Journal of Quality Measurement and Analysis
Jurnal Pengukuran Kualiti dan Analisis

JQMA 11(1) 2015, 1-10

VALUE-AT-RISK FOR SHARES OF COMPANIES LISTED UNDER THE FINANCIAL SECTOR OF MALAYSIAN STOCK EXCHANGE

(Nilai Berisiko untuk Saham Syarikat dalam Sektor Kewangan di Bursa Saham Malaysia)

NUR ATIKAH MOHAMED ROZALI, HUMAIDA BANU SAMSUDIN &
PREVENA NAMBIAR A/P SRIDAHRAN

ABSTRACT

Risk management is essential since stock prices of a company are often exposed to high level of market risk. One way to evaluate market risk is by determining the value-at-risk, which is the maximum probable loss that a financial instrument is exposed to at a given time. In this research, the value-at-risk was evaluated for all shares of companies listed under the financial sector of Malaysian Stock Exchange using non-parametric approach and Monte Carlo simulation method. The comparisons of risk faced by the shares of companies were also done. These methods were chosen to avoid wrong estimation of the value-at-risk if the data is fitted to an inaccurate distribution. The value-at-risk was determined using the non-parametric approaches, which are basic historical simulation, bootstrap historical simulation, age-weighted historical simulation and volatility-weighted historical simulation methods. Monte Carlo simulation was applied using the Geometric Brownian Motion. Findings of this study found that the shares of all companies produced slightly different results for each of the method with different level of sensitivity. The shares of Pan Malaysia Capital Berhad are the most risky because it produced the highest value-at-risk. The shares of LPI Capital Berhad and Public Bank Berhad are the least risky as they produced the lowest value-at-risk in comparison with the shares of all the other companies.

Keywords: market risk; non-parametric method; Monte Carlo simulation method

ABSTRAK

Pengurusan risiko amat penting kerana harga saham sesebuah syarikat sering terdedah kepada risiko pasaran yang tinggi. Satu cara untuk menilai risiko pasaran adalah dengan menentukan nilai berisiko, iaitu kerugian mungkin maksimum yang dihadapi oleh instrumen kewangan pada masa tertentu. Dalam kajian ini, nilai berisiko itu ditentukan untuk semua saham syarikat dalam sektor kewangan yang tersenarai di Bursa Saham Malaysia dengan menggunakan pendekatan tak berparameter dan kaedah simulasi Monte Carlo. Perbandingan risiko yang dihadapi oleh syarikat turut dikaji. Kaedah ini dipilih untuk mengelakkan salah anggaran nilai berisiko sekiranya data disuaikan dengan taburan yang kurang tepat. Nilai berisiko telah ditentukan dengan menggunakan pendekatan tak berparameter, iaitu simulasi bersejarah asas, simulasi bersejarah butstrap, simulasi bersejarah berpemberat usia dan simulasi bersejarah berpemberat kemeruapan. Kaedah simulasi Monte Carlo pula diguna pakai dengan menggunakan Gerakan Brownan Geometri. Berdasarkan dapatan kajian, saham kesemua syarikat memberikan keputusan yang sedikit berlainan bagi setiap kaedah dengan tahap kepekaan yang berbeza. Saham Pan Malaysia Capital Berhad adalah yang paling berisiko tinggi kerana ia memberikan nilai berisiko yang paling tinggi. Saham LPI Capital Berhad dan Public Bank Berhad pula paling kurang berisiko kerana memberikan nilai berisiko yang rendah berbanding dengan saham kesemua syarikat lain.

Kata kunci: risiko pasaran; kaedah tak berparameter; kaedah simulasi Monte Carlo

1. Introduction

Stocks are shares in a business that entitles the owners to receive dividends, vote and to have an ownership that is proportional to the amount of share owned (Dewan Bahasa dan Pustaka 2008). A company will issue shares when they want to expand their business, buy new assets, for example, land, building or equipment, and also when they are in need of capital to take on new projects. Shares are traded in a stock exchange market, which is a place where the buying and selling of shares take place. Risk exists in every aspect of life. According to Harrington and Niehaus (2003), risk is any situation that has the factor of uncertainty in the outcome. High risk can cause high losses to an organisation and when a loss occurs, it reduces the value of the shareholders and also the value of the organisation. This is where risk management plays an important role to reduce or avoid the impact of risk.

Risk management is the process of identifying the risk exposures faced by organisations and choosing the most effective method to reduce the impact of these risk exposures (Rejda 2011). Risk exposures are situations or events that may lead to the occurrence of losses, regardless of whether the loss has happened or not. There are two main types of risk, the diversifiable risk and the non-diversifiable risk. Diversifiable risk happens due to specific events and can be managed through insurance, whereas non-diversifiable risk is unavoidable, occurs due to events that affect many firms and can only be managed through hedging. Prices of shares are exposed to a high level of market risk. Market risk is a type of systematic risk that cannot be eliminated completely. This is why risk management practices have to be done so that the losses can be reduced. In order to reduce the impact of the market risk faced by the prices of the shares, the value-at-risk (VaR) can be determined so that companies will be more prepared for losses. Value-at-risk is the maximum potential loss in the asset value of a financial instrument with a given confidence level in a certain time period. The value-at-risk obtained summarises the entire risk of an asset to a single number (Jadhav & Ramanathan 2009).

The aim of this paper is to determine the value-at-risk for shares of all companies listed under the financial sector of the Malaysian Stock Exchange using the non-parametric approach and the Monte Carlo simulation method. A comparison of risk exposed to the shares of the companies will also be done to identify risky shares. The non-parametric approach was chosen for this study because it does not require the data to be classified into distribution which may lead to under or over estimating the value-at-risk if the distribution fitted is inaccurate (Cheung & Powell 2012a). For the non-parametric approach, the methods used were the basic historical simulation, bootstrap historical simulation, age-weighted historical simulation and volatility-weighted historical simulation method. The historical simulation methods use past data of the assets to estimate the value-at-risk and these methods assume that the share prices will follow a similar trend over the years. As for the Monte Carlo simulation method, the Geometric Brownian Motion will be applied to find the value-at-risk. This method repeats the sample from the probability distribution in finding the value-at-risk.

2. Value-at-Risk

The value-at-risk is the maximum loss faced by the assets at a given time. Organisations are now more focused at managing their risk rather than maximizing their profits. This is because, when the risk of a company is managed and monitored well, the company's profit will start growing as there will no extra expenses involved to pay for the losses. However, not all risk can be eliminated completely, for example, market risk. One way to handle market risk is by determining the value-at-risk. The value-at-risk provides the maximum amount of loss an asset will incur and by knowing the value-at-risk, companies will be more careful because they can somehow predict what they may face in the future and plan ahead the measures that should be taken. By finding the value-at-risk, investors will also be more confident to invest in the assets of the companies. The value-at-risk is frequently associated with the extreme negative returns that may lead to large losses.

In order to find the value-at-risk, the quantile of the distribution has to be determined. The value-at-risk that matches the $p\%$ percentile will be obtained for the $(100-p)\%$ value-at-risk. Alimohammadisagvand and Fransson (2011) have summarised the value-at-risk in a mathematical representation as follows:

$$\Pr\left(R \leq -\mathrm{VaR}\right) = 1-\alpha, \tag{1}$$

where it implies that the probability of return, R is less than –VaR is equal to the complement of the significance level α.

3. Data and Methodology

The data used in this research is the daily price of shares of companies listed under the financial sector of the Malaysian Stock Exchange. The daily data used are for a ten year period, which is from the 26th of February 2004 until the 26$^{\text{th}}$ February 2014 and the data was obtained from Datastream (2011). There are 37 companies listed under the financial sector but only 31 companies were studied in this research as the other six companies did not have data for a ten year period because they were listed in the Malaysian Stock Exchange after the 26$^{\text{th}}$ February 2004.

Factors that have to be considered in evaluating the value-at-risk include confidence level, the holding period return and the historical observation period. Confidence level is the probability of the maximum possible loss that may occur (Mun 2010). The confidence level *p,*can be defined as:

$$p = 1-\alpha, \tag{2}$$

where α is the significance level. The most common confidence levels used are 95% and 99% (Hendricks 1996). The Basel committee has set the standard confidence level of 99% to be used for official reporting purposes because a high confidence level is needed to be able to calculate the capital requirement (Bank Negara Malaysia 2012). However, confidence levels other than 99% can be used for internal purpose, including validating the VaR model used by the particular company (Bank Negara Malaysia 2012). In this research, 95% confidence level is used for the calculation of the value-at-risk.

The time period used to forecast the expected maximum loss is also known as the holding period. The holding period that can be used can vary from one day to a few years. For official reporting purpose, the Basel Committee has set a standard holding period return of ten days (Bank Negara Malaysia 2012). However, a holding period return of less than ten days can be used. According to the research done by Khindanova and Rachev (2000), a ten day holding period return is insufficient for assets that are traded frequently. Therefore in this study, the holding period return (HPR) used is one day. The calculation of the holding period return can be done using the formula below:

$$\mathrm{HPR} = \ln\frac{p_t}{p_{t-1}}, \tag{3}$$

where p_t is the price of the share at time t and p_{t-1} is the price of the share at time $t-1$.

The Basel Committee has set a standard minimum observation period of one year to be used in the evaluation of the value-at-risk (Bank Negara Malaysia 2012). According to Khindanova and Rachev (2000), a longer observation period will be able to predict the value-at-risk more accurately. In this research, the historical observation period used is ten years, which gives a total of 2610 data for each company's stock price.

3.1 *Non-parametric method*

The non-parametric method was chosen in this study to avoid any mis-estimation of the value-at-risk due to distribution misclassification of the stock returns (Cheung & Powell 2012a). The historical simulation method uses past data as a guide to predict what is going to happen in the future of the stock prices. This method allows the data to speak for themselves without any modifications. All four methods used in this study assume that the data will follow a similar trend in the future.

3.1.1 *Basic Historical Simulation Method*

According to Halulu (2012), the historical simulation method uses simulation and builds a cumulative distribution function to evaluate the value-at-risk for the returns of the assets. The basic historical simulation method uses the statistics of the sample's stock price that will be converted into the one-day holding period return to calculate the value-at-risk (Cheung & Powell 2012a). The Excel function used to calculate the value-at-risk in this method is:

$$\text{PERCENTILE(return series, } 1-\alpha\text{)}, \tag{4}$$

where the return series is the holding period return of the asset studied and α is the significance level of 0.95.

3.1.2 *Bootstrap Historical Simulation Method*

The bootstrap historical simulation method is a modification to the basic historical simulation method because this method is a product of the repeated trials done on the basic historical simulation method. This method involves the resampling of the research data to estimate the empirical approximation of the sample's distribution. The resampling can be done by using the randomisation function in Excel. The bootstrap historical simulation method will create changes to the assets or portfolio based on the changes in the historical market variable in the assets (Hull 2012). The historical data of the asset is said to have n observations, thus the bootstrapped observation, m, will also have n number of observations. The value-at-risk at 5% will be calculated for each m observation. In this research, the original model has 2609 data and resampling is done for 1000 times. Since the resampling is done for 1000 times, the value-at-risk for each resampled observation will be evaluated and an average value-at-risk will be calculated for each asset. The value-at-risk is calculated in the similar way as the basic historical simulation method.

3.1.3 *The Age-Weighted Historical Simulation*

The age-weighted historical simulation is a modification to the basic historical simulation where there will be a decaying factor, λ, that will hold a value between 0 and 1, depending on the decaying factor of an asset or portfolio. The value of λ that is closer to 0 signifies that the decaying process is fast whereas the value of λ that is closer to 1 signifies that the decaying process is slow. According to Birtoiu and Dragu (2011), if the λ is chosen correctly, it would be able to detect the extreme losses very effectively. Using this decaying factor, all the observations will be given a weight, $w(t)$, in which the more recent observations will be given a heavier weight compared to the older observations. The $w(t)$, is exponentially proportionate to λ. The summation of the weights will be equal to one, as follows:

$$\sum_{t=1}^{N} w(t) = 1. \tag{5}$$

There are six steps in the calculation of value-at-risk using this method. The first step is to number all the observations data from the most recent to the oldest observation. Then, the holding period returns will be arranged from the most negative return to the most positive return. The third step involves making a decision on the value of λ that is to be used and in this study, the value of λ used are 0.99 and 0.999, one to signify a faster decaying process and the other one to symbolise a slower decaying process. Then, the weight will be calculated for each observation using the formula below:

$$w(t) = \frac{\lambda^{t-1}(1-\lambda)}{1-\lambda^{n}}, \tag{6}$$

where n is the number of observation, λ is the decaying factor and t is the time period. After calculating the weight, the cumulative value will be obtained for each data. Finally, based on the confidence level chosen, interpolation is done to obtain the value-at-risk. The following formula was used to find the value-at-risk:

$$\text{VaR} = p_{t-1} - (p_{t-1} - p_t)\left(\frac{(1-k_{t-1}) - (1-\alpha)}{(1-k_{t-1}) - (1-k_t)}\right), \tag{7}$$

where p_t is the return for time t, k_t is the cumulative value for time t and α is the significance level.

3.1.4 *The Volatility-Weighted Historical Simulation*

In order to incorporate the volatility factor into the asset prices, the volatility-weighted historical simulation can be used. Hull and White (1998) suggested the incorporation of volatility into the basic historical simulation method. This can be done by using the generalised auto-regressive conditional heteroscedastic (GARCH) model or exponentially weighted moving average (EWMA) model. The volatility of a variable, σ, is the standard deviation of the daily returns for every unit per time of the variable if the returns are continuously compounded. In this study, the GARCH (1, 1) model will be used in the Risk Simulator software to predict the volatility for each return. According to Mun (2010), the GARCH model is frequently used to estimate the volatility in liquid assets and assets that are traded. After obtaining the value of σ, a new return will be calculated using the formula below:

$$r_{b_t} = \left(\frac{\sigma_{t+1}}{\sigma_t} \right) r_{a_t}, \tag{8}$$

where r_{b_t} is the new return at time t, σ_t is the volatility at time t, and r_{a_t} is the original holding period return of the data. Once the new return which incorporates volatility is obtained, the value-at-risk will be calculated using the same method as the basic historical simulation.

3.2 *Monte Carlo Simulation Method*

Monte Carlo simulation method uses random sampling of the simulated data of a known population to predict the statistical behaviour of the asset (Lewis-Beck *et al*. 2004). Olson and Wu (2013) defined simulation as the assumption sets related to the relationship of the components of the model. This simulation model uses randomisation to produce variable for samples that already exist. Monte Carlo simulation depends on the probability theory as the driving factor for the simulation process (Cheung & Powell 2012b). This method involves repeated trials on the input value based on an unknown probability distribution. All the input will be assumed to be a random variable. In the context of value-at-risk, the input of the asset returns are the returns of the assets and the output is the returns of the five percent value-at-risk. The process that links the input and output is called the Geometric Brownian Motion. This process will create thousands of scenarios to fully understand the characteristics of the asset returns. The asset prices are said to follow a stochastic process, known as the Geometric Brownian Motion and it is shown in the equation below:

$$S_{t+\Delta t} = S_t e^{\left(k\Delta t + \sigma\varepsilon_t \sqrt{\Delta t} \right)}, \tag{9}$$

where S_t indicates the asset price at time t, Δt is the increase in time as part of a year in a trading day, $k = \mu - \left(\sigma^2/2 \right)$ is the expected return and ε_t is the randomisation at time t, which is introduced to randomise the changes in the share prices. The variable ε_t is a random number which is produced from a standard normal distribution. The return of the asset price, $R_{t+\Delta t}$ is given by:

$$R_{t+\Delta t} = \ln \frac{S_{t+\Delta t}}{S_t} = k\Delta t + \sigma\varepsilon_t \sqrt{\Delta t}. \tag{10}$$

There are five steps in the calculation of the value-at-risk using the Monte Carlo simulation method (Cheung & Powell 2012b). The first step is to calculate all the parameters in the Geometric Brownian Motion process. Then, a distribution of pseudo random numbers between 0 and 1 will be generated. After this step, the pseudo random numbers will be converted into random numbers that are normally distributed. The fourth step is to apply the random numbers generated into the Geometric Brownian Motion to produce simulated asset returns. The last step is to calculate the value-at-risk at the five percent level.

4. Results and Discussions

Table 1 summarises all the value-at-risk obtained using all the methods of calculation for all shares of the companies studied. Based on the basic historical simulation method, the LPI Capital Berhad's shares are the least risky shares because they have the lowest value-at-risk, which is –1.4316%, which means that 5% of the returns are expected to be less than the value-at-risk amount. The shares of Pan Malaysia Capital Berhad is the most risky share because the value-at-risk for the returns of this share is the highest, which is, –7.5795%. This indicates that there is a 5% chances that the returns will be less than –7.5795%.

Table 1: Comparison of value-at-risk (%) obtained using all methods

Company	Basic	Bootstrap	Age-weighted (λ=0.99)	Age-weighted (λ=0.999)	Volatility-weighted	Monte Carlo
AFFIN	-2.5571	-2.5630	-1.4468	-2.3363	-2.7690	-2.6168
Alliance Finance	-2.4414	-2.4371	-2.1768	-2.3373	-2.7005	-2.4510
Allianz Malaysia	-1.7852	-1.7949	-2.0203	-1.9699	-1.7862	-2.8393
AMMB	-2.3599	-2.3712	-1.2871	-1.8976	-2.4828	-2.3960
Apex Equity	-3.5752	-3.5693	-3.3061	-3.3061	-3.5771	-4.0452
BIMB	-3.1293	-3.1265	-2.8167	-3.0990	-3.5067	-3.3287
CIMB Group	-2.5599	-2.5481	-1.7227	-2.1506	-2.6375	-2.3562
ECM Libra Finance	-3.4911	-3.4767	-2.0072	-3.0781	-3.6552	-2.8808
Hwang-Dbs (M)	-2.7705	-2.7716	-1.6470	-2.4038	-3.0722	-2.7460
Hong Leong Bank	-1.8838	-1.8792	-1.2886	-1.7695	-1.9371	-1.8170
Hong Leong Capital	-3.4598	-3.4592	-2.9261	-3.1499	-3.8503	-3.6884
Hong Leong Finance	-2.4073	-2.3871	-2.1931	-2.2218	-2.4754	-2.1951
Insas	-3.5940	-3.5915	-3.4207	-3.1102	-3.7421	-3.9252
Johan Holdings	-5.4067	-5.3662	-3.2790	-4.9727	-5.6993	-5.5469
KAF	-3.1901	-3.2218	-2.0737	-3.4191	-3.3515	-3.7731
K & N Kenanga	-3.9657	-4.0142	-1.6826	-3.5718	-5.0091	-4.5478
LPI Capital	-1.4316	-1.4373	-1.1849	-1.1813	-1.5013	-1.5368
MAA	-3.7430	-3.7336	-2.4989	-3.6984	-3.8833	-4.2991
Manulife	-2.0840	-2.0824	-1.4959	-1.9380	-2.2751	-2.3435
Malayan Banking	-1.9061	-1.9212	-1.4284	-1.7569	-2.0152	-1.9608
MBSB	-3.7192	-3.7536	-2.2897	-3.1894	-4.0091	-4.2005
MNRB	-1.8349	-1.8335	-1.7578	-1.9225	-1.9418	-2.0566
OSK	-3.0966	-3.1047	-1.3447	-2.6317	-3.3723	-3.1414
Pacific & Orient	-2.3945	-2.3706	-1.4599	-2.5702	-2.5338	-2.6659
Public Bank	-1.4884	-1.4892	-0.6303	-1.0172	-1.6397	-1.3958
Public Bank- Foreign	-1.9216	-1.9280	-0.6613	-1.4628	-1.9222	-1.7922
Pan Malaysia Capital	-7.5795	-7.5510	-13.351	-9.0972	-8.2572	-8.4498
RCE Capital	-4.0822	-4.0595	-2.0203	-3.5077	-4.2213	-4.8992
RHB Capital	-2.4856	2.4909	-1.6308	-2.0544	-2.6516	-2.4498
TA Enterprise	-3.0104	-3.0216	-2.3550	-2.7152	-3.2739	-3.3656
STMB	-3.0214	-3.0296	-1.7010	-2.8418	-3.1657	-3.4611

According to the results obtained from the bootstrap historical simulation method, the shares of LPI Capital Berhad are the least risky share and the shares of Pan Malaysia Capital Berhad have shown to be the most risky shares. The value-at-risk obtained for LPI Capital Berhad's share returns is -1.4373% and for the returns of Pan Malaysia Capital Berhad, the value-at-risk obtained is -7.5510%. This means that only 5% of the returns of LPI Capital Berhad's shares will fall lower than -1.4373% and only 5% of the returns of Pan Malaysia Capital Berhad's share will fall lower than -7.5510%.

The value-at-risk for the age-weighted historical simulation method was calculated for two values of the decaying factor, λ, 0.99 and 0.999. The value 0.99 indicates a faster decaying process and the value 0.999 indicates a slower decaying process of the shares. The least risky share using both values of λ is the Public Bank Berhad share and the most risky share using both values of λ is the shares of Pan Malaysia Capital Berhad. However, the value-at-risk obtained using both methods differ. For $\lambda = 0.99$, the value-at-risk obtained for the returns of Public Bank Berhad's share is -0.6303% and the value-at-risk obtained for the returns of Pan Malaysia Capital Berhad's share is -13.3530%. On the other hand, for $\lambda = 0.999$ the value-at-risk obtained for the returns of Public Bank Berhad's share is -1.0172%, which is a little bit higher compared to the value obtained using $\lambda = 0.99$. The value-at-risk obtained for Pan Malaysia Capital Berhad's share returns using $\lambda = 0.999$ is -9.0972%, which is lower than the value obtained using $\lambda = 0.99$. Based on the volatility-weighted historical simulation method, the share returns of LPI Capital Berhad has yet again given the lowest value-at-risk, -1.5013% and this indicates that 5% of the returns of the shares will be less than -1.5013%. The most risky share is the Pan Malaysia Capital Berhad's share, with a value-at-risk of -8.2572%. This means that 5% of the time, the returns of the shares will fall below -8.2572%. Thus, from this method, it can be concluded that the shares of LPI Capital Berhad are the least risky shares and the shares of Pan Malaysia Capital Berhad are the most risky shares.

Under the Monte Carlo simulation method, Public Bank Berhad's shares have indicated to be the least risky share, with a value-at-risk of -1.3958% and the Pan Malaysia Capital Berhad's shares have indicated to be the most risky share, with a value-at-risk of -8.4498%. From the analysis done using this method, 5% of Public Bank Berhad's share returns are expected to be less than -1.3958%, while 5% of Pan Malaysia Capital Berhad's share returns are expected to be less than -8.4498%.

The shares of the companies have given a very close value-at-risk for the basic historical simulation method and the bootstrap historical simulation method. This is because the bootstrap historical simulation method is an improvement to the basic historical simulation method, whereby 1000 repeated trials of the observations used in the basic historical simulation method are done for the bootstrap historical simulation method. For the age-weighted historical simulation, different companies have different levels of sensitivity towards the decaying process. Most of the shares of the companies are more sensitive towards a slower decaying process, using $\lambda = 0.999$, except for the share of Insas Berhad which produced the value-at-risk which is more sensitive towards a faster decaying process, using $\lambda = 0.99$. The shares of Apex Equity Holdings Berhad and LPI Capital Berhad gave almost the same value for both values of λ and this indicates that both the shares of these companies are least sensitive to different values of λ.

The volatility-weighted historical simulation method considers a very important factor in the market, which is the volatility of the asset prices. Volatility is usually associated with the risk of a financial instrument. Most of the shares of the companies have given a slightly higher value for the volatility-weighted historical simulation method compared to all the other methods because the calculation took into consideration the volatility factor of the asset prices. On the other hand, the Monte Carlo simulation method incorporated the changes in the market variable into the calculation of the value-at-risk and this method also gave a higher value of value-at-risk for most of the shares of the companies. However, the values obtained using this method was not as high as the values obtained using the volatility-weighted historical simulation.

5. Conclusion

The results of the analysis have shown that all methods of calculation yielded value-at-risks that are not too different for most of the companies. The value-at-risk under all the methods showed that the share of Pan Malaysia Capital Berhad gave the highest value-at-risk, which indicates that this share is the most risky shares. For the basic historical simulation, bootstrap historical simulation and volatility-weighted historical simulation method, the share of LPI Capital Berhad gave the lowest value-at-risk, whereas for the age-weighted historical simulation method using both values of λ and for the Monte Carlo simulation method, the share of Public Bank Berhad gave the lowest value-at-risk. This means that the shares of LPI Capital Berhad and Public Bank Berhad are the least risky shares.

Acknowledgements

This work was supported by the Universiti Kebangsaan Malaysia under Grant GGPM-2012-007.

References

Alimohammadisagvand B. & Fransson C. 2011. Market risk in volatile times: a comparison of methods for calculating value-at-risk. Master Thesis. Lund University.

Bank Negara Malaysia. 2012. Capital Adequacy Framework (Basel II - Risk Weighted Assets). http://www.bnm.gov.my/guidelines/01_banking/01_capital_adequacy/Capital_Adequacy_Framework-BaselII-Risk-Weighted_Assets_270613.pdf (1 May 2014).

Birtoiu A. & Dragu F. 2011. Market Risk Management: The Applicability and Accuracy of Value-at-Risk Models in Financial Institutions. Master Thesis. Lund University.

Cheung Y. H. & Powell R. J. 2012a. Anybody can do value at risk: a nonparametric teaching study. *Australasian Accounting, Business and Finance Journal* **6**(1): 111-123.

Cheung Y. H. & Powell R. J. 2012b. Anybody can do value at risk: a teaching study using parametric computation and Monte Carlo simulation. *Australasian Accounting, Business and Finance Journal* **6**(5): 101-118.

Dewan Bahasa dan Pustaka. 2008. *Kamus Pelajar Bahasa Malaysia*. 2nd Ed. Kuala Lumpur: Dewan Bahasa dan Pustaka (in Malay).

Halulu S. 2012. Quantifying the risk of portfolios containing stocks and commodities. Master Thesis. Boğaziçi University.

Harrington S. & Niehaus G. 2003. *Risk Management and Insurance*. 2nd Ed. New York: McGraw-Hill/Irwin.

Hendricks D. 1996. Evaluation of value-at-risk models using historical data (digest summary). *Economic Policy Review Federal Reserve Bank of New York* **2**(1): 39-67.

Hull J. 2012. *Risk Management and Financial Institutions + website*. 3rd Ed. Hoboken: John Wiley & Sons.

Hull J. & White A. 1998. Incorporating volatility updating into the historical simulation method for value-at-risk. *Journal of Risk* **1**(1): 5-19.

Jadhav D. & Ramanathan T. V. 2009. Parametric and non-parametric estimation of value-at-risk. *The Journal of Risk Model Validation* **3**: 51-71.

Khindanova I. N. & Rachev S. T. 2000. Value-at-risk: Recent advances. In Anastassiou G. (ed.). *Handbook on Analytic Computational Methods in Applied Mathematics*: 801-858. Boca Raton: Chapman & Hall/CRC.

Lewis-Beck M., Bryman A. E. & Liao T. F. 2004. *The SAGE Encyclopedia of Social Science Research Methods*. Thousand Oaks: SAGE Publications.

Mun J. 2010. *Modeling Risk: Applying Monte Carlo Risk Simulation, Strategic Real Options, Stochastic Forecasting, and Portfolio Optimization*. 2nd Ed. Hoboken: John Wiley & Sons.

Olson D. L. & Wu D. 2013. The impact of distribution on value-at-risk measures. *Mathematical and Computer Modelling* **58**(9): 1670-1676.

Rejda G. E. 2011. *Principles of Risk Management and Insurance*. 11th Ed. Essex: Pearson.

Thomson Reuters. 2011. Datastream. https://www.thomsonone.com/DirectoryServices/2006-04-01/Web.Public/Login.aspx?brandname=datastream (1 May 2014)

Pusat Pengajian Sains Matematik
Fakulti Sains dan Teknologi
Universiti Kebangsaan Malaysia
43600 UKM Bangi
Selangor DE, MALAYSIA
E-mail: nur.atikah@ukm.edu.my, humaida@ukm.edu.my, prevena89@gmail.com*

*Corresponding author