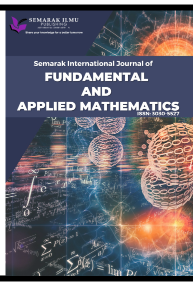
Semarak International Journal of Fundamental and Applied Mathematics

Journal homepage:
https://semarakilmu.my/index.php/sijfam/index
ISSN: 3030-5527



Non-Parametric Approach in Measuring Value-at-Risk using Historical Simulation Method

Ahmed Adrees Meah Azlan Meah[2], Siti Nur Iqmal Ibrahim[1,2,*]

[1] Institute for Mathematical Research, Universiti Putra Malaysia, 43400 UPM Serdang, Selangor, Malaysia
[2] Department of Mathematics and Statistics, Faculty of Science, Universiti Putra Malaysia, 43400 UPM Serdang, Selangor, Malaysia

ARTICLE INFO

Article history:
Received
Received in revised form
Accepted
Available online

Keywords:
Value-at-risk; stock price; historical simulation; Geometric Brownian motion; Monte Carlo simulation

ABSTRACT

Risk assessment is fundamental to determine if an investment in stocks is worthwhile and what steps may be taken to alleviate risk. It determines what rate of return is necessary to make a particular investment in a stock succeed. One method to gauge the market risk is by calculating the Value-at-Risk (VaR) of the stock. VaR measures statistically, the potential loss amount of a risky asset or investment portfolio on the stock over a defined timeframe for a given confidence level. In this study, VaR of stocks for companies listed by the Kuala Lumpur Stock Exchange are being measured using the non-parametric approach which is the historical simulation method. Geometric Brownian Motion is then used to predict the stock prices for the first two weeks. The outcome shows that Malaysia Building Society Berhad is the riskiest as it gives the highest value at risk while Hong Leong Bank Berhad shows the lowest.

1. Introduction

A stock is a type of security that represents ownership in a listed company and a claim on part of the corporation’s assets and earnings. They are shares or equities 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. Stocks are traded in Bursa Malaysia, the Malaysian stock exchange market, which is a place where the buying and selling of shares take place. For example, an investor purchases a stock or share of the company like Apple, he now owns a part of it at a small fraction of it because Apple is huge with a large market capitalization and they go public so that when investors purchase the stock, he is buying a part of the company. Typically, companies do this for investors to invest in the company to gain revenue so they can build or grow the company and to sell more of its products and by that they will be needing different kinds of equipment and labor, and it may require a huge amount of capital. In order to make this happen, instead of going to the bank and applying for loans which can be more costly and difficult for the loan to be approved, companies will find investors to put in their money in return with a financial gain where a fixed percentage of equity or ownership on the

* *Corresponding author.*
E-mail address: iqmal@upm.edu.my

https://doi.org/10.37934/sijfam.7.1.2338

company within a fixed period of time until their investments are paid back. Either way both parties benefit from these investments where the investors are always looking to be a part of the company and gain revenues while the company itself can expand their business to globalize to better educate their customers about their products and innovations.

According to Harrington *et al.,* [15], risk involves the uncertainty of outcomes in any given situation. Risk management refers to the process by which organizations identify their exposure to risks and implement the most suitable strategies to minimize their potential impact. Risk assessment is a widely applied concept across various industries, used to evaluate the probability of loss associated with an asset, investment, or loan. This process helps in determining whether investing in stocks or shares is viable and what measures can be implemented to mitigate potential risks. It also aids in identifying the required rate of return needed for an investment to be considered successful [6]. Risk assessment involves a thorough evaluation of the potential risks associated with a particular investment. Financial analysts typically examine numerous factors such as volatility, historical performance, predictability, the experience of the investment management team, and the capital invested. For instance, a highly volatile investment that yields consistently low returns may be deemed unfavourable. Therefore, higher-risk investments should only be pursued when there is a corresponding potential for substantial returns [11].

The Value-at-Risk, VaR model is applied in most financial institutions in measuring risk management to make better decisions and avoid huge losses in stocks investments and equity. In its most general form, VaR measures statistically the potential loss of a risky asset or investment portfolio on the stock over a defined timeframe for a given confidence level. VaR model measures market risk by determining how much value of a portfolio could drop over a given period with a given probability because of changes in market prices or rates. Companies can be prepared for losses when VaR is determined to lower the impact of the market risk upon the prices of shares. VaR has been introduced first in the late 1980s by brokerage and investment funds to gauge the risk of their trading portfolios. VaR is a quantile of a return distribution function where the portfolio represents the percentile of its return distribution of two parameters, a period and a confidence level. It measures the maximum loss of the portfolio value that will occur over some period at some specific confidence level due to risky market factors [21]. Various approaches to estimating Value-at-Risk (VaR), including historical simulation, parametric, and Monte Carlo methods, have been thoroughly discussed in the literature [9]. The Monte Carlo simulation is about imagining hypothetical future data whereas the non-parametric approach uses actual historical data while the parametric approach does not require any data. Monte Carlo simulation is a widely used method in financial engineering to model the risk and uncertainty of complex portfolios [13].

The historical simulation is a non-parametric approach to find VaR where the return on the portfolio is calculated over a period using historical data and the VaR is taken to be the loss that is exceeded within the sample. Historical simulation provides a practical, non-parametric method of estimating VaR without relying on distributional assumptions [2]. It uses past data as a guide to what will happen in the future. As discussed by Hull and White [17], the first step is to determine the market variables affecting portfolio typically be interest rate, equity prices and so on. Specifically, in the case of historical simulation, this applies to the asset or the portfolio, the historical returns are taken and sorted from worst to gains to provide a normal distribution curve and a confidence level is selected, for example a confidence level at 95% represents such that 95% of the historical returns were gains and the remaining five percent were worse, therefore we can say that on a historical basis, we are 95% confident that our losses will not be worse than the 5% lower level. Nevertheless, the historical simulation method assumes that the future return distribution for a portfolio will be like that of the past. As stated by the Bank Negara Malaysia, the Basel committee has fixed a definitive confidence level of 99% used in any official reports as a higher confidence level is required to measure the capital demand, but the 95% confidence level can be used for verifying the VaR model.

The Geometric Brownian Motion (GBM) is a continuous stochastic process where the logarithm of the randomly varying quantity follows the Brownian Motion or the Wiener process. GBM is commonly used in financial mathematics to compute stock prices so that forecasting can be made.

Investors face market risk in stocks investment every day and experience losses due to factors that affect the overall performance of the financial markets in which the investors are involved. To hedge against it, Value at Risk can show the probability of how much loss can occur by using the historical simulation method. Therefore, in this study, two main objectives were proposed, to compute the VaR value of ten stocks based on the top 10 companies to invest in the first quarter of 2017 listed by the Malaysian Stock Exchange using the non-parametric approach of historical simulation method, and to use the Geometric Brownian Motion to predict the future prices of stocks for the 14 days and calculate the Mean Absolute Percentage Error (MAPE).

2. Literature Review

VaR can be calculated with various methods and research has been carried out to analyse each result obtained from all methods. Bo and Dai [4] studied on both parametric and non-parametric approach in calculating VaR and concluded that the VaR modelling is the prediction of the highest expected loss for a given portfolio and estimate losses by approximating the lower quantile in the portfolio return distribution.

Later, Kondapaneni and Rajesh [22] described the Delta-Normal method of computing VaR and compared it to the Historical Simulation and Monte Carlo method. He found out that Delta-Normal would be suitable if the distribution is normal and Historical Simulation method of calculating Value-at-Risk would be ideally suited if the distribution is non-normal, based on the normality of the distribution of the portfolio risk factors. The risk factors refer to represent market variables such as prices, interest rates, spreads or implied volatility.

VaR can calculate the probability of maximum loss not only in stocks investment but also for bonds, securities, commodities and others. Haugland and Jone [16] did a study on the historical simulation VaR on oil prices and showed that the amount of subadditivity is found to be strongly dependent on the correlation is steadily dependent between the individual portfolios.

The research department of J.P. Morgan has been actively studying VaR and produced a program called RiskMetrics to easily calculate VaR. In the September 2008 Investment Analytics and Consulting Newsletter by Berry and Romain [3] demonstrated the analytical VaR by collecting the historical data on securities in a portfolio and estimated the expected prices, volatility and correlations, and focused on market risk. He uses two sophisticated stages to computing VaR: outlining the positions to risk factors and choosing the volatility model of a portfolio after expressing the VaR mathematically.

Malaysian investment firms have also started to use VaR and research has been made to support the application of VaR on the Malaysian Stock Exchange. Dargiri *et al.,* [7] presented a study on the application of VaR and Conditional VaR (CVaR) method with both parametric and non-parametric approaches on the shares of Malaysian Industries and put into use the backtesting technique to measure the accuracy of predicted VaR and CVaR. The result shows a significant difference between both VaR models where VaR is likely to underrate the risk while CVaR overrates it. Recent literature has expanded the application of VaR models with enhancements that incorporate machine learning and real-time data modelling to increase accuracy and responsiveness [26]. These developments reflect a broader shift toward adaptive and data-driven forecasting in financial risk management.

Recent studies have extended traditional VaR estimation approaches. For instance, Xie [25] conducts a comparative evaluation of historical simulation, variance-covariance, and Monte Carlo methods using NASDAQ data and finds that Monte Carlo and parametric models are more responsive to tail risk. Huo *et al.,* [18] propose a novel Period VaR (PVaR) methodology that measures risk over intervals rather than at a fixed horizon, using Monte Carlo estimation to improve precision. Darmawan *et al.,* [8] compare all three major VaR approaches in Indonesian mining sector stocks, demonstrating distinct sensitivity by method. On the forecasting side, Ibrahim *et al.,* [20] assess GBM, fractional GBM, and Jump-Diffusion models for Malaysian rubber prices, highlighting the efficacy of jump-diffusion in capturing volatility shocks.

Investors will have a better insight into the investments or trading that they have made if they are enlightened or know the worst loss they may face in their investments. Nevertheless, it will be better if the investors can forecast the prices of the stocks for the next day to have a more reliable and safer trading and investments. Ladde *et al.,* [23] worked on research where historical stock prices and basic statistics have been used to test the accuracy of the GBM model. The results showed that data partitioning produces a better outcome on the usage of GBM model and the historical data. In addition, environmental random disruptions affect an alteration on the parameters in the GBM model.

In research conducted by Brewer *et al.,* [5], a financial modeling of the Geometric Brownian Motion process is computed using a simulation with Windows Excel following a stochastic process of the stock price shift. This exercise is based on the Black-Scholes option pricing model and is widely used in investment firms as it is the simplest stochastic method. Abidin *et al.,* [1] have used the Geometric Brownian Motion method in their research where they made a forecast on the stock prices of SMEs or small and medium sized companies listed by Bursa Malaysia. They showed how GBM is used and proved that GBM is suitable for short-term investment since investors are looking to make a profit in a short period of time. Later, they used the Mean Absolute Percentage Error (MAPE) method to calculate the error between the actual closing price and the forecasted price. It has been identified that a one-week historical price is sufficient to generate the predicted prices under the GBM process.

Estember *et al.,* [10] carried out research to prove that GBM is a method that is effective and accurate in predicting future daily stock prices as compared to the Artificial Neural Network where the historical prices of companies are taken from the Philippine Stock Exchange. It produced a positive result as proposed earlier that the GBM method is more accurate than the Artificial Neural Network and hence GBM method gives investors' confidence to choose which stocks to invest in. Other than stock prices, the GBM method can also be used to forecast the price of precious metals and commodities. As shown in research by Ibrahim and Iqmal [19], the GBM method is being demonstrated in computing the predicted future price of rubber and latex. Similarly, the mean, volatility and drift are required for the parameters of the GBM method. The MAPE is later calculated to identify the error difference between the actual and forecasted price.

3. Methodology

3.1 Value-at-Risk

We know that VaR represents the worst expected loss, then we will identify the distribution of portfolio return. The data of the stock prices must be normally distributed with mean, μ, and standard deviation, σ. Let $f_{\Delta P}$ be the probability distribution function (pdf) of ΔP and c be the confidence level. Then, we have:

$$1 - c = \int_{-\infty}^{-VaR} f_{\Delta P}(x)dx. \quad (1)$$

To obtain VaR, let:

$$\alpha = \frac{z-\mu}{\sigma}. \quad (2)$$

Then, we have $z = -VaR$ and $\alpha = -\alpha$, since VaR represents loss in negative value. Hence,

$$VaR = \alpha\sigma - \mu, \quad (3)$$

where σ can be obtained from the standard normal table corresponding to the confidence level. In this case, we know that α is 2.33 if c is 99% and α is 1.65 if c is 95%. But since VaR is located at the left tail, we take $\alpha = -\alpha$.

Fransson *et al.,* [12] presented with the mathematical representation of VaR as follows:

$$P(R \leq -x_a) = 1 - \alpha, \quad (4)$$

where the probability of return, R, is less than $-x_a$ and equals to the complement of the significance level α. The portfolio return, ΔP, is denoted by,

$$\Delta P = P_{t+1} - P_t, \quad (5)$$

where P_t and P_{t+1} are the portfolio values at time t and $t+1$, respectively. The arithmetic rate of return, R_a is given by:

$$R_a = \frac{P_t + P_{t-1}}{P_{t-1}}. \quad (6)$$

The geometric rate of return R_t is given by:

$$R_t = \ln \frac{P_t}{P_{t-1}} = \ln(1 + R_a). \quad (7)$$

where P is the price and t is the number of days. Let $R_{t,n}$ be the rate of return during the last n periods, the geometric return would be:

$$R_{t,n} = \ln \frac{P_t}{P_{t-n}} = \ln \frac{P_t}{P_{t-1}} + \ln \frac{P_t}{P_{t-2}} + \cdots + \ln \frac{P_t}{P_{t-n}} = R_t + R_{t-1} + \cdots + R_{t-n+1}. \quad (8)$$

where $R_{t,n}$ is the rate of return during the last n periods is the sum of n previous rate Jorion [21]. Therefore, VaR can be written as:

$$VaR_{1-\alpha} = -x_\alpha R_t. \quad (9)$$

Assume that a portfolio of n financial assets and denote the price of i-th financial asset at day t as $P_t^i (i = 1, \ldots, N; t = T - n + 1)$ where T is today. The portfolio value at time T is given by:

$$P_T = \sum_{t=1}^{N} w_t P_t^i, \quad (10)$$

where w_t is the weight of each stock in the portfolio at time T. The relative return of each stock is given by:

$$R_t = \left(\ln \frac{P_t}{P_{t-i}}\right) 100y, \tag{11}$$

Where y denotes the investment value. Since z_α is the left-tail α percentile of a standard normal distribution, we have:

$$z_\alpha = \frac{x_\alpha - \mu}{\sigma}, \tag{12}$$

and x_α can be written as $x_\alpha = \mu + \sigma z_\alpha$. Hence, VaR can be obtained by:

$$VaR_{1-\alpha} = -(\mu + \sigma z_\alpha)R_t, \tag{13}$$

where μ is the weighted mean of the asset, and σ is the standard deviation.

We take the initial price of a portfolio P_0, and the rate of return R for this portfolio is normally distributed with mean μ, and standard deviation σ, the portfolio value at the end of the time horizon is $P_1 = P_0(1 + R)$ with mean $P_0(\mu)$ and standard deviation $P_0(\sigma)$. Denoting the lowest portfolio value at some confidence level, C as $P_1^* = P_0^*(1 + R)$. Then, the VaR relative to the expected return is $VaR(mean) = P_0(\mu - R^*)$. Assuming the expected return is zero, then $VaR\ (zero) = -P_0R^*$. Transforming $R^* = -(\alpha\sigma - \mu)$, we have $VaR(mean) = P_0\alpha\sigma$.

3.2 Historical Simulation

Halulu and Sila [14] states that the non-parametric approach uses historical data to run the simulation statistically and produces a cumulative distribution function to compute the VaR for the relative returns. The data used are the daily prices of stocks of companies listed in Bursa Malaysia for a ten-year period and the data was obtained from Yahoo Finance.

The first step to compute the Value-at-Risk in Microsoft excel is to find the logarithmic return of the closing prices as stated in Eq. (7) where the current price is divided by the price of the previous day and the natural logarithm is applied to it. Secondly, we set the value of portfolio investment to RM10,000 so that we can calculate the relative daily return value and compare among all other stocks. This will produce a series of return values, and it will then be inserted into the excel formula as discussed above. In this research both 99% and 95% confidence level is computed as a comparison.

3.3 Geometric Brownian Motion

In this section, we will show how the future stock prices of the 10 companies listed previously using the Geometric Brownian Method (GBM) as it is suitable to forecast the short-term investment whereas the Markov-Fourier grey model can be used for long-term investment. In this case, investors can gain more profit after investment even in a short period of time and they can decide immediately. This section discusses the results obtained from the surface pressure measurement study. The effects of angle of attack, Reynolds number and leading-edge bluntness are discussed in the next sub section.

The daily closing prices of the stocks are collected daily for a two-week period and the prices are forecasted for the next two weeks. The GBM follows the Markov and Martingale properties. A stochastic process has the Markov property if the conditional probability distribution of future states of the process which is conditional on both past and present states, depends only upon the present state, not on the sequence of events that preceded it. Whereas the Martingale property states that the expectation of the next value in the sequence is equal to the present observed value even given knowledge of all prior observed values.

The GBM process depends on four main requirements which are the volatility, randomness, return on investment and drift to form the stochastic differential equation. Wilmott and Paul [24] states that investors are more interested in the return on investment or simply the growth in their portfolio value. Therefore, we take the previous definition of the arithmetic rate of return in Eq. (6). We take n as the number of returns in this observation, then we represent the mean of the return's distribution as the drift μ as follows:

$$\mu = \overline{R_a} = \frac{1}{n}\sum_{t-1}^{n} R_a. \tag{14}$$

Now we represent the sample standard deviation as the volatility σ as follows:

$$\sigma = \sqrt{\frac{1}{n-1}\sum_{t-1}^{n} R_a - \overline{R_a}}. \tag{15}$$

Now we form the stochastic model with the price of stock at time, P, the volatility σ, the random value at time t, X_0, and the drift μ, represented as follows:

Given that $e^c = P_0$, then the stochastic differential equation for $\ln P$ is:

$$P_t = P_0 e^{\left(\mu - \frac{1}{2}\sigma^2\right)t + \sigma(X_t - X_0)}. \tag{16}$$

3.4 Mean Absolute Percentage Error (MAPE)

The computation of the MAPE is defined as such:

$$MAPE = \frac{\sum\left|\frac{A_t - F_t}{A_t}\right|}{n}, \tag{17}$$

where A_t is the actual price at time t, n is the number of forecast periods, and F_t is the forecast price at time t. Table 1 shows the scale of judgement of forecasting accuracy using MAPE as stated by Abidin *et al.,* [1].

Table 1
Scale of judgement of forecast accuracy

MAPE	Accuracy
$\leq 10\%$	Highly accurate
$11 - 20\%$	Good
$21 - 50\%$	Reasonable
$\geq 51\%$	Inaccurate

The lower the MAPE value, the forecasting model gets more accurate as the error difference between the actual price At and forecast price Ft is relatively small. With this MAPE method and the forecasting scale stated in Table 1, some analysis can be made on the forecast price computed by the GBM method.

4. Results Summary

In the beginning of this chapter, we present the numerical results of the value-at-risk of the stocks listed by the Malaysian Stock Exchange under the historical simulation method. All investigations were carried on using Microsoft Excel as stated in the previous chapter. The following table is the list of top 10 stocks to invest in the first quarter of 2017 provided by Yahoo! Finance.

Table 2
Top 10 stocks to invest in 2017

	Code	Symbol	Name
1	1155	MAYBANK	Malayan Banking Berhad
2	5347	TNB	Tenaga Nasional Berhad
3	1023	CIMB	Cimb Group Holdings Berhad
4	5819	HLBANK	Hong Leong Bank Berhad
5	1066	RHB	Rhb Bank Berhad
6	3336	IJM	Ijm Corporation Berhad
7	5099	AIRASIA	Airasia Berhad
8	1015	AMMB	Ammb Holdings Berhad
9	5014	MAHB	Malaysia Airports Holdings Bhd
10	1171	MBSB	Malaysia Building Society Bhd

First, we show that the historical data of each stocks follows a log-normal distribution based on the logarithmic returns calculated form the set of data of daily prices for 10 years from January 2007 to December 2016 and the pattern is shown as Figure 1 – Figure 10 below:

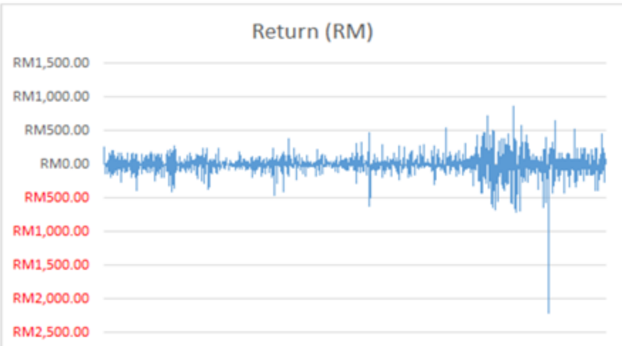


Fig. 1. MAYBANK

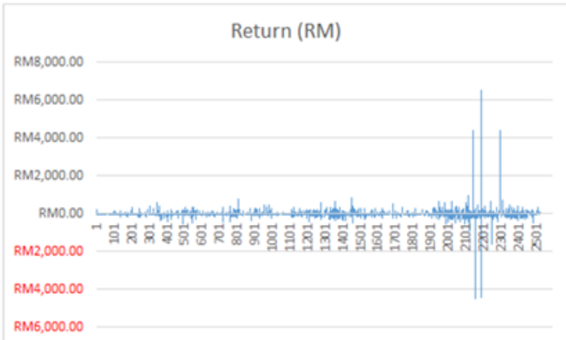


Fig. 2. TNB

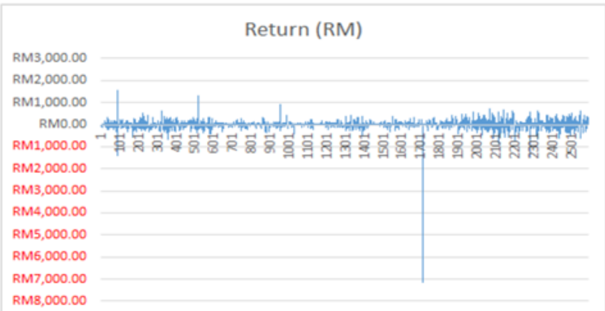


Fig. 3. CIMB

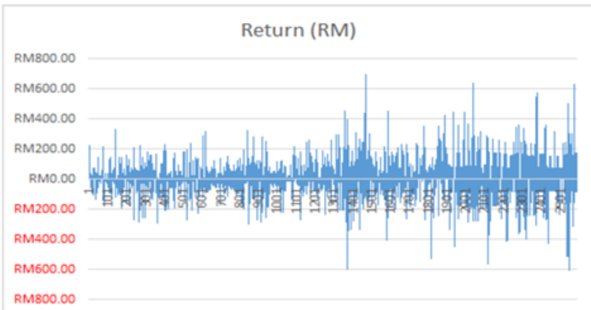


Fig. 4. HLBANK

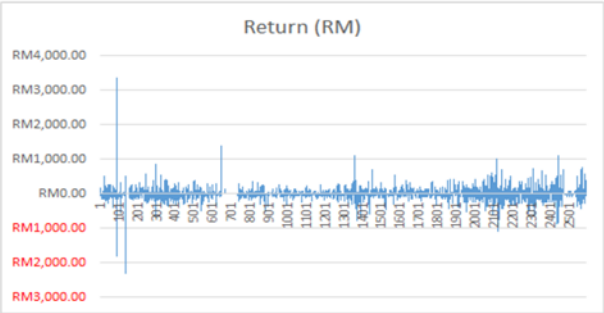


Fig. 5. RHB

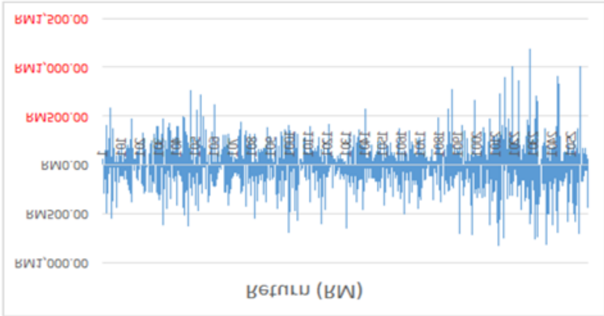


Fig. 6. IJM

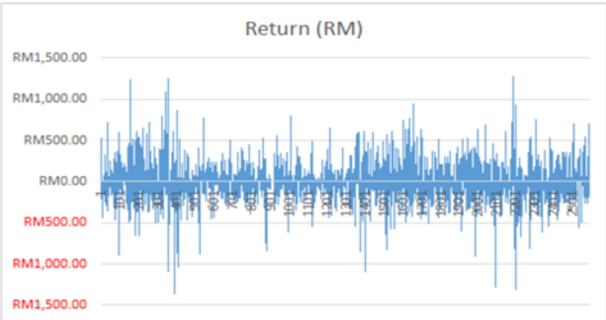


Fig. 7. AIRASIA

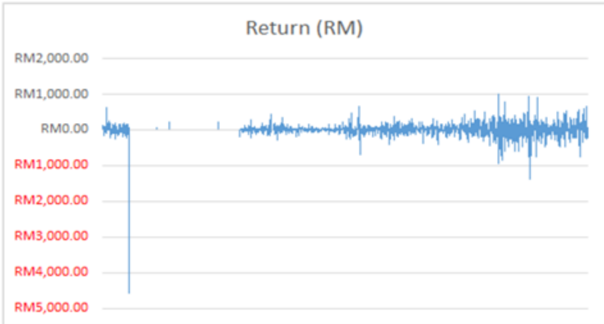


Fig. 8. AMMB

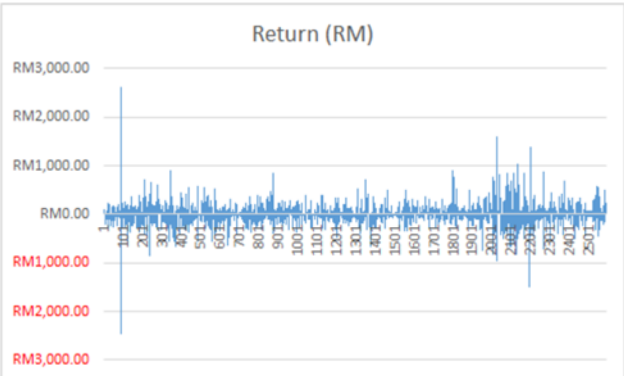


Fig. 9. MAHB

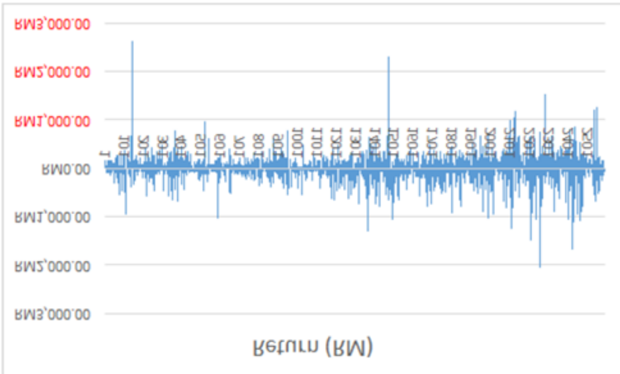


Fig. 10. MBSB

As we can see from all the charts above, they show a similar trend or pattern on the distribution of the returns on the daily investment but there may be an outlier as it is possible for a high jump or drop in the prices to occur under several circumstances, that effects the distribution to have an anomaly in the charts. Since, the distribution is log-normally distributed, we can now find the Value-at-Risk of each stocks using the historical data and a confidence level of 99% and 95% with an investment value of RM10,000. The result is shown in Table 3.

Table 3
VaR value of each stock

	Stocks	VaR	
		99%	95%
1	HLBANK	2.93%	1.74%
2	TNB	3.92%	2.11%
3	MAYBANK	4.04%	1.81%
4	AMMB	4.45%	2.02%
5	CIMB	4.54%	2.55%
6	RHB	4.62%	2.40%
7	MAHB	4.79%	2.83%
8	IJM	4.90%	2.79%
9	AIRASIA	5.76%	3.37%
10	MBSB	6.72%	3.24%

Now we calculate the forecasted price under the GBM model and the MAPE of each stock, and we display the results in Tables 4 - 13.

Table 4
MAYBANK

Date	Actual	Forecast	Error
12/14/2016	7.95	8.16	0.03
12/15/2016	7.92	8.46	0.07
12/16/2016	7.94	7.71	0.03
12/19/2016	7.92	7.66	0.03
12/20/2016	7.91	7.85	0.01
12/21/2016	7.87	7.79	0.01
12/22/2016	7.76	7.58	0.02
12/23/2016	7.74	7.68	0.01
12/26/2016	7.74	7.78	0.01
12/27/2016	7.75	8.03	0.04
12/28/2016	7.95	8.13	0.02
12/29/2016	7.98	8.25	0.03
12/30/2016	8.20	8.11	0.01
Total			0.31
Daily Variance			0.00
Annualized Variance			0.02
Annualized Standard Deviation			0.15
n			13
MAPE			2.41%
VaR (99%)		(RM404.11)	4.04%
VaR (95%)		(RM181.15)	1.81%

Table 5
TNB

Date	Actual	Forecast	Error
12/14/2016	13.78	13.69	0.01
12/15/2016	13.76	13.41	0.03
12/16/2016	13.76	13.42	0.02
12/19/2016	13.70	13.61	0.01
12/20/2016	13.72	13.92	0.01
12/21/2016	13.76	14.26	0.04
12/22/2016	13.74	14.13	0.03
12/23/2016	13.66	14.29	0.05
12/26/2016	13.66	13.85	0.01
12/27/2016	13.62	13.85	0.02
12/28/2016	13.60	13.55	0.00
12/29/2016	13.90	13.45	0.03
12/30/2016	13.90	13.10	0.06
Total			0.31
Daily variance			0.00
Annualized Variance			0.00
Annualized Standard deviation			0.06
n			13
MAPE			2.41%
VaR (99%)		(RM391.98)	3.92%
VaR (95%)		(RM210.97)	2.11%

Table 6
CIMB

Date	Actual	Forecast	Error
12/14/2016	4.65	4.64	0.00
12/15/2016	4.62	4.80	0.04
12/16/2016	4.60	4.49	0.02
12/19/2016	4.60	4.33	0.06
12/20/2016	4.60	4.49	0.02
12/21/2016	4.54	4.60	0.01
12/22/2016	4.57	4.70	0.03
12/23/2016	4.58	4.63	0.01
12/26/2016	4.58	4.68	0.02
12/27/2016	4.58	4.57	0.00
12/28/2016	4.56	4.23	0.07
12/29/2016	4.56	4.36	0.04
12/30/2016	4.51	4.03	0.1
Total			0.45
Daily variance			0.00
Annualized Variance			0.02
Annualized Standard deviation			0.16
n			13
MAPE			3.43%
VaR (99%)		(RM454.38)	4.54%
VaR (95%)		(RM254.75)	2.55%

Table 7
HLBANK

Date	Actual	Forecast	Error
12/14/2016	13.36	13.34	0.00
12/15/2016	13.34	13.57	0.02
12/16/2016	13.22	13.63	0.03
12/19/2016	13.28	13.51	0.02
12/20/2016	13.26	13.50	0.02
12/21/2016	13.24	13.46	0.02
12/22/2016	13.16	13.92	0.06
12/23/2016	13.08	13.81	0.06
12/26/2016	13.08	13.76	0.05
12/27/2016	13.06	13.69	0.05
12/28/2016	13.08	13.44	0.03
12/29/2016	13.38	13.80	0.03
12/30/2016	13.50	14.02	0.04
Total			0.41
Daily variance			0.00
Annualized Variance			0.01
Annualized Standard deviation			0.08
n			13
MAPE			3.18%
VaR (99%)		(RM293.48)	2.93%
VaR (95%)		(RM173.67)	1.74%

Table 8
RHB

Date	Actual	Forecast	Error
12/14/2016	4.84	5.06	0.04
12/15/2016	4.77	4.75	0.00
12/16/2016	4.82	5.47	0.13
12/19/2016	4.82	4.99	0.04
12/20/2016	4.77	4.77	0.00
12/21/2016	4.70	4.40	0.06
12/22/2016	4.68	4.07	0.13
12/23/2016	4.65	4.30	0.08
12/26/2016	4.65	4.57	0.02
12/27/2016	4.64	4.36	0.06
12/28/2016	4.65	4.28	0.08
12/29/2016	4.74	4.69	0.01
12/30/2016	4.71	4.83	0.03
Total			0.68
Daily variance			0.00
Annualized Variance			0.09
Annualized Standard deviation			0.30
n			13
MAPE			5.24%
VaR (99%)		(RM462.15)	4.62%
VaR (95%)		(RM239.91)	2.40%

Table 9
IJM

Date	Actual	Forecast	Error
12/14/2016	3.30	3.32	0.01
12/15/2016	3.30	3.49	0.06
12/16/2016	3.30	3.46	0.05
12/19/2016	3.30	3.49	0.06
12/20/2016	3.40	3.65	0.07
12/21/2016	3.40	3.41	0.00
12/22/2016	3.42	3.60	0.05
12/23/2016	3.42	3.78	0.11
12/26/2016	3.42	3.93	0.15
12/27/2016	3.42	3.78	0.11
12/28/2016	3.40	3.48	0.02
12/29/2016	3.40	3.29	0.03
12/30/2016	3.40	3.38	0.01
Total			0.72
Daily variance			0.00
Annualized Variance			0.13
Annualized Standard deviation			0.36
n			13
MAPE			5.54%
VaR (99%)		(RM489.72)	4.90%
VaR (95%)		(RM279.11)	2.79%

Table 10
AIRASIA

Date	Actual	Forecast	Error
12/14/2016	2.52	2.46	0.02
12/15/2016	2.53	2.60	0.03
12/16/2016	2.50	2.61	0.04
12/19/2016	2.46	2.42	0.02
12/20/2016	2.40	2.06	0.14
12/21/2016	2.35	2.13	0.09
12/22/2016	2.35	2.29	0.02
12/23/2016	2.31	2.31	0.00
12/26/2016	2.31	1.98	0.14
12/27/2016	2.21	2.02	0.08
12/28/2016	2.33	2.13	0.09
12/29/2016	2.28	2.15	0.06
12/30/2016	2.29	2.31	0.01
Total			0.76
Daily variance			0.00
Annualized Variance			0.10
Annualized Standard deviation			0.31
n			13
MAPE			5.82%
VaR (99%)		(RM575.96)	5.76%
VaR (95%)		(RM337.48)	3.37%

Table 11
AMMB

Date	Actual	Forecast	Error
12/14/2016	4.45	4.74	0.06
12/15/2016	4.43	4.78	0.08
12/16/2016	4.44	4.68	0.05
12/19/2016	4.40	4.56	0.04
12/20/2016	4.40	3.81	0.13
12/21/2016	4.36	3.61	0.17
12/22/2016	4.28	3.57	0.17
12/23/2016	4.26	3.70	0.13
12/26/2016	4.26	3.74	0.12
12/27/2016	4.28	4.20	0.02
12/28/2016	4.32	4.22	0.02
12/29/2016	4.25	4.20	0.01
12/30/2016	4.31	4.42	0.03
Total			1.04
Daily variance			0.00
Annualized Variance			0.12
Annualized Standard deviation			0.35
n			13
MAPE			8.00%
VaR (99%)		(RM445.17)	4.45%
VaR (95%)		(RM202.03)	2.02%

Table 12
MAHB

Date	Actual	Forecast	Error
12/14/2016	6.06	6.66	0.10
12/15/2016	6.00	6.19	0.03
12/16/2016	6.00	5.48	0.09
12/19/2016	5.97	5.49	0.08
12/20/2016	6.01	5.55	0.08
12/21/2016	6.01	5.80	0.04
12/22/2016	6.06	5.91	0.02
12/23/2016	6.19	6.15	0.01
12/26/2016	6.20	6.43	0.04
12/27/2016	6.23	6.30	0.01
12/28/2016	6.25	6.57	0.05
12/29/2016	6.32	6.30	0.00
12/30/2016	6.37	6.99	0.10
Total			0.64
Daily variance			0.00
Annualized Variance			0.06
Annualized Standard deviation			0.25
n			13
MAPE			4.95%
VaR (99%)		(RM478.67)	4.79%
VaR (95%)		(RM282.8)	2.83%

Table 13
MBSB

Date	Actual	Forecast	Error
12/14/2016	0.90	0.93	0.04
12/15/2016	0.91	0.89	0.02
12/16/2016	0.90	0.95	0.06
12/19/2016	0.90	0.91	0.01
12/20/2016	0.90	0.84	0.06
12/21/2016	0.90	0.85	0.06
12/22/2016	0.91	0.89	0.02
12/23/2016	0.91	0.89	0.02
12/26/2016	0.91	0.86	0.06
12/27/2016	0.92	0.86	0.06
12/28/2016	0.92	0.91	0.01
12/29/2016	0.90	0.94	0.05
12/30/2016	0.90	0.95	0.05
Total			0.51
Daily variance			0.00
Annualized Variance			0.03
Annualized Standard deviation			0.17
n			13
MAPE			4.00%
VaR (99%)		(RM671.62)	7.00%
VaR (95%)		(RM323.79)	3.00%

5. Conclusion

In conclusion, this study successfully demonstrates the application of the Value-at-Risk (VaR) model using the historical simulation method to assess market risk in stock investments. The VaR model provides a quantitative measure of the potential loss in value of a portfolio under normal market conditions, thereby supporting investors and institutions in making informed risk management decisions. Additionally, the Geometric Brownian Motion (GBM) model was employed to forecast stock prices over a 14-day horizon, with the Mean Absolute Percentage Error (MAPE) used to evaluate the forecasting accuracy. The results indicate that both objectives of the study were achieved, affirming the effectiveness of non-parametric VaR analysis and GBM-based prediction for stock price behaviour. Future research can explore advanced risk estimation techniques such as the Delta-Normal and Delta-Gamma approaches, as well as integrating machine learning models to enhance forecasting precision and risk prediction in volatile markets.

Acknowledgement
This research was not funded by any grant.

References
[1] Abidin, Siti Nazifah Zainol, and Maheran Mohd Jaffar. "Forecasting share prices of small size companies in Bursa Malaysia using geometric Brownian motion." *Applied Mathematics & Information Sciences* 8, no. 1 (2014): 107. https://doi.org/10.12785/amis/080112
[2] Alexander, Carol. *Market risk analysis, quantitative methods in finance*. John Wiley & Sons, 2008.
[3] Berry, Romain. "Value-at-Risk: An overview of analytical VaR." *Investment Analytics and Conculting, Septermber* (2008).
[4] Bo, Dai. "Value at risk." *The National University of Singapore, Department of Mathematical* (2001).

[5] Brewer, Kevin D., Yi Feng, and Clarence CY Kwan. "Geometric Brownian motion, option pricing, and simulation: Some spreadsheet-based exercises in financial modeling." *Spreadsheets in Education* 5, no. 3 (2012): 4598.
[6] Christoffersen, Peter. *Elements of financial risk management*. Academic press, 2011. https://doi.org/10.1016/B978-0-12-374448-7.00011-7
[7] Dargiri, M. N., H. A. Shamsabadi, C. K. Thim, D. Rasiah, and B. Sayedy. "Value-at-risk and conditional value-at-risk assessment and accuracy compliance in dynamic of Malaysian industries." *Journal of Applied Sciences* 13, no. 7 (2013): 974-983. https://doi.org/10.3923/jas.2013.974.983
[8] Darmawan, Muhammad Rizky, and Fathi Atha Putra Widyono. "Comparative Analysis: Value at Risk (VaR) with Parametric Method, Monte Carlo Simulation, and Historical Simulation of Mining Companies in Indonesia." *International Journal of Quantitative Research and Modeling* 5, no. 4 (2024). https://doi.org/10.46336/ijqrm.v5i4.834
[9] Dowd, Kevin. *Measuring market risk*. John Wiley & Sons, 2007.
[10] Estember, Rene D., and Michael John R. Maraña. "Forecasting of stock prices using Brownian motion–Monte Carlo simulation." In *International conference on industrial engineering and operations management*, pp. 8-10. 2016.
[11] Fabozzi, Frank J., and Harry M. Markowitz, eds. *The theory and practice of investment management: Asset allocation, valuation, portfolio construction, and strategies*. Vol. 198. John Wiley & Sons, 2011. https://doi.org/10.1002/9781118267028
[12] Fransson, Cecilia, and Behnaz Alimohammadisagvand. "Market risk in volatile times: a comparison of methods for calculating Value at Risk." (2011).
[13] Glasserman, Paul. *Monte Carlo methods in financial engineering*. Vol. 53. New York: springer, 2004. https://doi.org/10.1007/978-0-387-21617-1
[14] Halulu, Sıla. "Quantifying the risk of portfolios containing stocks and commodities." PhD diss., Master Thesis. Boğaziçi University, 2012.
[15] Harrington, Scott E., and Greg Niehaus. "Risk management and insurance." (1999).
[16] Haugland, Jone. "Value-at-risk: A coherent measure of risk?." *management* 53, no. 3: 483-494.
[17] Hull, J. and White, A., 1998. Incorporating volatility updating into the historical simulation method for value-at-risk. *Journal of risk*, *1*(1), pp.5-19. https://doi.org/10.21314/JOR.1998.001
[18] Huo, Yanli, Chunhui Xu, and Takayuki Shiina. "Period value at risk and its estimation by Monte Carlo simulation." *Applied Economics Letters* 29, no. 18 (2022): 1675-1679. https://doi.org/10.1080/13504851.2021.1958136
[19] Ibrahim, Siti Nur Iqmal. "Modeling rubber prices as a GBM process." *Indian J. Sci. Technol* 9 (2016): 1-6. https://doi.org/10.17485/ijst/2016/v9i28/97353
[20] Ibrahim, Siti Nur Iqmal, and Nasrin Zulaikha Muda. "Comparison of GBM, GFBM and MJD models in Malaysian rubber prices forecasting." *Malaysian Journal of Fundamental and Applied Sciences* 19, no. 1 (2023): 73-81. https://doi.org/10.11113/mjfas.v19n1.2763
[21] Jorion, P. (1997). Value at risk. McGraw-Hill, New York.
[22] Kondapaneni, Rajesh. "A Study of the Delta-Normal Method of Measuring VaR." PhD diss., Worcester Polytechnic Institute, 2005.
[23] Ladde, G. S., and Ling Wu. "Development of modified geometric Brownian motion models by using stock price data and basic statistics." *Nonlinear Analysis: Theory, Methods & Applications* 71, no. 12 (2009): e1203-e1208. https://doi.org/10.1016/j.na.2009.01.151
[24] Wilmott, Paul. *Paul Wilmott on quantitative finance*. John Wiley & Sons, 2013.
[25] Xie, Y. "Historical Simulation, Variance-Covariance and Monte Carlo Simulation Methods for Market Risk Assessment": From NASDAQ Index 2015–2024. *Advances in Economics, Management and Political Sciences*, 171, 24–31. (2025). DOI: 10.54254/2754-1169/2025.21835. https://doi.org/10.54254/2754-1169/2025.21835
[26] Zhao, Y., Wang, J., & Li, X. "Stock price forecasting using GBM and deep learning hybrid models." *Expert Systems with Applications*, 179, 115059. (2021).