with the corresponding performances of the relevant Stock Exchange of Thailand SET50 portfolios, employing the data covering the period of year 2002 until the year 2012 on a quarterly basis. The empirical result indicates that historical simulation generates the relative higher performance measurements as well as the larger expected losses and Monte Carlo simulation demonstrates relatively higher degree of expected volatility.*

Key Words: *Value at Risk, Historical Simulation, Monte Carlo Simulation, Portfolio Management*

1. INTRODUCTION

Although active trading strategy and passive strategy with number of sub-strategies demonstrate the certain level of efficiency, the risk of facing market lossesis often implied in the dynamic portfolio management. Value at risk (VaR) measurement highlights the financial institution and investors concern, focus on the worst expected loss of the portfolio over specified period of time given an accepted confidence level.However, VaR is a measure of the worst expected loss under a normal market condition over a specific time period at a given confidence level, and it does not give the information of extreme cases. Recognizing the limitation of traditional VaR application, the study appliesVaRmeasurement to the stock exchange of Thailand by employing the hypothetical portfolio of SET50 index which is assumed to be well diversified. To be reminder, the study explores the amount of maximum loss under normal market condition if we invest in SET50 for a given significance level, and it still bears the downturn risk of extreme losses. With regarding tothe different methods for calculating VaR, i.e. historical simulation, Monte Carlo simulation, beside the complexity and data requirement, the attention lays on the different impacts on the results of portfolio management, which influence the performance judgment and capital requirement.

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Butler and Schachter (1996) indicated that historical simulation should have three components, which are composed of the historical return of the portfolio, an empirical distribution of factor returns, and the change in risk factors that related to the return of the portfolio. It is suggested that by using historical simulation, the data were allowed to present in the form of the return distribution. However, DarryllHendriks (1995) found the limitation of historical simulation if the length of the observation period was too short. In other words, in order to increase the efficient for the estimation of VaR, it was necessary to gather the data for a longer period of time. Moreover, Matthew Pritsker (2001) also found the hidden limitation of the historical simulation approach, that the method was under responsive to the changes in conditional risk. The estimated risk would not change much when the portfolio generated a large gain while the risk did increase if the portfolio experienced a large loss. However, in order to increase the ability of VaR under historical simulation approach, PhillipeJorion (2006) suggested that the model needed the enormous data to perform well at a higher confidence level. Ali Khadar (2011) concluded that in order to simulate VaR, it was necessary to gather a large data of the underlying asset return over a period of time, so this would increase the effectiveness of the estimation and the reasons that historical simulation still widely used were its simplicity and ability to produce a good result.

In relating to Monte Carlo simulation, according to Simon Benninga (2008), it calculates the outcome over and over, and, for each time, it uses the different sets of random values to calculate. It could possibly recalculate the result for many thousands times. The process of recalculation for the outcome is called iteration. Benninga suggested that the approach is a variety of a random simulation used to determine the value of parameters. Most of the times, the purpose of the Monte Carlo is to find the possible outcome that is not deterministic. In other words, if the result can be calculated by a single formula and have only one outcome, it is unnecessary to apply Monte Carlo simulation. Therefore, the method will produce the distribution of outcome values. By applying Monte Carlo simulation, the method will produce a distribution of possible results. There are many types of distribution such as normal, lognormal, and uniform. Each distribution performs different functions. However, according to Cohen and Whitten (1980), they suggested that the variable that will be able to describe the stock price is called lognormal distribution. The lognormal distribution does not have the same shape as the normal distribution, which has a bell shape. Its values are positively skewed. Therefore, it represents the values that will not less than zero but can be increased to a large positive value such as real estate price, stock price, and oil price.

The study employs the Monte Carlo simulation to estimates the risk of return for SET50with the lognormal distribution which is necessary to generate the changes in return. In addition, Yapa (1980) implied that a sample mean can represent the population mean if the overall sample size is very large. Caffo, Jank, and Jones (2005) also suggested that, under Monte Carlo simulation, the sample size should be very large in order to cover the risk of the estimation error. To support the recommendation of Caffo, Jank, and Jones, Benniga (2008), who did the experiment of Monte Carlo simulation by applying the method to find the value of π (Pi), discovered that if he used more of random data, the value of will be more accurate. The study aims the relative large data of set for the efficient purpose.

Since the study has two different simulations, which are applied to the SET50 index, the study targets determinative results whether historical simulation or Monte Carlo simulation will generate better performance evaluations. There are many different ways to benchmark the performance of the portfolio. One of the earliest measurements is Treynor ratio, introduced by Treynor (1966). The purpose of Treynor ratio is to measure the risk premium return over the beta coefficient, the market risk exposure. Jobson and Korkie (1981) studied the behavior of Treynor ratio. They found that the ratio required a large sample to accurately evaluate the sample. Pilotte and Sterbenz (2006) examined Treynor ratio over the US treasury bills and discovered that the outcome of the measurement varied with maturity and increased the most for the short-term bills. However, the ratio considered only the systematic risk, so it could not specify about the diversification of the portfolio as it was argued by Brown and Reilly (2009). After the creation of Treynor ratio, Sharpe (1966) came up with the new portfolio performance evaluation that considered the overall risk of the portfolio, represented as standard deviation, called Sharpe ratio. The Sharpe ratio could provide the measurement the rate of return by the portfolio per unit of risk. Nielsen and Vassalou (2004) modified the ratio in order to fit with the continuous time performance measures. They indicated that because of the time issue, the modified Sharpe ratio should contain higher volatility. Also, if there were two funds that generated equal ordinary Sharpe ratio, the one with higher variation should rank higher. However, Ingersoll, Spiegel, and Goetzmann (2007) criticized the Sharpe ratio that it could be manipulated by the fund managers, who may sell put option at fair market prices, so they can generate very high Sharpe ratio without using investment skills. Moreover, they found that the overall Sharpe ratio was maximized by holding a portfolio that maximized the future Sharpe ratio. For instance, if the manager was lucky in the past and achieved a higher than anticipated Sharpe ratio, then the portfolio should be targeted in the future at a lower mean excess return than it has realized. This allowed the past fortune to weigh more heavily in the overall measure. Despite these limitations, however, Aragon and Ferson (2007) still supported the ratio to be used in practice as a measure of portfolio performance measurement, and it still remained important in empirical asset pricing.Even though Sharpe ratio has numerous advantages and was widely applied by many users, there are some shortcomings. Treynor and Jack (1973) realized the limitations of the Sharpe ratio, so they introduced the Information ratio to address the problems. The concept of the ratio is quite similar to the one that Sharpe initiated. Clement (2009) suggested that Information ratio measures the portfolio's excess return over a suitable benchmark compared with the standard deviation of those excess returns. Moreover, Blatt (2004) highlighted the importance of the appropriate selection of benchmark by stating that the benchmark should be related to the assets in the portfolio. For instance, if the asset class is a large capitalization US stock, the appropriate benchmark would be S&P500. Chincarini and Kim (2007) also implied that performance of the Information ratio can be increased if the portfolio managers can increase the of the regression, which can be done by finding more relevant or better predicting factors or by increasing the numbers of factors, without decreasing the average contribution of the factors. Finally, Kidd (2011) concluded that the ratio is regularly selected by the investors to set the objectives and the constraints of the portfolio for their fund managers such as tracking risk restrictions or achieving a minimum information ratio. As a result, after conducting the evaluation of the portfolio performance, the study determines the correlation between historical simulation and Monte Carlo simulation for VaR estimation and the portfolio performance measurements. The relationship between them allowsthe exploration about under which simulation that VaR estimation will be larger and also the predicted performance measurement of the portfolio will be increased as well as the variation of the results. The study is conducted to determine the risk analysis of VaR estimation on the SET50 index under both historical simulation and Monte Carlo simulation as well as to evaluate the performance of the portfolio, by applying Treynor ratio, Sharpe ratio, and Information ratio, in order to capture the relationship between each simulation in terms of the average return per day, the worst expected loss, the performance measurements, and the variation of the result. To determine the certainty of the future return for the portfolio is the task that is very difficult to accomplish, but to estimate the amount of the worst expected loss under a specified percentage can be done by applying Value-at-Risk (VaR) estimation. In order to generate VaR, we have to adopt two simulations, which are historical simulation and Monte Carlo simulation. Since both simulations generate different results for SET50, the study evaluates the performance by applying Treynor ratio, Sharpe ratio, and Information ratio. Therefore, the study identifies the different results of historical simulation and Monte Carlo simulation, which generate non-identicalVaRtherefore the deviated performance measurements prediction as well as the volatility of the predicted portfolio.

2. THEORETICAL FRAMEWORK

As mentioned in the first chapter about overview of our study, our research will concentrate on the risk analysis of VaR and the portfolio performance measurement under historical simulation and Monte Carlo simulation. Therefore, the result will generate the expected amounts of loss from the investment, which is the SET50 index, under both simulations, and also, the performance measurements will be applied to evaluate the performance of SET50 under both models.Our study begins by applying VaR estimation on the SET50 index. Before the testing starts, it is necessary to collect the historical data as the first process. The data that will be used in the study is the return from SET index, SET50 index, and the risk-free rate. Since there are many suggestions that using long period information will increase the accuracy of the estimation, we decided to use ten years historical data for the calculation. Therefore, since we plan to apply VaR to the SET50, we will be able to determine the expected maximum loss under normal market condition if we invested in SET50 for a given confidence level.In order to calculate for VaR, there are many methods to be applied, but in this study, we decide to apply two main approaches, which are historical simulation and Monte Carlo simulation. For historical method, the estimated loss would be determined by using 10 years daily historical data of SET50. As a result, historical simulation will be able to generate the answer for the question of, under a given confidence level, how much the worst expected loss will be.Like the concept of historical simulation, the second approach of VaR calculation is Monte Carlo simulation. The method also requires the use of long period of historical data. However, there is one main different property between historical simulation and Monte Carlo simulation. The difference is that under Monte Carlo, the method will randomly determine the value of the worst loss by recalculating the outcome for thousand times. The reason why we have to apply Monte Carlo is that the return from investing in SET50 index is not deterministic. In other words, the return cannot be predictable, or it is a stochastic return over time. After finishing VaR estimation, we will compare the mean and the variation of the return of SET50 under both simulations. In this case, the decision rule that will be applied is p-value, which the information about it will be provided in the next chapter. Therefore, at the end, we will be able to conclude the relationship of VaR estimation between historical simulation and Monte Carlo simulation.Then the next process is to determine the performance of the investment under both historical simulation and Monte Carlo simulation. It is necessary to conduct the portfolio performance measurements, but there are too many methods for the evaluation process. Thus, we decided to select three of them, which are Treynor ratio, Sharpe ratio, and Information ratio. Furthermore, since those methods are widely used in practical, we will apply all of them to evaluate the performance of SET50 under both models. Treynor ratio is the first performance evaluation method for our study. The numerator is the difference between the average rate of return of the portfolio and the average rate of return of the risk-free investment, and the numerator is the systematic risk measure, beta coefficient, so the result from the ratio indicates the risk premium return per market risk. However, there is another method that covers the overall risk of the portfolio. Therefore, we have to apply the second performance evaluation, which is Sharpe ratio. Like the concept of Treynor ratio, the calculation of Sharpe ratio and Treynor ratio is almost identical. In contrast, only one different is in the denominator, where Treynor ratio used beta coefficient, but Sharpe ratio used standard deviation. Using standard deviation helped to perceive the risk premium return per unit of the overall risk. In other words, Sharpe ratio can measure the total risk of the portfolio while Treynor ratio concerned about the systematic risk represented as beta coefficient. However, about seven years after the introduction of Sharpe ratio, Jack and Treynor introduced the new evaluation method that adapted from Sharpe's concept. They invented what they called the Information ratio. For the third portfolio performance measurement, we will apply Information ratio. The ratio was developed in order to improve the performance of Sharpe ratio because it has the ability to evaluate the active performance of the portfolio. The calculation is slightly different from both two mentioned ratios. The main concept is to compare the excess return with the benchmark over the overall risk of the portfolio. Therefore, we will be able to generate the result of portfolio performance evaluation from three different methods. Finally, we will apply the null hypothesis testing to prove whether the performance measurements of SET50 under historical simulation and Monte Carlo simulation have the same mean and variation or not.After estimating the worst loss by applying VaR and the process of performance evaluation of the SET50 under historical simulation and Monte Carlo simulation, we will be able to determine whether historical simulation or Monte Carlo simulation will generate largerVaR, and also which simulation will be able to increase the portfolio performance measurement.

3. RESEARCH METHODOLOGY AND EMPIRICAL STUDY

The first process of our research is to collecting ten years historical data of the daily return from SET, SET50, and the one-year government bond rate (risk-free rate). We divided the 10 years daily information into 41 quarters. As a result, the data that will be applied to our study will be from the beginning of 2002 to the end of March 2012. However, since our historical data includes both trading days and non-trading days, we have to exclude those non-trading days such as public holiday from our daily information. Finally, there will be 2,507 days for our research.The next step is to begin the process of estimation expected worst loss by applying VaR analysis under historical simulation and Monte Carlo simulation. Then, under historical simulation, it is necessary to find the return per day of SET50. We apply the concept of lognormal return or periodic return, which has the formula as follow:

$$Daily\,Return = \ln\left(\frac{S_t}{S_0}\right)$$

The lognormal property will be applied to all daily historical data. After that, we will sort all periodic return by ascending order and apply the percentage of confidence level in order to capture VaR estimation of the expected loss for a given level of confidence. Thus, we will be able to generate 41 quarters of VaR under historical simulation.

For Monte Carlo simulation, we also apply continuous compounding to determine the daily return as our first step. The reason that we have to find the daily return is that we want to average the return per day of each quarter, which we call it as Drift (Daily). Another requirement that also need the information of daily return is Daily Volatility or the standard deviation per day of each quarter. Thus, we will be able togenerate the volatility each day and the average return per day, so the next step is to determine what we called "Drift (Mean)", which has the formula as follow:

$$\bar{U} = Drift(Daily) - \left[\frac{1}{2}(\delta^2)\right]$$

Then we will use the function of "NORMINV" to determine the random variable that will be applied to our model, which is Brownian Motion Model. The random variables is represented as N(0,1) or Z in our formula. Therefore, as a result, the formula of periodic return under Monte Carlo simulation can be written as follows:

$$\Delta S = \bar{U} + \delta \times Z$$

After we could generate the change in daily return under Monte Carlo simulation by applying Brownian motion model, we will apply the function percentile by giving 95 percent of confidence level. Finally, we can generate 41 quarters of VaR under Monte Carlo simulation.Moreover, we also want to measure the performance of SET50 under historical simulation and Monte Carlo simulation, so we will apply three performance evaluation methods, which are Treynor ratio, Sharpe ratio, and Information ratio.All of the three measurements are quite similar between each other. Treynor ratio will measure the excess return over the systematic risk, represented by beta coefficient (β). The beta coefficient in our study is calculated by determining the slope between SET index and SET50 index. On the other hands, Sharpe ratio is the measurement of the portfolio excess return over the overall risk, which is standard deviation (δ). In this case, the standard deviation will be computed from the periodic return of SET50 index. Finally, the Information ratio compares the performance of the portfolio with the benchmark. Therefore, we decide to apply these evaluations to SET50 under both historical simulation and Monte Carlo simulation.

There are 41 results of VaR under historical simulation and another 41 results of VaR under Monte Carlo simulation. In addition, after applying the portfolio performance measurements, the study getsthe 246 different results generated from three evaluation methods under both simulations. Therefore, there will be eight different samples, which can be divided into two main groups based on the type of simulation. The first group can be categorized as follows;

1. VaR under historical simulation (VHS)
2. Treynor ratio under historical simulation (THS)
3. Sharpe ratio under historical simulation (SHS)
4. Information ratio under historical simulation (IHS)

The second group is the measurement under Monte Carlo simulation, which can be divided as follows:

1. VaR under Monte Carlo simulation (VMS)
2. Treynor ratio under Monte Carlo simulation (TMS)
3. Sharpe ratio under Monte Carlo simulation (SMS)
4. Information ratio under Monte Carlo simulation (IMS)

Therefore, it comes to the process of comparing the mean and the equality of variances of these measurements under both models. The statistical test that we will apply for our study is p-value, which, in our study, the p-value will be compared with the level of significance. To begin the computation, the very first process is to set the null hypothesis and the alternative hypothesis. In our research, there will be four null hypotheses in order to compare the mean for each measurement. The first hypothesis testing is to see the difference in mean of VaR under historical simulation and Monte Carlo simulation, which can be written as follows:

$$H_{01} : \mu_{VHS} - \mu_{VMS} \geq 0$$

$$H_{11} : \mu_{VHS} - \mu_{VMS} < 0$$

Similar to the first null hypothesis, the null hypothesis for Treynor ratio, Sharpe ratio and information ratio are provided below:

For Treynor ratio;

$$H_{02} : \mu_{THS} - \mu_{TMS} \geq 0$$

$$H_{12} : \mu_{THS} - \mu_{TMS} < 0$$

For Sharpe ratio;

$$H_{03} : \mu_{SHS} - \mu_{SMS} \geq 0$$

$$H_{13} : \mu_{SHS} - \mu_{SMS} < 0$$

For Information ratio;

$$H_{04} : \mu_{IHS} - \mu_{IMS} \geq 0$$

$$H_{14} : \mu_{IHS} - \mu_{IMS} < 0$$

Then the second process is to set the level of significance, which in this case, the significance level is equal to 95 per cent. Since the study selects p-value hypothesis testing, the next process is to state the decision rule as provided below:

Reject H_0 : if p-value < Significance Level

The study begins testing the null hypothesis by applying the program "Stat Tools" to run the hypothesis, which it provides the calculation for p-value, mean of each observations, and also the decision for each significance level. Therefore, if the p-value is larger than the significance level, we will not reject the null hypothesis, which means that the average VaR and performance measurement under historical simulation is larger than the one under Monte Carlo simulation. As a result, the study is able to determine that under which simulation will be able to increase the performance measurements as well as largerVaR.

Moreover, the studyperforms the variance comparison between the samples under both models. Similar to the mean comparison, it applies p-value testing for the variance comparison. The first step is to construct the hypothesis testing. We will have another four different hypotheses testing also, which are:

For VaR,

$$H_{05} : \hat{\delta}^2_{VHS} \geq \hat{\delta}^2_{VMS}$$
$$H_{15} : \hat{\delta}^2_{VHS} < \hat{\delta}^2_{VMS}$$

For Treynor Ratio,

$$H_{06} : \hat{\delta}^2_{THS} \geq \hat{\delta}^2_{TMS}$$
$$H_{16} : \hat{\delta}^2_{THS} < \hat{\delta}^2_{TMS}$$

For Sharpe Ratio,

$$H_{07} : \hat{\delta}^2_{SHS} \geq \hat{\delta}^2_{SMS}$$
$$H_{17} : \hat{\delta}^2_{SHS} < \hat{\delta}^2_{SMS}$$

For Information Ratio,

$$H_{08} : \hat{\delta}^2_{IHS} \geq \hat{\delta}^2_{IMS}$$
$$H_{18} : \hat{\delta}^2_{IHS} < \hat{\delta}^2_{IMS}$$

Before beginning the computation of the variance, the next step is to set up the decision rule. The statement below is the decision rule of p-value with the level of significance equals to 95 percent:

Reject H_0 : if p-value < Significance Level

Similar to the process of testing the mean of differences hypothesis, we will also apply Stat Tools to help us compare the variances of our samples. Stat Tools will calculate the ratio of two sample variances, which will determine which simulation will contain higher risk. Moreover, it also gave the calculation of p-value. Therefore, if the p-value is higher than the significance level, we can conclude that the variation of return under historical simulation is more volatile than that under Monte Carlo simulation.

4. CONCLUSIONS

Estimating the worst expected loss from an investment, although VaRreceives the most attention from the investors,the result of using VaR to predict the performance of portfolio is inclusive in terms of estimating approaches. The study highlights the significant analysis for the VaR application in terms of the ex ante performance valuation of the portfolio. The two most popular measurements, i.e.historical simulation and Monte Carlo simulation, have been adopted for the empirical testing of the hypothetical portfolio, SET50 index. Historical simulation has the simplicity of implementation, and it is simply to understand. However, for Monte Carlo simulation, it is complicated but the result is trustworthy. Thus, after both models have been applied to SET50 index and are analyzed by VaR, there will be three evaluation methods to measure the performance of the SET50 index predicted under these two simulations.

For the risk analysis of VaR, the study discovers that, statistically the historical simulation can generate the worst expected loss for 95 percent confidence level larger than Monte Carlo simulation, and the result under historical simulation is more volatile. The study further explores the reason that the historical model anticipates larger loss, is that it contains an actual economic crisis in the data. For instance, in the fourth quarter of 2008, which is in the period of hamburger crisis, our study generates the worst VaR estimation under historical simulation about -7.56% while Monte Carlo simulation anticipates the worst VaR about -5.32%. it implies that when there is any unexpected situation occurs, investors always have the intention to oversell their investments for a period of time such as a few days or a week, and it causes the price of the investments, which, in this case, is the SET50 index, to decrease sharply causing the historical simulation anticipates larger VaR as well as more volatility. However, the Monte Carlo simulation randomly generates the return for the investment, so the loss that produces by the model may not as large as the historical simulation doeseven in the period of the crisis.

The second concentration of the research is about the portfolio performance measurements, Treynor ratio, Sharpe ratio, and Information ratio. By examining the empirical outcome, all three measurements share the similar result. It indicates that the SET50 index under historical simulation can generate, in average, better performance evaluation than the SET50 index under Monte Carlo simulation. However, the testing result about the equality of the variance is different from the risk analysis. The outcomes of all three performance measurements under Monte Carlo simulation are more volatile. According to the result, it implies that the return of the SET50 index from Monte Carlo model is more pessimistic even though, in some quarters, the average return per day is higher than historical simulation. Moreover, the range of the return from Monte Carlo simulation is larger, and that is why the variance of the simulation is highly unstable. Based on the hypothesis testing, in comparing the p-value of all three performance measurements, it suggests that the Information ratio generated from Monte Carlo simulation is the most volatile, following by Sharpe ratio, and finally, Treynor ratio. On the other hands, for the largest difference of means between historical simulation and Monte Carlo simulation, Treynor ratio is the largest, then Sharpe ratio, and Information ratio.

In conclusion, the study have found that the historical simulation can generate a larger expected loss as well as a higher performance measurements, which are Treynor ratio, Sharpe ratio, and Information ratio when compare to the Monte Carlo simulation. However, the volatility is quite different. For the VaR estimation, the variance under historical model is less stable than Monte Carlo model does. On the other hands, for the portfolio performance evaluations, all three methods show that the variance under Monte Carlo simulation is more volatile than the previous one.

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