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Applying Value-at-Risk on A Portfolio Investment in The Cambodia Securities Exchange

Siphat Lim*

ABSTRACT

Value-at-Risk (VaR) is a very famous and popular model which has been widely used to measure the potential exposure of the value of loss of an underlying asset or an investment portfolio at a certain confidence level and holding period. The main objective of this paper is the implement all of the three approaches applicable to estimate VaR namely non-parametric, parametric, and Monte-Carlo simulation VaR on the synthetic investment portfolio which consists of HKL's bond and five stocks listing and trading in CSX besides the securities the portfolio also includes the FX and commodity, such as, gold and crude oil. At the position date the initial market value of this portfolio is KHR 591,514,539. With the confidence level of 95% and the holding period of 1 day VaR is KHR 6,198,453, KHR 5,523,467 and KHR 5,354,189 estimated by the non-parametric, parametric and Monte-Carlo simulation respectively. This research also indicates that the non-parametric VaR is very simple to implement; therefore, this approach is highly recommended for the investors who intention is the estimate the risk exposure of the value of the assets or portfolio. On the other, the parametric and Monte-Carlo simulation approaches, which is perceivably more difficult than the non-parametric, are highly recommended for the study which intention is to seek high accuracy.

***Keywords:* VaR, CSX, Monte-Carlo Simulation, investment portfolio.**

1. INTRODUCTION

The value of the assets and the investment portfolios can change anytime at any moment by many factors namely the market factor of demand and supply of the underlying assets, and the risk encounter by the investors now and in the future. The uncertainty in the value of the underlying assets, especially the value of the financial assets and the commodity, has posted as an obstacle to the investors to maximize the profit of the investment portfolios hold in the balance sheet. Both the internal and external factors can cause an investment portfolio to loss its value at a short period of time and make the prediction a job of expertise which requires a lot of time, efforts and resources, yet vital to do. Although, the financial analysts cannot be 100 per cent sure about the future, their job is vital to ensure that the future is comprehensible and necessary measures is undertaken effectively to protect the investors and their investment from the potentially liquidity risk which can result in financial recession and bankruptcy.

In fact, various approaches have been developed by the professionals and researchers to predict and estimate the change in the value of the underlying assets and the investment portfolios. Significantly, the prediction and estimation of the variation of value of the underlying assets and investment portfolios are pivotal for managing risk, constructing the financial report and managing the finance to guarantee that the capital are effectively invested to maximize the profit, and the liquidity risk and insolvency risk are minimized to lowest level possible.

Among the many approaches, the Value at Risk (VaR) was developed in 1980s and has become a popular quantitative measurement technique in the early 1990s. VaR, moreover, is widely recognized and adopted by the analysts, professionals and researchers as a prolific technique to accurately measure the risk exposure of the underlying assets and investment portfolios. In accordance to Jorion (2007) claimed that with a predetermined confident level, VaR is able to generate the worst loss over a target horizon. With the ability to comprehend the worst future, the model enables the investors to make necessary preparation to ensure that they are secured from the liquidity risk. Basically, three

* This research was supported by a grant from the CamEd Business School. Correspondence concerning this article should be address to addressed Siphat Lim, CamEd Business School, No. 64 Street 108, Phnom Penh, Cambodia. Contact: lsiphat@cam-ed.com

different methods have been adopted to calculate VaR namely the historical stimulation also known as the non-parametric VaR, the parametric VaR or delta-gamma VaR and the Monte-Carlo simulation VaR.

The main purpose of this research paper is to calculate the Value at Risk of an investment portfolio which includes the financial assets, such as, all of five stocks and the Hattha Kaksekar Limited's bond which are listed and trading at Cambodia Securities Exchange (CSX), two commodities, gold and crude oil, and the foreign exchange (FX) are included in this investment portfolio. This study will employ all of three methods including the non-parametric VaR, the parametric VaR and the Monte-Carlo simulation VaR, as specified above to calculate the Value at Risk of this investment portfolio.

2. LITERATURE REVIEW

Measuring the capital at risk in the portfolio investment under the extreme scenario plays a vital role to enable the traders to foreseen the potential maximum capital loss at a particular time frame. The Value-at-Risk (VaR) is extensively adopted by the numerous financial institutions, investors and creditors as a risk assessment method to measure the maximum capital loss to an investment portfolio or risky assets over a period of time under the provided confidence interval. Soon after, it was introduced by J. P. Morgan in 1998 in their RiskMetrics which purposefully aims to publish the volatility and correlation information for stocks listed on the major markets in the world (Kaura, n.d.). Pafka and Kondor (2001) argued that the popular RiskMatrics is the artifice of the choice of risk assessment. Provided that the exceptional performance of volatility estimates is because of the short forecasting horizon and the satisfactory performance in obtaining the VaR is because of the choice of the confidence level.

The VaR method, however, is comprehensively conducted to determine the exposure of the capital to the potential market risks which is the extensively used by the creditors, such as, commercial and investment banks to study about the exposure of their portfolio investment to risk over a particular time to ensure that their capital and cash reserve can cover the value-at-risk without putting the firms at the financial distress. (Kaura, n.d.), Koch (2006), Goorbergh and Vlaar (1999), Shirazi (n.d.), Gregory and Reeves (2008), Hong, Hu, and Liu (2014), Linsmeier and Pearson (2000), Borgdan, Baresa, and Ivanovic (2015), Jorion (2007) and Wong, Cheng, and Wong (2003) have all comprehensively employed the VaR method in studying the exposure of the market risks on the portfolio investment. The Value at Risk can be computed by three methods, namely, the historical VaR, the parametric VaR and the Monte Carlo Simulation VaR with each method offers certain pros and cons.

The historical analysis, first and foremost, adopts the historical data from the market ratio or prices to empirically analyse the value at risk. Considered as the easiest method to measure the value at risk, this nonparametric method uses essentially the empirical distribution of portfolio returns, and is not required to fulfil any distributional assumptions (Goorbergh and Vlaar, 1999). The realistic historical information of the past event enables the researchers to accurately predict the possible future event (Kuara, n.d.). The readily available data also adds more simplicity to the method. For example, the historical trading data, such as, securities, is publicly available (Borgdan, Baresa, and Ivanovic, 2015). Only predetermining the time horizon of the data is required, and no mapping is required in comparison with the parametric method. On the contrary, the major drawback of this method is if the composition of the portfolio investment changes over time, collecting large sample size is unmanageable. Therefore, making this method becomes less feasible (Koch, 2006). The historical simulation approach using the historical asset returns data, however, is applicable to dealt with this problem. Yet, intensive computation is required for the large portfolio investment (Kuara, n.d.).

The parametric VaR method, which is also called by other names, including variance-covariance, and linear or delta normal VaR, is another popular method to measure the value-at-risk. According to Lausbch (1999), the parametric method also uses the historical data to measure the potential risk. Unlike the previous method, this method does not require long historical data which allows this method to be quickly and easily calculated. The mean value of the yield rate and the standard deviation of the same data are the two major variables used by the parametric method in the calculation. The primary requirement of the parametric method, however, is the data has to be normal distribution (Value-at-Risk, n.d.). Meaning that the mean value, arithmetic mean, mode and median are the same size and it has a bell shape. Lausbch (1999), on the other hand, stated that the hypothesis of the normal distribution is main disadvantage of the parametric model which makes it less feasible for the nonlinear portfolios and distorted distribution. Jackson, Maude and Perraudin (1997) which VaR was applied on the trading book of an anonymous bank, have concluded that the simulation approach provides more accurate measures of tail probabilities comparing to the parametric VaR. This can happen due to the arise of a serious non-normality of financial return. Lausbch also anticipated that the major limitation of the parametric model is the constancy of the computed standard deviation and correlation coefficients, in which value changes throughout the time. Hence, if the researchers fail to modify the computation due to the extreme values of VaR, it will result in the misinterpretation of the results.

Last but not least, Monte Carlo Simulation is last method for forecasting VaR. The Monte Carlo, basically, is a justify name for the stochastic method for computing VaR. Due to the fact that the method involves the computer simulation of various influences on the observed portfolio of securities (Borgdan, Baresa, and Ivanovic, 2015). Similar to the historical method, this method involves complex computation of the historical data to predict the future risk and potential loss with a statistical confidence interval. The complex computation which involves hundreds or thousands of possible scenarios and generates the feasible solution makes this method to be the most reliable method to compute VaR (Borgdan, Baresa, and Ivanovic, 2015). This method, additionally, can be employed to calculate both the value of stochastic and non-stochastic. Vose (1997) indicated that Monte Carlo is the mathematical risk analysis techniques which describe the impact of risk and uncertainty on the problem. The uncertain parameters in the model are characterised by distribution of probabilities. While that shape and size of these distribution describes range of values that parameters can have with their relative probabilities. Ostojić, Pokorni, Rakonjac, and Brkićm (2012) and Lausbch (1999) agreed that a major advantage for Monte Carlo method would be its effectiveness to accurately calculate the risk value of various financial instruments, yet this method does not necessarily require large historical data. Significantly, the Monte Carlo method support the use of different distribution, including t-distribution, normal and similar. While the major drawbacks for this method are the requirement for complex analysis and really time consuming. Finally, selecting the proper distribution is also vital to quantify the risk of thickened tail distribution.

VaR, in conclusion, is the maximum potential loss to a portfolio investment at a particular period of time. This risk assessment method is very handy for the investors and creditors to estimate the potential loss due to its applicability and simplicity, and the model itself has passed numerous modifications which aim to improve the precision to forecast the value-at-risk. Hendricks (1996) applied the VaR on 1,000 randomly selected foreign exchange portfolios from 1983-94. The study suggested that among the twelve approaches which was applied, none is perceived to have more superiority over the others. The choice on the confidence level, however, appears to have significant influence on the performance of VaR. Borgdan, Baresa, and Ivanovic, (2015), on the other hand, claimed that besides the many advantages that this model contains, the model should be applied with some precautions, for example, the model focus mainly on the portfolio losses but cannot entirely forecast the future losses. Most importantly, the dramatic price fluctuations can probably influence the computed value-at-risk and generate false security, such as, undervalued or overvalued risk. Hence, the VaR method has the best applicability in the stable market conditions.

In this paper, the VaR methods will be applied to study the expected loss of a constructed portfolio investment in the Cambodia Securities Exchange (CSX). This paper will employ the three estimated methods of VaR which are historical VaR, parametric VaR, and Monte Carlo Simulation VaR on a constructed portfolio investment in the CSX. The assets which are going to include in the constructed portfolio are fixed-income security, equities, commodities and FX.

3. METHODOLOGY

The main purpose of this research paper is to calculate the Value at Risk of an investment portfolio which includes the financial assets, such as, all of five stocks and the Hattha Kaksekar Limited's bond which are listed and trading at Cambodia Securities Exchange (CSX), two commodities, gold and crude oil, and the foreign exchange (FX) are included in this investment portfolio. This study will employ all of three methods including the non-parametric VaR, the parametric VaR and the Monte-Carlo simulation VaR, as specified above to calculate the Value at Risk of this investment portfolio. The position of this investment portfolio was constructed in January 22, 2019. Considering from that time period, only five stocks from five different companies were listed and trading at CSX. The detail information, the synthetic investment portfolio and the number of the position which are hold in this investment portfolio are all listed in Table 1.

Table 1: Synthetic Portfolio			
Classification	**Assets**	**Name**	**Units**
Fixed-income Security	Bond	Hattha Kaksekar Limited	100
Equity	PWSA	Phnom Penh Water Supply Authority	1,000
	GTI	Grand Twin International	1,000
	PPAP	Phnom Penh Autonomous Port	1,000
	PPSP	Phnom Penh SEZ Plc.	1,000
	PAS	Sihanoukville Autonomous Port	1,000
Commodity	Gold	Gold	100
	Crude Oil	Crude Oil	100
Foreign Exchange	FX	Khmer Riel/US Dollar	500

This study will use the daily data from January 2, 2018 to January 22, 2019 which the last date is regarded as the position date. Furthermore, the daily data is retrieved from the Bloomberg Terminal. On the other hand, the data of the Hattha Kaksekar Limited's bond are collected from CSX. Last but not least, to quote the daily bond price, the zero coupon yield (ZCY) will be used. However, because ZCY data of Cambodia is not available, Thailand ZCY will be adopted as the proxy. The ZCY will be retrieved from the Thai BMA which includes the ZCY-3-month, ZCY-6-month, ZCY-1-year, ZCY-2-year and ZCY-3-year. However, due to the fact that all of those ZCY are not fit with the time of cash of the HKL's bond, hence, the interpolated yield will, instead, be used to solve this problem.

$$Z_{0.3068} = Z_{0.2493} + \frac{(t_{0.3068} - t_{0.2493})(Z_{0.4986} - Z_{0.2493})}{(t_{0.4986} - t_{0.2493})}$$

$$Z_{0.8110} = Z_{0.4986} + \frac{(t_{0.8110} - t_{0.4986})(Z_1 - Z_{0.4986})}{(t_1 - t_{0.4986})}$$

$$Z_{1.3096} = Z_1 + \frac{(t_{1.3096} - t_1)(Z_2 - Z_1)}{(t_2 - t_1)}$$

$$Z_{1.8137} = Z_1 + \frac{(t_{1.8137} - t_1)(Z_2 - Z_1)}{(t_2 - t_1)}$$

$$Z_{2.3096} = Z_2 + \frac{(t_{2.3096} - t_2)(Z_3 - Z_2)}{(t_3 - t_2)}$$

$$Z_{2.8137} = Z_2 + \frac{(t_{2.8137} - t_2)(Z_3 - Z_2)}{(t_3 - t_2)}$$

The calculated result of the interpolated yield will be used as the discount rate to calculate the present value of the expected future cash flow of HKL's bond and the daily bond price using the below formula:

$$Bond\ Price = \sum_{i=1}^{N} \frac{CF_i}{\left(1 + \frac{ZYC_i}{100}\right)^i}$$

To calculate the VaR, two factors are required the confidence level and holding period or horizon. Five main step are required to calculate the VaR.

1. Mark position to market
2. Measure variability of the risk factors
3. Set time horizon
4. Set confidence level
5. Report potential loss

3.1. Non-parametric VaR

The initial value of the investment portfolio is notated by W_0 which create the return of investment R. In this study, the holding period is 1 day. Therefore, the value of this portfolio can be written as below after the next 1 day.

$$W = W_0 + W_0R = W_0(1+R)$$

Where, the expected value of R is and the standard deviation or volatility is .

Other the hand, the minimum value of portfolio with the confidence level, c can be written as the following:

$$W^* = W_0 + W_0R^* = W_0(1+R^*)$$

The money loss in comparison with the mean is called relative VaR.

$$\begin{aligned} VaR(mean) &= E(W) - W^* = W_0 + W_0E(R) - W_0 - W_0R^* \\ &= -W_0R^* + W_0E(R) = -W_0[R^* - E(R)] \\ &= -W_0(R^* - \mu) \end{aligned}$$

Since, $E(R) = \mu$

Thus,

$$VaR(0) = -W_0R^*$$

Other than this, VaR can also be calculated using the probability distribution of the future value of the portfolio f(w). The estimated minimum value of the portfolio W* which the probability can exceed W* is the confidence level, c which can we written as the below:

$$c = \int_{W^*}^{\infty} f(w)dw$$

Or

$$1 - c = \int_{-\infty}^{w^*} f(w)dw = P(w \leq W^*)$$

3.2. Parametric VaR

This method relies on the standard deviation of the portfolio which require the assumption of normal distribution. The expected value of the portfolio, f(w) is assumed to follow the standard normal distribution, $\Phi(\epsilon)$ where $\epsilon \sim (0,1)$ As demonstrated above, the minimum value of the portfolio can be written as:

W* = w (1+R*) which R* has a negative number, -|R*|

Thus,-Z_α score of-|R*| can be written as the following:

$$-Z_\alpha = \frac{-|R^*| - \mu}{\sigma} \quad (*)$$

Which is equivalent to:

$$1 - c = \int_{-\infty}^{W^*} f(w)dw = \int_{-\infty}^{-|R^*|} f(r)dr = \int_{-\infty}^{-Z_\alpha} \Phi(\epsilon)d\epsilon$$

From equation (*), the cutoff return is:

$$R^* = -Z_\alpha \sigma + \mu$$

According to the equation (*) and time interval, Δt

$$VaR(mean) = -W_0(R^* - \mu) = W_0 Z_\alpha \sigma \sqrt{\Delta t}$$

As demonstrated in equation (*) the main variables to calculate VaR is portfolio standard deviation. The first step required to undergo is to define the risk factor (RF) of each underlying asset in the portfolio (See Table 2.). The second step is to calculate the percentage of daily change of risk factor of each underlying asset using the formula below:

$\Delta RF = (S_t - S_{t-1}) \times 100$, for ZCY and FX

$\Delta RF = LN(S_t / S_{t-1})$, for fixed income security, equity and commodity

Table 2. Asset Classification and Risk Factor

Classification	Assets	Risk Factor
Fixed-income Security	Bond	ZCY
Equity	PWSA	PROP
	GTI	PROP
	PPAP	PROP
	PPSP	PROP
	PAS	PROP
Commodity	Gold	Gold Price and FX
	Crude Oil	Crude Oil Price and FX
Foreign Exchange	FX	USD

After ΔRF is calculated. The next step is calculate the Variance-Covariance Matrix (VCM) of ΔRF of all assets in the portfolio. In fact, a number of method, such as, Equal Weight (EW), Moving Average (MA), GARCH and ARCH, all can be employed for the calculation of VCM. In this research, however, EW will be adopted in the calculation of VCM. After the VCM is calculated, the portfolio standard deviation $SD(\sigma)$ can be calculated as below:

$$\sigma = \sqrt{\delta^T \Omega \delta}$$

Where:

σ : Portfolio standard deviation,

δ : Vector of change of value profit/loss with respect to change of risk factors,

Ω : Variance-Covariance Matrix

The parametric VaR can be written in a specific form as the following:

$$VaR = -Z_\alpha \times \sqrt{\delta^T \Omega \delta} \times \sqrt{HP}$$

Because this study chooses to use the 5% level of significant. Therefore, the Z-value is equal to 1.64. Additionally, the holding period (HP) is 1 day.

Down below is illustration of the Delta-Normal Method or change of value profit/loss with respect to change of risk factor of each asset.

Fixed-Income Security (Bond)

To estimate the change in Profit/Loss (P/L) of the investment on the fixed-income security or bond, in this research, the dollar value per one basis point (DV01) will be used and can be calculated using the formula below:

$$DV01 = \sum_{i=1}^{N} -\frac{t_i}{10000} \times CF_i \times \frac{1}{\left(1 + \frac{ZCY_{t_i}}{100}\right)^{t_i+1}}$$

Actually, HKL's Bond created cash flow six times counting from the issuing date until the maturity date which consists of three years from 2019 to 2021. Each year, the bond interest will be paid twice during May 14 and Nov 14 of each year. Due to the fact that the ZCY consists of only five periods which is ZCY-3-month, ZCY-6-month, ZCY-1-year, ZCY-2-year and ZCY-3-year, thus, mismatch with the cash flow of six periods. Therefore, to match the zero coupon yield with the cash flow, the cash flow mapping will be used with the adoption of weight (α). To calculate the weight which is notated by α, a quadratic form of equation is constructed as the following:

$$\alpha\,\alpha^2 + b\alpha + c = 0$$

To solve for α the below formula can be applied.

$$\alpha = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a}$$

Where:

$$a = \sigma_i^2 - 2\rho_{ij}\sigma_i\sigma_j$$

$$b = 2\rho_{ij}\sigma_i\sigma_j - 2\sigma_i^2$$

$$c = \sigma_j^2 - \sigma_i^2$$

Where:

σ_i^2 : Variance of ZCY_i

σ_i : Standard deviation *of* ZCY_i

σ_j^2 : Variance of ZCY_j

σ_j : Standard deviation of ZCY_j

ρ_{ij} : Correlation between of ZCY_i and ZCY_j

Table 3. Cash Flows Mapping

Cash Flows	ZCY-3M	ZCY-6M	ZCY-1Y	ZCY-2Y	ZCY-3Y
PVCF1	$\alpha_1 \times PVCF_1$	$(1-\alpha_1) \times PVCF_1$			
PVCF2		$\alpha_2 \times PVCF_2$	$(1-\alpha_2) \times PVCF_2$		
PVCF3		$\alpha_3 \times PVCF_3$	$(1-\alpha_3) \times PVCF_3$		
PVCF4			$\alpha_4 \times PVCF_4$	$(1-\alpha_4) \times PVCF_4$	
PVCF5				$\alpha_5 \times PVCF_5$	$(1-\alpha_5) \times PVCF_5$
PVCF6				$\alpha_6 \times PVCF_6$	$(1-\alpha_6) \times PVCF_6$
Synthetic Cash Flows of HKL21A	Total	Total	Total	Total	Total

Equity (Stocks)

The Delta-Normal for stock can be estimated using the method as the following:

$$MV \text{ of Stock}_i \times \beta_i$$

Where:

Market Value (MV) of Stock$_i$

= Number of Invested Shares × Current Market Price Per Share

While β (Beta) of Stock$_i$ can be estimated using the below formula:

$$\beta_i = \frac{\sigma_{i,CSX}}{\sigma_i^2}$$

Where:

$\sigma_{i,CSX}$: Covariance between return of Stock$_i$ and return of stock market index, CSX,

σ_i^2 : Variance return of Stock$_i$

Commodity

The Delta-Normal of commodity can be estimated using the method as the following:

MV of Commodity$_i$ in KHR = MV of Commodity$_i$ in US Dollar × FX

Where:

MV of Commodity$_i$ in US Dollar

= Number of Position Hold × Current Market Price in US Dollar

Foreign Exchange (FX)

$$Delta\ normal\ of\ FX = Number\ of\ Position\ Hold \times \frac{1}{100}$$

$$Delta\ normal\ of\ FX, Commodity_i = MV\ of\ Commodity_i\ in\ US\ Dollar \times \frac{1}{100}$$

3.3. Monte-Carlo Simulation VaR (MCS VaR)

MCS VaR can be estimated following four major steps:

1. Choose the stochastic process and parameters
2. Construct the stochastic value of the assets:

   $S_{t+1}, S_{t+2}, \ldots, S_{t+n}$
3. Calculate the value of the portfolio at the target horizon, $F_{t+n} = F_T$ based on the series of value in the portfolio
4. Repeating step 2 and 3 over and over again, this research will replicate 1,000 scenario simulations, K= 1,000.

After fulfilling all of the four steps and creating 1,000 portfolio values of $F_T^1, \ldots, F_T^{1,000}$. Then, all of the portfolio values will be arranged from smallest values to the largest values and the quantile Q (F,c), which is the value exceeded in C times 1,000 replications. Relative VaR can be estimated using the following formula:

$$VaR\ (c,T) = E(F_T) - Q(F_T, c)$$

or

$$VaR\ (c,T) = -Q(F_T, c), \text{ if } E(F_T) = 0$$

4. EMPIRICAL RESULT

The main purposes of this research paper are to implement all the approaching in estimating the VaR namely historical simulation VaR, parametric VaR and Monte-Carlo simulation on the synthetic portfolio investment which consists of HKL's bond, gold, crude oil, FX and the equity of PWSA, GTI, PPAP, PPSP, and PAS. As demonstrated, the estimation of VaR requires two major variables the confidence level which is 95% and the holding period which is assumed to be 1 day.

First, estimating the VaR using the non-parametric or the historical simulation VaR, is beginning with the estimation of the market value of each asset by multiplying the number of each invested asset with the market value. Then, the daily market portfolio value can be can calculated by add up the daily market value of each asset. After that, the daily portfolio profit or loss can be calculated by minus the daily market value today with the daily market value of tomorrow. Last but not least, the estimated daily portfolio's profit or loss will be sorted from the smallest to the highest. The 5% percentile of daily portfolio can be generated thanks to the holding period which is 1 day. Therefore, the square root of 1 day equals 1. Hence, the 5% percentile of daily portfolio's profit or loss is the value at risk. However, before the result of the historical simulation VaR is shown, the summary statistics of return of each individual asset and portfolio's profit or loss will be shown first in Table 4.

Table 4. Summary Statistics of Return of Each Individual Asset and Portfolio's Profit/Loss

	Bond	*USD*	*Gold*	*CO*	*PWSA*	*GTI*	*PPAP*	*PPSP*	*PAS*	*CSX*	*Portfolio's Profit/Loss*
Mean	-2E-05	-2E-05	-0.0001	-0.0003	0.0008	0.0010	0.0032	0.0004	0.0039	0.0023	-11468
Standard Error	2E-05	5.2E-05	0.00041	0.0013	0.0010	0.0020	0.0013	0.0011	0.0014	0.0008	214949
Median	-2E-05	0	-3E-05	0.0012	0.0000	0.0000	0.0000	0.0000	0.0000	0.0005	80893
Mode	0	0	#N/A	#N/A	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	#N/A
Standard Deviation	0.00031	0.00081	0.00638	0.0197	0.0161	0.0307	0.0209	0.0178	0.0216	0.0125	3371340
Sample Variance	9.6E-08	6.6E-07	4.1E-05	0.0004	0.0003	0.0009	0.0004	0.0003	0.0005	0.0002	1.13659E+13
Kurtosis	4.92614	6.94705	0.91093	2.4189	13.9665	4.1997	6.8017	16.2599	8.9305	8.3844	0.8687
Skewness	-0.3794	0.7843	-0.0888	-0.6383	-0.2493	0.0372	1.1124	0.1754	1.3638	1.4645	-0.1863
Range	0.00289	0.00704	0.03815	0.1475	0.1981	0.2007	0.1890	0.1999	0.1842	0.1193	20365163
Minimum	-0.0015	-0.0027	-0.0206	-0.0718	-0.1041	-0.1054	-0.0937	-0.1045	-0.0899	-0.0397	-10498621
Maximum	0.0014	0.00434	0.01754	0.0758	0.0940	0.0953	0.0953	0.0953	0.0942	0.0795	9866542
Sum	-0.0059	-0.006	-0.0332	-0.0658	0.1875	0.2508	0.7789	0.1054	0.9487	0.5623	-2821249
Count	246	246	246	246	246	246	246	246	246	246	246

Table 5. Historical Simulation (HS) VaR

Confidence Level	95%
Holding Period	1
VaR	-6,198,453
VaR as % of MV	-1.05%

Figure 1. Historical Simulation VaR

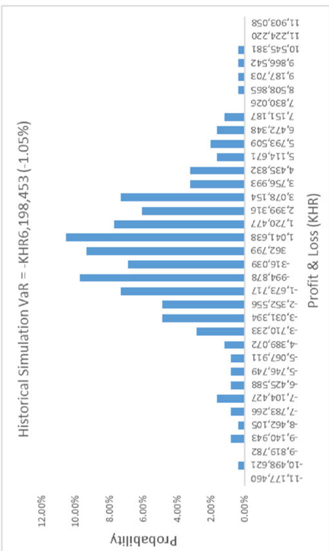


Table 6. Profit and Loss Distribution, HS VaR

For Graphic Display on PandL Distribution

Classification	**Assets**	**Risk Factor**
Bin Range	Frequency	% Frequency
-11,177,460	0	0.00%
-10,498,621	1	0.41%
-9,819,782	0	0.00%
-9,140,943	2	0.81%
-8,462,105	1	0.41%
-7,783,266	2	0.81%
-7,104,427	4	1.63%
-6,425,588	2	0.81%
-5,746,749	2	0.81%
-5,067,911	2	0.81%
-4,389,072	3	1.22%
-3,710,233	7	2.85%
-3,031,394	12	4.88%
-2,352,556	12	4.88%
-1,673,717	18	7.32%
-994,878	24	9.76%

-316,039	17	6.91%
362,799	23	9.35%
1,041,638	26	10.57%
1,720,477	19	7.72%
2,399,316	15	6.10%
3,078,154	18	7.32%
3,756,993	8	3.25%
4,435,832	8	3.25%
5,114,671	4	1.63%
5,793,509	5	2.03%
6,472,348	4	1.63%
7,151,187	3	1.22%
7,830,026	0	0.00%
8,508,865	1	0.41%
9,187,703	1	0.41%
9,866,542	1	0.41%
10,545,381	1	0.41%
11,224,220	0	0.00%
11,903,058	0	0.00%

Counted from Jan 2, 2018 to Jan 22, 2019, the total observations are 247 because 1 observation is loss when the portfolio's profit or loss is calculated. Therefore, the total observations have only 246 left. Based on the steps demonstrated above with the confidence level of 95% and the holding period of 1 day, VaR equals to KHR 6,198,453 which is approximately 1.05% of total portfolio value of KHR 591,514,539.83 calculated at the position date.

In fact, the estimation of VaR using the parametric approach is more difficult than the previous approach which requires to undergo many steps. Among that the Delta-Normal Method is most important and difficult step to achieve before the portfolio standard deviation and parametric VaR can be estimated.

To construct the Delta-Normal for the HKL's bond, first of all, the zero coupon yield correlation matrix needs to be generated. Table 7 indicated the zero coupon yield which the interpolated yield been applied to make the it fit to use with the expected cash flow of the HKL's bond.

Table 7. Correlation Matrix, Zero Coupon Yield (ZCY)

Correlation Matrix	$ZYC_{0.3068}$	$ZYC_{0.8110}$	$ZYC_{1.3096}$	$ZYC_{1.8137}$	$ZYC_{2.3096}$	$ZYC_{2.8137}$
$ZYC_{0.3068}$	1	0.9490	0.8616	0.8059	0.7781	0.7682
$ZYC_{0.8110}$	0.9490	1	0.9690	0.9263	0.9068	0.9021
$ZYC_{1.3096}$	0.8616	0.9690	1	0.9231	0.9081	0.9114
$ZYC_{1.8137}$	0.8059	0.9263	0.9231	1	0.9980	0.9900
$ZYC_{2.3096}$	0.7781	0.9068	0.9081	0.9980	1	0.9955
$ZYC_{2.8137}$	0.7682	0.9021	0.9114	0.9900	0.9955	1

The correlation between ZCY which is shown above including with the quadratic form as below:

$$a\alpha^2 + b\alpha + c = 0$$

Where:

$$a = \sigma_i^2 - 2\rho_{ij}\sigma_i\sigma_j$$

$$b = 2\rho_{ij}\sigma_i\sigma_j - 2\sigma_i^2$$

$$c = \sigma_j^2 - \sigma_i^2$$

Where:

σ_i^2 : Variance of ZCY_i

σ_i : Standard deviation of ZCY_i

σ_j^2 : Variance of ZCY_j

σ_j : Standard deviation of ZCY_j

ρ_{ij} : Correlation between of ZCY_i and ZCY_j

Weight (α) for each time to maturity can be calculated using the below formula and selected Weight (α) is illustrated in Table 8.

Table 8. Present Value of Expected Future Cash Flows of HKL's Bond and Selected Weight

Time to Maturity (TTM), Day	112	296	478	662	843	1,027
Time to Maturity (TTM), Year	0.3068	0.8110	1.3096	1.8137	2.3096	2.8137
ZCY InterYield on Position Date	1.6480	1.7426	1.7919	1.7562	1.7815	1.8246
Cash Flow (CF), HKL	4,250	4,250	4,250	4,250	4,250	104,250
Present Value of CF	4,228.74	4,190.87	4,152.29	4,117.90	4,080.16	99,078.93
ZCY SD InterYield	0.1435	0.1562	0.1541	0.2131	0.2250	0.1994
ZCY Variance InterYield	0.0206	0.0244	0.0238	0.0454	0.0506	0.0398
a	0.0023	0.0016	0.0016	0.0099	0.0002	0.0014
b	-0.0050	-0.0042	-0.0042	-0.0353	0.0001	0.0117
c	0.0022	0.0010	0.0017	0.0054	-0.0001	-0.0023
Selected α	0.5764	0.2688	0.4783	0.1600	0.4882	0.1912

The present value of the expected cash flow of HKL's bond and the selected weight (α) are used to generate the cash flows mapping which is way of fitting the cash flow with the zero coupon yield as shown in Table 9.

Table 9. Cash Flows Mapping

Cash Flows	ZCY-3M	ZCY-6M	ZCY-1Y	ZCY-2Y	ZCY-3Y	Total
PVCF1	2,437.39	1,791.34				4,228.74
PVCF2		1,126.50	3,064.37			4,190.87
PVCF3		1,986.15	2,166.14			4,152.29
PVCF4			658.83	3,459.07		4,117.90
PVCF5				1,991.77	2,088.39	4,080.16
PVCF6				18,941.54	80,137.38	99,078.93
Synthetic Cash Flows of HKL21A	2,437.39	4,904.00	5,889.34	24,392.38	82,225.77	119,848.88

The above result of the synthetic cash flow of HKL's bond will then be used to calculate the Delta-Normal of the bond which is known as the dollar value per one basis point (DV01). DV01 is used to measure the volatility of the bond price when the discount rate change by one basis point.

Table 10. Price per Unit of Each Asset on the Position Date, 22 January 2019

Assets	USD (KHR/ USD)	Gold ($)	CO ($)	PWSA (KHR)	GTI (KHR)	PPAP (KHR)	PPSP (KHR)	PAS (KHR)
Price/ Unit	4,017.50	1,282.11	62.70	4,680	6,040	11,200	3,000	12,860

The market value of each asset at the position date, Jan 2, 2018 to Jan 22, 2019 is indicated in Table 10 above. With the number of each asset which is designated by the synthetic portfolio as shown in Chapter 3 at the position date, market value of the synthetic portfolio has the total value of KHR 591,514,539.83 (See Table 11). Please be noted that the market value of each asset and the market value of the portfolio are all characterized in Khmer Riel.

Table 11. Portfolio Value on the Position Date, 22 January 2019

Trading Position				Market Value
Type of Asset	Asset	Risk Factor	Unit	KHR
Fixed-Income Security	Bond	ZCY	100	11,448,372.33
Foreign Exchange	FX	USD	500	2,008,750.00
Commodity	Gold	Gold price and FX	100	515,087,692.50
Commodity	Crude Oil	Crude oil price and FX	100	25,189,725.00
Equity	PWSA	PROP	1,000	4,680,000.00
Equity	GTI	PROP	1,000	6,040,000.00
Equity	PPAP	PROP	1,000	11,200,000.00
Equity	PPSP	PROP	1,000	3,000,000.00
Equity	PAS	PROP	1,000	12,860,000.00
			Initial value of portfolio =	591,514,539.83

Table 12. Delta-Normal Method

Delta-Normal Method Change of value of (P/L) with respect to changes of risk factor	ZCY-3M	ZCY-6M	ZCY-1Y	ZCY-2Y	ZCY-3Y	USD	Gold	CO	PWSA	GTI	PPAP	PPSP	PAS
Time	0.24932	0.49863	1	2	3								
HKL21A's Synthetic CF	2,437.39	4,904.00	5,889.34	24,392.38	82,225.77								
HKL21A's PV	2,427.59	4,862.67	5,787.40	23,558.19	77,847.86								
HKL21A's DV01/PVBP	-0.05955	-0.23839	-0.56872	-4.63037	-22.93229								
FX						5							
Gold						1,282.11	515,087,693						
Crude Oil						62.7		25,189,725					
PWSA									1,606,795				
GTI										1,049,476			
PPAP											2,939,663		
PPSP												528,037	
PAS													6,182,993
Delta	-0.05955	-0.23839	-0.56872	-4.63037	-22.93229	1,349.81	515,087,692.50	25,189,725.00	1,606,794.77	1,049,476.47	2,939,663.46	528,037.37	6,182,993.39

Table 13. Variance-Covariance Matrix (VCM), Change in Risk Factor of Assets

VCM	ZCY-3M	ZCY-6M	ZCY-1Y	ZCY-2Y	ZCY-3Y	USD	Gold	CO	PWSA	GTI	PPAP	PPSP	PAS
ZCY-3M	1.9857	1.4848	0.6060	0.8586	0.4683	31.24	0.0001	-0.0022	0.0025	0.0006	0.0004	0.0022	-0.0014
ZCY-6M	1.4848	1.4202	0.5889	0.8709	0.5179	37.11	0.0000	-0.0011	-0.0008	-0.0002	0.0007	0.0010	-0.0006
ZCY-1Y	0.6060	0.5889	0.4740	0.5403	0.3266	42.61	-0.0001	0.0008	-0.0002	-0.0010	0.0006	-0.0002	0.0007
ZCY-2Y	0.8586	0.8709	0.5403	3.2166	1.4637	130.85	-0.0004	0.0023	-0.0013	0.0012	-0.0001	-0.0012	0.0000
ZCY-3Y	0.4683	0.5179	0.3266	1.4637	1.5858	49.07	-0.0006	0.0028	-0.0010	0.0002	-0.0023	-0.0009	-0.0011
USD	31.24	37.11	42.61	130.85	49.07	108823	0.0326	0.2279	-0.3420	-0.3994	-0.6339	-0.1468	-0.1437
Gold	0.0001	0.0000	-0.0001	-0.0004	-0.0006	0.0326	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
CO	-0.0022	-0.0011	0.0008	0.0023	0.0028	0.2279	0.0000	0.0004	0.0001	0.0001	0.0000	0.0000	0.0000
PWSA	0.0025	-0.0008	-0.0002	-0.0013	-0.0010	-0.3420	0.0000	0.0001	0.0003	0.0000	0.0001	0.0000	0.0000
GTI	0.0006	-0.0002	-0.0010	0.0012	0.0002	-0.3994	0.0000	0.0001	0.0000	0.0009	0.0000	0.0000	0.0001
PPAP	0.0004	0.0007	0.0006	-0.0001	-0.0023	-0.6339	0.0000	0.0000	0.0001	0.0000	0.0004	0.0000	0.0001
PPSP	0.0022	0.0010	-0.0002	-0.0012	-0.0009	-0.1468	0.0000	0.0000	0.0000	0.0000	0.0000	0.0003	0.0000
PAS	-0.0014	-0.0006	0.0007	0.0000	-0.0011	-0.1437	0.0000	0.0000	0.0000	0.0001	0.0001	0.0000	0.0005

After the Delta-Normal of each asset: HKL's bond, FX, gold, crude oil, PWSA, GTT, PPAP, PPSP, and PAS, is calculated (See Table 12), also the matrix variance and the covariance of change in risk factor of assets in the portfolio (See Table 13), the portfolio standard deviation can be calculated using the formula below:

$$\sigma = \sqrt{\delta^T \Omega \delta} = KHR3{,}358{,}029$$

The parametric VaR is calculated as below

$$VaR = -Z_\alpha \times \sqrt{\delta^T \Omega \delta} \times \sqrt{HP}$$

$$VaR = -1.64 \times 3{,}358{,}029 \times \sqrt{1} = -KHR5{,}523{,}467$$

Which is about 0.93% of the market value of the portfolio in the period of one day.

Table 14. Parametric VaR	
Confidence Level	95%
Holding Period	1
Portfolio Stdev	3,358,029
z	-1.64
VaR (KHR)	-5,523,467
VaR as % of MV	-0.93%

Figure 2. Parametric VaR

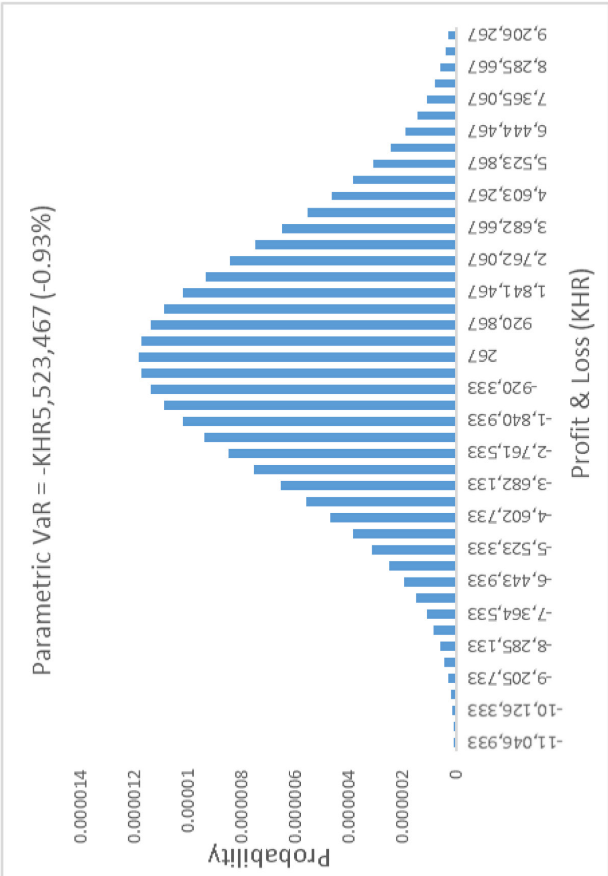


Table 15. P/L Distribution, Parametric VaR	
For Graphic Display Normal VaR	
Classification	**Assets**
Bin Range	Frequency
-11,046,933	5.578E-08
-10,586,633	8.64E-08
-10,126,333	1.314E-07
-9,666,033	1.96E-07
-9,205,733	2.871E-07
-8,745,433	4.128E-07
-8,285,133	5.825E-07
-7,824,833	8.068E-07
-7,364,533	1.097E-06
-6,904,233	1.464E-06
-6,443,933	1.917E-06
-5,983,633	2.464E-06
-5,523,333	3.109E-06
-5,063,033	3.851E-06
-4,602,733	4.681E-06
-4,142,433	5.586E-06
-3,682,133	6.542E-06
-3,221,833	7.52E-06
-2,761,533	8.484E-06
-2,301,233	9.396E-06
-1,840,933	1.021E-05
-1,380,633	1.09E-05
-920,333	1.141E-05
-460,033	1.173E-05
267	1.183E-05
460,567	1.172E-05
920,867	1.139E-05
1,381,167	1.087E-05
1,841,467	1.017E-05
2,301,767	9.351E-06
2,762,067	8.436E-06
3,222,367	7.47E-06
3,682,667	6.492E-06
4,142,967	5.538E-06
4,603,267	4.637E-06
5,063,567	3.811E-06
5,523,867	3.074E-06
5,984,167	2.434E-06
6,444,467	1.892E-06
6,904,767	1.443E-06
7,365,067	1.08E-06
7,825,367	7.939E-07
8,285,667	5.726E-07
8,745,967	4.054E-07
9,206,267	2.817E-07

Besides the two approach used above, Monte-Carlo simulation will also be applied in the estimation of VaR. The most important port of the MCS is the simulation of profit or loss (P/L) of the investment portfolio. This study the simulations will be conducted for 1,000 times. First, the matrix of random number which consists of 1,000 rows and 13 columns based on the number of simulations and the risk factor respectively will be generated. Then the Lower Cholesky Matrix (LCM) will be constructed based on the variance and co-variance matrix (See Table 16).

Table 16. Lower Cholesky Matrix

LCM	ZCY-3M	ZCY-6M	ZCY-1Y	ZCY-2Y	ZCY-3Y	USD	Gold	CO	PWSA	GTI	PPAP	PPSP	PAS
ZCY-3M	1.4092	0	0	0	0	0	0	0	0	0	0	0	0
ZCY-6M	1.0537	0.5567	0	0	0	0	0	0	0	0	0	0	0
ZCY-1Y	0.4300	0.2439	0.4792	0	0	0	0	0	0	0	0	0	0
ZCY-2Y	0.6093	0.4111	0.3713	1.5932	0	0	0	0	0	0	0	0	0
ZCY-3Y	0.3323	0.3012	0.2300	0.6603	0.9464	0	0	0	0	0	0	0	0
USD	22.166	24.701	56.465	54.115	-15.272	318.389	0	0	0	0	0	0	0
Gold	0.0001	-0.0002	-0.0002	-0.0002	-0.0004	0.0001	0.0063	0	0	0	0	0	0
CO	-0.0016	0.0010	0.0026	0.0012	0.0018	0.0002	0.0016	0.0192	0	0	0	0	0
PWSA	0.0018	-0.0048	0.0004	-0.0003	0.0000	-0.0008	0.0001	0.0035	0.0148	0	0	0	0
GTI	0.0004	-0.0011	-0.0020	0.0013	0.0000	-0.0011	-0.0024	0.0059	0.0014	0.0299	0	0	0
PPAP	0.0003	0.0007	0.0006	-0.0005	-0.0026	-0.0022	0.0004	0.0013	0.0038	0.0007	0.0202	0	0
PPSP	0.0016	-0.0012	-0.0012	-0.0007	-0.0003	-0.0002	-0.0021	0.0005	0.0015	0.0001	0.0004	0.0174	0
PAS	-0.0010	0.0008	0.0020	-0.0003	-0.0014	-0.0008	-0.0011	-0.0008	0.0029	0.0024	0.0047	-0.0001	0.0205

The multiplication of random number matrix (1,000 rows x 13 columns) with Lower Cholesky Matrix (13 rows x 13 columns) will generate another matrix (1,000 rows x 13 columns). The sum-product of this matrix with delta-normal vector in Table 12 will generate 1,000 simulations of profit or loss of the portfolio. The Monte-Carlo Simulation VaR is the 5% percentile of simulations of profit or loss. Since the holding period is 1 day which equals to –KHR 5,354,189.

Table 17. Monte Carlo Simulation (MCS) VaR

Confidence Level	95%
Holding Period	1
VaR (KHR)	-5,354,189
VaR as % of MV	-0.91%

Figure 3. Monte Carlo Simulation VaR

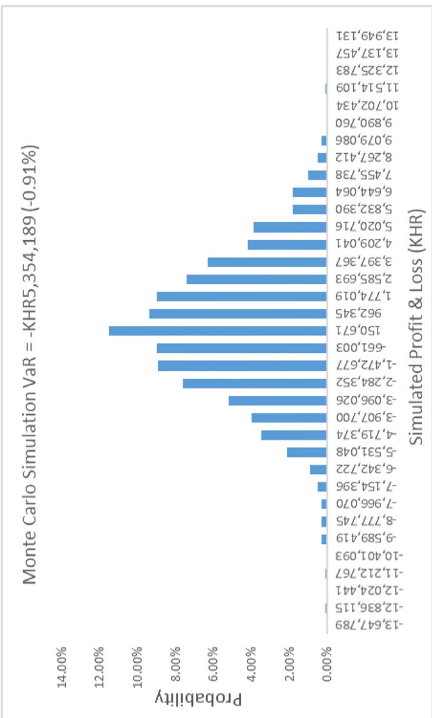


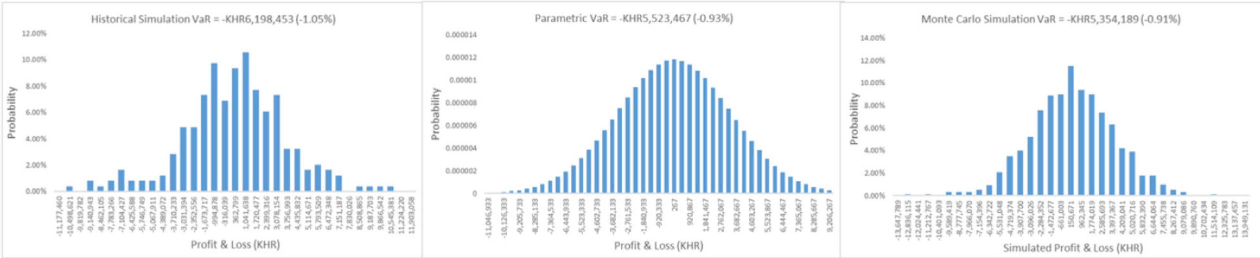
Table 18. Profit and Loss Distribution, MCS VaR
For Graphic Display on PandL Distribution

Bin Range	Frequency	% Frequency
-13,647,789	0	0.00%
-12,836,115	1	0.10%
-12,024,441	0	0.00%
-11,212,767	1	0.10%
-10,401,093	0	0.00%
-9,589,419	3	0.30%
-8,777,745	3	0.30%
-7,966,070	3	0.30%
-7,154,396	5	0.50%
-6,342,722	9	0.90%
-5,531,048	21	2.10%
-4,719,374	35	3.50%
-3,907,700	40	4.00%
-3,096,026	52	5.20%
-2,284,352	76	7.60%
-1,472,677	89	8.90%
-661,003	90	9.00%
150,671	115	11.50%
962,345	94	9.40%
1,774,019	90	9.00%
2,585,693	74	7.40%
3,397,367	63	6.30%
4,209,041	42	4.20%
5,020,716	39	3.90%
5,832,390	18	1.80%
6,644,064	18	1.80%
7,455,738	10	1.00%
8,267,412	5	0.50%
9,079,086	3	0.30%
9,890,760	0	0.00%
10,702,434	0	0.00%
11,514,109	1	0.10%

12,325,783	0	0.00%
13,137,457	0	0.00%
13,949,131	0	0.00%

Table 19. Comparison Value-at-Risk (VaR)

Historical Simulation VaR		Parametric VaR		Monte Carlo Simulation VaR	
VaR	VaR as % of MV	VaR	VaR as % of MV	VaR	VaR as % of MV
-KHR 6,198,453	-1.05%	-KHR 5,523,467	-0.93%	-KHR 5,354,189	-0.91%



5. CONCLUSION

In fact, estimating the potential loss or value loss of the investment portfolio hold by an individual investor or an investment institution is not easy job, yet pivotal to do. For instance, the measure of liquidity risk not only did it play a vital for the private firm for risk management but it also plays a significant role for the regulators in drafting the regulations and laws to serve the purpose of maintaining the stability and robustness of the whole financial institution.

The Value-at-Risk is one of the most popular approach for estimating the potential loss or value loss of an underlying asset or investment portfolio at a particular confidence level and holding period. Three main approaches can be implemented to estimate VaR namely the non-parametric VaR, parametric VaR and Monte-Carlo simulation. The result of this study indicated that with the confident level of 95% and the holding period of 1 day, the value at risk of the synthetic portfolio with the approximately of KHR591,514,539 is KHR 6,198,453, KHR5,523,467 and KHR 5,354, 189 based upon the approaches of historical VaR, parametric VaR and Monte-Carlo simulation VaR respectively. The study also suggested that in the case that the historical VaR is adopted the investment portfolio contains the highest value at risk which equivalent to approximately 1.05% at the holding period of 1 day. On the other hand, if the parametric VaR and Monte-Carlo simulation VaR are implement the value at risk is very similar at around 0.93% and 0.91% respectively. The small variation between this two approaches, perceivable, caused by the fact that these two approaches share the same delta normal vector.

Among the three approaches implemented, the historical VaR is considered as the simplest one because this approach uses the historical data which does not specifically define the distribution return of each asset as well as the distribution of portfolio profit or loss. In contrast, the parametric VaR is a bit challenging to implement due to the fact that the approach predetermines the distribution of each asset and the portfolio value (Normal distribution is set for this research). Meanwhile, the calculation of the delta-normal of each asset to serve the purpose of calculating the standard deviation of the portfolio also posts extra challenge for the implementation of this approach. Although, the result generated by the parametric VaR is considered to more accurate in comparison with historical VaR, the approach still depends heavily on the historical data. Finally, the Monte-Carlo simulation VaR, however, is considered to be the most accurate approach for estimating the VaR thanks to the fact that the portfolio's profit or loss are randomly generated and in this study a large scenario of 1,000 simulations are produced which further increases its accuracy. Giving its accuracy comparing to the two prior approaches, this approach is also considered as the most difficult approach to implement.

The estimating of VaR may appears challenging, yet provide a rewarding result for both an individual investor and firms to measure the risk exposure of their underlying assets or portfolio value to be aware of the potential future loss for the purpose of risk management. The study also further suggested that for the simple calculation of VaR, the historical VaR is recommended. However, for the desire to pursue better accuracy for estimating the VaR, the parametric VaR and Monte-Carlo simulation are highly recommended.

Finally, for the future research which intended to extend the study of the VaR in the future for the investment portfolio at CSX or other security market the Back Test and the Stress Test are highly recommended to be included.

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