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Value-at-Risk on Different Economic Sectors in Malaysia

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Abstract: There are many methods used in determining the performance of a stock. None of them offer the investor a correct risk analysis of their holding and they frequently exposed to a high market risk. However, a sector that is worth investing can also be determined by researching its riskiness in the market. By adapting VaR measurement, this study aims to determine the least risky and the riskiest economic sector for investment in Malaysia. Two approaches used in estimating the VaR for the selected economic sector namely the historical simulation and Monte Carlo simulation. Results of the analysis show that the manufacturing sector have been the least risky sector for investment and the riskiest sector is telecommunication sector. The choice of which to invest depends on the risk appetite of investors. Historical simulation being the most appropriate approach to measure value at risk in this particular study as it results a smaller value of mse and made and also based on backtesting using Kupiec's test.

Key words: Value-at-risk, Kupiec backtesting, Monte Carlo, historical simulation, telecommunication

INTRODUCTION

Risk management is the process of identifying, analyzing and either accepting or mitigating any uncertainty in investment decision-making. Risk management is important in managing the risk involved in making an investment. The most common risk that an investor or a broker may face while dealing with stock prices trading in the stock exchange is market risk. This study used stock prices of selected companies where it is highly exposed to market risk. Fortunately, the market risk is a type of diversifiable risk and its impact can be reduced by using the approach of value at risk. Value at Risk (VaR) will prepare the investor of the maximum possible loss that an organization or an investor may face at a certain confidence level and at certain period of time.

VaR have become a popular tool in managing risk and will be the main area that this study will look into. By implementing the VaR method onto major economic sectors in Malaysia namely agriculture, construction, manufacturing, telecommunication, oil and gas and real estate and property.

The objective of this study is to estimate the VaR of the selected major economic sectors in Malaysia using historical simulation and Monte Carlo simulation, evaluate the VaR estimation and determine the appropriate method between the two.

Literature review

Value-at-Risk Model: There are many methods to determine the Value at Risk (VaR) which related to the financial institution and financial market instruments. VaR can be used to determine the risk associated with the stock (Chen and Chen, 2013; Corkalo, 2011; Terinte, 2015) global and local indices portfolios (Fan and Gu, 2003; Wu *et al.*, 2012) currencies (Poornima *et al.*, 2014; Rejeb *et al.*, 2012) multiple instruments (Wu *et al.*, 2012) as well as the financial institution performance (Perignon and Smith, 2008).

Most commonly VaR methods used are historical simulation, variance covariance, bootstrapping, Monte Carlo simulation, Exponentially Weighted Moving Average (EWMA) and linear parametric value at Risk approaches (Chen and Chen, 2013; Perignon and Smith, 2008; Poornima *et al.*, 2014; Rejeb *et al.*, 2012; Terinte, 2015; Wu *et al.*, 2012). There are also another eight model in calculating the VaR namely the risk metrics, GARCH and GARCH student-t residual, hybrid historical simulation, filtered historical simulation, conditional and unconditional extreme value model, simple and time weighted moving average.

The different models are to cater the characteristic of the data tested as such the conditional and unconditional extreme value. This model is used on the volatile financial market instrument such as derivatives markets. Monte

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Carlo Model is best in measuring the VaR for stock, indices and currency market (Chen and Chen, 2013; Poornima *et al*., 2014; Terinte, 2015). Historical simulation is then best for portfolios investment and performance of an institution (Perignon and Smith, 2008; Wu *et al*., 2012).

Accuracy of VaR Model: Based on the previous literatures, it can be concluded that the main concern of the researchers is on determining the most appropriate model of value at risk calculation. There are also some suggested accuracy testing on the VaR Model used so that it can produce a more consistent analysis results on the tested data. Several evaluation tests are suggested such as expected shortfall, mean relative bias and root mean square relative bias to help in the VaR analysis (Rejeb *et al*., 2012). Monte Carlo was the most chosen model in calculating VaR (Chen and Chen, 2013; Poornima *et al*., 2014; Terinte, 2015) and it accuracies can be verified commonly by back testing, mean square error and mean absolute deviation error. The accuracy of the VaR calculation can also be back tested by conditional and unconditional coverage tests (Poornima *et al*., 2014).

VaR should be back tested and supported by stress testing in order to obtain a more reliable result (Corkalo, 2011). Common back tested test used are failure likelihood ratio test (Kupiec test) conditional testing (Christoffersen test) and quadratic loss function (Lopez test) (Baharul *et al*., 2012, 2014). These tests determine which model provide the most accurate calculation in estimating VaR other than that VaR also can be tested for accuracy by using the measure of exceedance ratio against confidence level, mean absolute deviation error, square-root absolute deviation error and independence test (Fan and Gu, 2003).

This study determines the VaR of the selected economic sector in Malaysia in which each sector consist of the stock prices with high market capitalization. For simplicity, this research adopted the measures of mean square error and mean absolute deviation error evaluating the estimation of VaR to determine the best method between historical simulation and Monte Carlo in calculating VaR of selected dataset.

MATERIALS AND METHODS

This research used daily historical data on major economic sector's companies. The 501 days of historical data is the most common choice for numbers of days of data used (Hull, 2006). Therefore, this research used 501 trading days of historical stock prices. The 5 stocks were selected to represent each economic sector and is based on the highest market capitalization in Malaysia's market. The return then is calculated from the daily closing stock prices. The mathematical expression of VaR is as follows:

$$\Pr(R \leq -\text{VaR}) = 1\text{-a}$$

Where:

R = Return on the stock prices
α = Significance level

Historical simulation: This method is the simplest method because any assumption on the distribution of the return is unnecessary and not required. To estimate the VaR of an individual stock price, the returns have to be calculated first and then are ranked from the highest to the lowest. To determine the VaR, the excel is used and the function is as:

$$\text{PERCENTILE}\ (\text{return series, } 1\text{-}\alpha)$$

where the return series is one being calculated beforehand and α is the significance level of 95 and 99%. The first step in applying the historical simulation was to calculate the value of each scenario created. The value of each scenario can be calculated using the following expression (Hull, 2006):

$$\text{Scenario} = V_n \cdot V_i / V_{i-1}$$

Where:

v_n = Stock price on day n
v_i = Stock price on day i
v_{i-1} = The stock price on day i-1

The next step is to calculate the portfolio values and the losses that incurred from the portfolio for each scenario. Then, the losses were ranked from the highest to the lowest. The VaR was the fifth highest loss and the 25th highest loss for 99 and 95% confidence level, respectively (Hull, 2006).

Monte Carlo simulation: There are 5 steps in order to determine VaR. First, calculate all the parameters available in the lognormal distribution equation (Hull, 2006; Jorion, 2007). Rearranging the expression of lognormal equation, return expression can be obtained as:

$$R_t = \ln\frac{S_t}{S_t + \Delta_t} = k\Delta_t + \sigma\varepsilon_t\sqrt{\Delta_t}$$

Therefore, the parameters that are needed to be calculated are k, Δ_t and σ. The next step was to generate the pseudo random number (ε_t) from the expression above between 0 and 1. These pseudo random numbers are uniformly distributed. Then, the next step is to convert these numbers to become normally distributed. After this step, the simulated return is generated based on the expression above. The final step was to calculate VaR based on the simulated returns generated using the similar method of historical simulation.

Evaluation on value at risk estimation: Mean square error have been widely used in statistics. It measures the average of the squares of the errors. Meanwhile, mean absolute deviation error is the average of the absolute error:

$$MSE = \frac{1}{n}\sum_{s=t-n-1}^{t-1}(R_{p,s} - VaR)^2$$

$$MADE = \frac{1}{n}\sum_{s=t-n-1}^{t-1}\left|R_{p,s} - VaR\right|$$

Where:

n = The number of observations

$R_{p,s}$ = The return calculated for each day of each portfolio

VaR = The value at risk estimated for two different approaches at two different confidence levels

Another test to measure the accuracy of VaR estimation is Proportion of Failures (POF) test or also known as Kupiec's test (Kupiec, 1995). The test statistic takes the form:

$$LR_{POF} = -2\ln\left(\left((1-p)^{T-x}p^x\right)/\left(\left[1-\left(\frac{x}{T}\right)\right]^{T-x}\left(\frac{x}{T}\right)^x\right)\right)$$

Where:

T = Number of observations

x = Number of exceptions

p = Confidence level

If the value of the LR statistic exceeds the critical value of the χ^2 distribution for the critical values, the null hypothesis will be rejected and the model is deemed as inaccurate.

RESULTS AND DISCUSSION

Experimental result: Table 1 summarizes all the VaR estimation for selected sectors in Malaysia. VaR estimation of agriculture sector at 95% confidence level which is 1,249.60 million MYR indicates that for a sector that has a value of 76 billion MYR stock price holding, the investor will be 95% confident that the maximum possible losses is 1.2 billion MYR. Based on the results obtained, manufacturing sector has the lowest VaR estimation for both methods at both 95 and 99% confidence levels. Thus, manufacturing sector exhibits low risk of having a greater loss. Therefore, this sector may seem attractive for a risk averse investor. The telecommunication sector considered as a risky sector for an investor to invest. This is because the telecommunication sector has the highest value of VaR.

Therefore, the telecommunication sector seems to be less attractive for a very risk averse investor. The decision whether to invest or not depend on the type of risk the investor willing to take. Based on the VaR estimation, telecommunication and manufacturing sector are the riskiest and least risky, respectively for an investor to invest in. As in the Malaysia Investment Performance Report, it is stated that in 2014, there is a total of 4.5 billion MYR investment came for the telecommunication sector. It is much lower compared to investment invested in the manufacturing sector. For the manufacturing sector a total of 112 billion MYR investment approved in 2014. The small value of investment in telecommunication sector supported the fact that the sector is risky in the point of view of an inve stor. Meanwhile, large amount or investment in manufacturing sector make it seems less risky as the return is guaranteed.

Evaluation: Based on Table 2 shows all the riskiest and least risky company in each sector. For manufacturing sector, using the approach of historical simulation at 95% confidence level, KNM group berhad recorded as the riskiest share with highest value at risk estimation of -4.771%. This means that there is 0.05 probability that the returns are expected to be less than -4.771%. It is also the same company when tested at 99% confidence level as well as using Monte Carlo simulation at both confidence levels. Meanwhile, top glove is the least risky share as it has the lowest Value at Risk estimation using both methods and both confidence levels but only at 99% confidence level by historical simulation.

Based on all Table 2-4, it is observed that the VaR estimation at 99% confidence level always significantly greater than the 95% confidence level. The greater the confidence level, the higher the value at risk estimation.

Table1: Value at risk estimation of all sectors

	Historical simulation (VaR value)		Monte Carlo simulation (VaR value)	
Portfolio (sector)	95 (%)	99 (%)	95 (%)	99 (%)
Agriculture (AGRI)	1,249.60	1,977.91	1,910.89	2,693.10
Construction (CONS)	638.16	1,080.26	993.53	1,402.30
Manufacturing (MFT)	257.18	384.49	332.81	473.33
Oil and Gas (O and G)	1,135.67	2,323.55	1,514.71	2,122.56
Telecommunication (TEL)	1,679.20	2,955.28	2,749.71	3,898.66
Real Estate and Property (REP)	318.30	644.41	560.49	793.76

Table 2: Eiskiest and least risky asset by sector

		Historical Simulation		Monte Carlo Simulation	
Sector	Risk level	Company (95% VaR)	Company (99% VaR)	Company (95% VaR)	Company (99% VaR)
AGRI	Riskiest	FGV (-3.932)	FGV (-9.264)	FGV (-4.792)	FGV (-6.668)
	Least risky	KLK (-2.052)	Genting plantations Bhd (-3.164)	United plantations Bhd (-1.993)	United plantations Bhd (-2.812)
CONS	Riskiest	WCT holding Bhd (-3.375)	WCT holding Bhd (-5.993)	WCT holding Bhd (-3.689)	WCT holding Bhd (-5.186)
	Least risky	IJM corp Bhd (-1.725)	IJM corp Bhd (-3.049)	IJM corp Bhd (-1.868)	IJM corp Bhd (-2.649)
MFT	Riskiest	KNM group (-4.771)	KNM group (-9.144)	KNM group(-5.785)	KNM group (-8.154)
	Least risky	Globetronics technology (-2.448)	Top glove (-4.214)	Top glove (-2.826)	Top glove (-4.060)
O&g	Riskiest	Hibiscus petroleum Bhd (-5.271)	Hibiscus petroleum Bhd (-9.800)	Hibiscus petroleum Bhd (-6.978)	Hibiscus petroleum Bhd (-9.644)
	Least risky	Petronas gas Bhd (-1.879)	Petronas gas Bhd (-3.274)	Petronas gas Bhd (-2.015)	Petronas gas Bhd (-2.839)
TEL	Riskiest	Time dotcom (-2.656)	Time dotcom (-4.464)	Time dotcom (-2.748)	Time dotcom (-3.939)
	Least risky	Axiata group (-1.348)	Axiata group (-2.474)	Axiata group (-1.599)	Axiata group (-2.249)
REP	Riskiest	Glomac Bhd (-2.741)	Glomac Bhd (-5.079)	Glomac Bhd (-2.927)	Glomac Bhd (-4.107)
	Least risky	IGB corp Bhd (-1.499)	IGB corp Bhd (-2.713)	IGB corp Bhd (-1.628)	IGB corp Bhd (-2.289)

Table 3: MSE and MADE using historical Carlo simulation

	MSE		MADE	
Sectors	95% (α = 0.05)	99% (α = 0.01)	95% (α = 0.05)	99% (α = 0.01)
Agriculture	0.0003732	0.0006982	0.0169543	0.0244894
Construction	0.0003017	0.0006693	0.0153985	0.0243660
Manufacturing	0.0006076	0.0010993	0.0218762	0.0308299
Oil and gas	0.0005262	0.0012024	0.0205468	0.0328974
Telecommunication	0.0001612	0.0003805	0.0109634	0.0182565
Real estate and property	0.0002014	0.0006104	0.0124609	0.0235551

Table 4: MSE and MADE using Monte Carlo simulation

	MSE		MADE	
Sectors	95% (α = 0.05)	99% (α = 0.01)	95% (α = 0.05)	99% (α = 0.01)
Agriculture	0.0008452	0.0014791	0.0254468	0.0354381
Construction	0.0007090	0.0012407	0.0233062	0.0324569
Manufacturing	0.0015765	0.0027588	0.0347536	0.0483990
Oil and gas	0.0008960	0.0015680	0.0262004	0.0364875
Telecommunication	0.0004081	0.0007141	0.0176812	0.0246235
Real estate and property	0.0005891	0.0010309	0.0212447	0.0295861

The hypothesis indicates that the choices of confidence level depend upon the investors (Chen and Chen, 2013). Aggressive investors might choose a slightly lower confidence level for example 95% and cautious investors might choose a higher confidence level such as 99%. Other values of confidence levels are also acceptable and can be exercised. Also, the value at risk estimation using different approaches does not differ much at a smaller confidence level compared to at a higher confidence level. We concluded that historical simulation is a better method in estimating VaR.

Based on MSE, MADE and Kupiec's test, historical simulation approach is chosen as the more appropriate method in estimating VaR. It means that it is better to use the actual returns as it reflects the actual condition and situation of the stock price itself (Perignon and Smith, 2008; Wu *et al*., 2012). From Table 3-5, the VaR estimation using the historical simulation approach is slightly better as it produces a smaller value of MSE and MADE. Therefore, the historical simulation approach is a better approach in estimating value at risk in this research.

Table 5: Kupiec's test result

Sector	Percentage	LR_{POF}	Critical value $\chi^2(1)$	Outcome
Historical simulation	95	0.04265	3.84	Accept
	99	0.21687	3.84	Accept
Monte carlo simulation	95	Undefined	3.84	Reject
	99	0.01013	3.84	Accept

CONCLUSION

Investment is becoming one of the important factors in order to increase the overall gross domestic product of one's country and hence becoming a developed nation. However, before making an investment, one of the crucial factor to be considered is whether the investment will have a good return or not based on the level of riskiness of the investment. To measure the risk involved of a sector, VaR has become an important tool. Out of the six selected economic sectors, the manufacturing sector portfolio seemed to be the least risky sector to be invested in. These findings are supported as the manufacturing sector contributes the most toward the gross domestic product in Malaysia as well as having the most total investment during 2014 and early 2015.

Meanwhile, the telecommunication sector is the riskiest sector to be invested in. Based on the result, historical simulation is considered as the best approach in measuring VaR of selected economic sectors in Malaysia as per in the previous literatures (Hendricks, 1996; Perignon and Smith, 2008; Wu *et al*., 2012). Many studies have been made on the methods available in estimating value at risk and they all came up with different methods as the best method. However, in this study, the most appropriate approach is by adapting historical simulation in calculating VaR.

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REFERENCES

Baharul, U.Z.K.A., I. Ahmad and S.N. Binti, 2012. Assessing the accuracy of risk models in the Malaysian market. Asian J. Bus. Manage. Sci., 1: 48-59.

Baharul, U.Z.K.A., I. Ahmad, N. Salamudin and T.S. Lim, 2014. The analysis of risk models for malaysias non-financial sectors. Malaysian J. Bus. Econ., 1: 1-18.

Chen, Q. and R. Chen, 2013. Method of value-at-risk and empirical research for Shanghai stock market. Procedia Comput. Sci., 17: 671-677.

Corkalo, S., 2011. Comparison of value at risk approaches on a stock portfolio. Croatian Oper. Res. Rev., 2: 81-90.

Fan, J. and J. Gu, 2003. Semiparametric estimation of value at risk. Econ. J., 6: 261-290.

Hendricks, D., 1996. Evaluation of value-at-risk models using historical data. Econ. Policy Rev., 2: 39-67.

Hull, J.C., 2006. Options, Futures and Other Derivatives. 6th Edn., Prentice-Hall, Upper Saddle River, NJ.

Jorion, P., 2007. Value at Risk: The New Benchmark for Managing Financial Risk. 3rd Edn., McGraw Hill, New York.

Kupiec, P., 1995. Techniques for verifiying the accuracy of risk management Models. J. Derviatives, 3: 73-84.

Perignon, C. and D.R. Smith, 2008. A new approach to comparing VaR estimation methods. J. Derivatives, 16: 54-66.

Poornima, B.G., Y.S. Reddy and Y.V. Reddy, 2014. Indian currency market risk analysis: Value-at-risk approach. IUP. J. Financial Risk Manage., 11: 45-56.

Rejeb, A.B., O.B. Salha and J.B. Rejeb, 2012. Value-at-risk analysis for the Tunisian currency market: A comparative study. Int. J. Econ. Financial Issues, 2: 110-125.

Terinte, P.A., 2015. Applicability of value at risk on Romanian capital market. J. Public Administration Finance Law Spec., 2: 104-110.

Wu, P.C., C.K. Kuo and A.C. Lee, 2012. Evaluation of multi-asset value at risk: Evidence from Taiwan. Global J. Bus. Res., 6: 23-34.