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POST-PANDEMIC ANALYSIS FOR VALUE AT RISK OF REAL ESTATE INVESTMENT TRUST IN MALAYSIA UNDER QUANTITATIVE APPROACH

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ABSTRACT

A Real Estate Investment Trust (REIT) is a fund or trust that owns and manages commercial real estate and generates revenue. After two years of the COVID-19 pandemic, the whole REITs sector suffered from lockdown, diminishing revenue from office and shopping mall rentals. Hence, investors may lose more than expected on invested capital without further analysing this situation. This highlights the importance of investors knowing the risk of investing in REITs to plan their investment strategies appropriately. The Value at Risk (VaR) is widely employed to calculate the investment risk under a

mathematical model to achieve this. A past review suggested that two approaches had been utilised for modelling, i.e., parametric and non-parametric methods. The methods under non-parametric include historical simulation, Monte Carlo simulation, and bootstrapping simulation. Thus, comparing parametric methods, historical simulation, Monte Carlo simulation, and bootstrapping simulation is essential in determining the best method to analyse the VaR in the Malaysia REITs (M-REITs) sector, which particularly focuses on Malaysia. Actual previous five-year history raw price data for each REIT in Malaysia are extracted from Yahoo Finance, Refinitiv Eikon, and DataStream via University Utara Malaysia's (UUM) e-resources database. The result of VaR from those methods is compared and validated using backtesting. Other than that, the result reveals that the parametric method and Monte Carlo simulation are good methods for REIT's VaR calculations in Malaysia, which are close to the current value for 12 from 17 M-REITs companies.

Keywords: Bootstrapping simulation, Historical Simulation, Monte Carlo Simulation, M-REITs, Value at Risk.

INTRODUCTION

A Real Estate Investment Trust (REIT) is a fund or trust that owns and manages commercial real estate that generates revenue. Commercial real estate includes shopping complexes, hospitals, plantations, industrial properties, hotels, and office blocks (Bursa Malaysia, 2020). Investors buy a share of REIT due to its liquidity and spread the underlying property's investment risk. In 2020, Malaysia REITs (M-REITs) will be the fourth largest REIT market in Asia-Pacific. Due to the changes in the Securities Commission Malaysia (SC) guidelines, property development activities are allowed in REIT companies after 2018 (Lim, 2020). However, in 2020, the world was facing a coronavirus pandemic, also recognised as the COVID-19 pandemic. On 11 March 2020, the World Health Organization (WHO) declared the COVID-19 pandemic a global pandemic. Due to that, the whole REITs sector suffered from lockdown, resulting in diminishing revenue. David et al. (2020) and Cai et al. (2022) analysed the net impact of COVID-19 on United States REITs (US-REIT). Meanwhile, Milcheva (2022) studied the affection of the COVID-19 pandemic on

risk-return in developed countries, i.e., Hong Kong, Japan, China, and Singapore. Thus, there is a need to analyse the impact of COVID-19 on REIT returns, especially in Malaysia as a developed country.

A common tool employed to calculate the risk of REITs is identified as Value at Risk (VaR). It is a single figure representing the maximum amount of money that an investor might lose with a particular degree of confidence. Its origin can be traced back to capital requirements on the New York Stock Exchange in 1922 (Holton, 2002). Markowitz and Roy (1952) published their paper regarding VaR. However, some technologies' boundaries made their VaR measures appear theoretical and impractical (Flodman & Karlsson, 2011). After the 1970s, the market became more volatile, and financial risk measures were needed. Therefore, investors may lose more than expected on invested capital. Risk managers bring this information into the models. A problem can be caused when models cannot fully capture the market changes, as it could lead to underestimations in risk.

Some researchers employed mathematical techniques to calculate the VaR in REITs. For instance, researchers from Taiwan compared five methods, including the Equally Weighted Moving Average (EQWMA) method, Equally Weighted Moving Average with *T*-distribution (EQWMAT) method, Exponentially Weighted Moving Average (EWMA) method, historical simulation, and Bootstrap in VaR calculations on 12 REITs. Subsequently, results revealed that different confidence levels have a suitable method for VaR calculations. The backtest revealed that the EWMA method performed really well at a 95% confidence level. However, it became the worst at a 99% confidence level. Meanwhile, EQWMA might overestimate the VaR in four or five portfolios among 12 at a 95% confidence level but emerged as the best using a 99% confidence level (Lu et al., 2009). Choi (2015) applied VaR on REITs to determine the factors which affect the return on REIT yield in South Korea. After analysing REIT returns data between May and July 2014, the VAR model's predictability is relatively higher than that of the Autoregressive Integrated Moving Average (ARIMA) model. Other than that, returns on REITs were discovered to be affected by market fundamental variables.

In Malaysia, there are several previous research about REITs. For example, the result of the risk-adjusted performance analysis of

M-REITs from the year 2007 to 2012 suggested that all beta values were smaller than one (less volatile than the overall market) and that the total risk of REIT funds was linked to the unsystematic risk component (Low & Johari, 2014). In spite of conventional REITs, Islamic REIT (I-REIT) is one of Malaysian researchers' focus since it is favourable to compare with conventional REITs, according to the efficiency ratios of Return of Asset (ROA) and Return of Equity (ROE) (Khairulnuwar & Chuweni, 2020).

Past literature reflected that Malaysia involves less research on REIT compared to other common stocks in Bursa Malaysia. The restriction of movements and its implementation due to the COVID-19 pandemic has affected the general economy as well as real estate and REITs adversely (Akinsomi, 2021). Due to the vast number of methods employed to analyse VaR for REIT, some researchers work on method comparison in Malaysia for the finance sector (Günay, 2016; Mohamed Rozali et al., 2015) and non-financial sectors (Ahmad Baharul Ulum et al., 2015). For example, Mohamed Rozali et al. (2015) stated that there was no significant difference in several methods, namely the basic historical simulation method, Bootstrap historical simulation method, age-weighted historical simulation, volatility-weighted historical simulation and Monte Carlo simulation method for the VaR results of financial listed companies in Malaysia. Therefore, in this paper, we aim to calculate the VaR of M-REITs using four methods and compare their results from these methods. This includes historical simulation, parametric method, Monte Carlo simulation, and Bootstrapping simulation, which is better at calculating VaR close to the real market value.

This paper is organised as follows. In the next section, we present the concept of VaR and review some methods employed for VaR analysis in finance. The methodology section details pre-assumptions and the steps involved in three phases. Next in line is the results and analysis section, which discusses the findings of this work. Finally, the last section is the conclusion.

LITERATURE REVIEW

In this section, we brief the concept of VaR and review a comparison of some methods employed for VaR analysis in finance.

Value at Risk

VaR suggests the maximum amount of dollars expected to lose in specific periods based on the expected volatility (Wipplinger, 2007).

For example, a

$Var(95) = \$1 \text{ Million}$,

implies that there is a 95% confidence level that the portfolio will not lose more than \$1 million in the following month.

VaR is always a positive value since it already means a loss. The value needed to calculate VaR is the investment/portfolio value, expected volatility, time horizon, and confidence level. VaR, in a normal distribution, is denoted as the value of X in the Z -score.

$$Z = \frac{X - \mu}{\sigma},$$

$$X = Z\sigma + \mu, \tag{1}$$

$$Var(95) = Z\sigma + \mu,$$

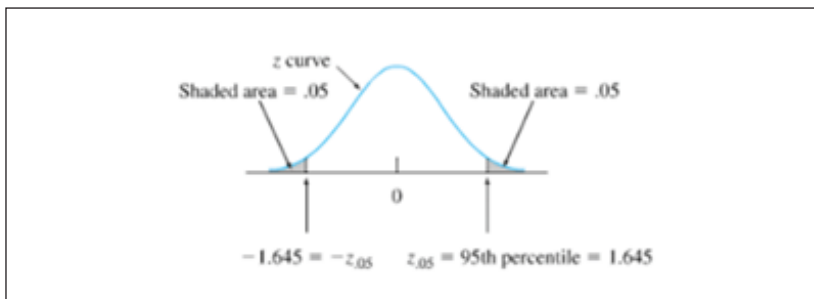
$$Var(95) = \mu - 1.64485\sigma,$$

where z is the value of $NORM.S.INV(0.05)$ in Excel when the confidence interval is 0.05, as displayed in Figure 1.

There are two major ways to calculate VaR: parametric and non-parametric methods. The key difference between them is that the parametric is a normal distribution, while the non-parametric is not based on the normal distribution.

Figure 1

The 90% Confidence Level of Normal Distribution



The Parametric Method

The parametric method can be identified as a variance-covariance method since volatility (variance) is fixed as a constant, and then a normal distribution will be analysed. Note that the expected value (return) and the standard deviation (volatility) are predictable. The formula needed for normal distribution is provided below:

$$VaR (1 - \alpha) = \mu + z\sigma, z \text{ is the } z \text{ score} \quad (2)$$

Harry Max Markowitz, the receiver of the 1990 Nobel Memorial Prize in Economic Sciences, due to his famous Modern Portfolio Theory (MPT), where this theory was the basis for Capital Asset Pricing Model (CAPM). The author established the variance-covariance matrix in his portfolio risk method (Markowitz, 1959). Correspondingly, risk managers have begun investigating simulation approaches to address challenges with linearising derivative positions and accounting for expiring contracts (Barone-Adesi et al., 2000). Although the parametric method is simple and quick to construct, it has limitations related to the incorrect distribution assumption. The VaR may underestimate since majority of financial returns exhibit heavy taileds (Lu et al., 2009). Therefore, we can minimise this limitation using a non-parametric approach.

Non-parametric method

The non-parametric method consists of three methods, including the historical simulation, Monte Carlo simulation, and Bootstrapping simulation.

Historical Simulation

The historical method is the method based on price history when calculating VaR. Actual market price data for the last 252 days (one year have approximately 252 days of trading) is obtained to calculate the percentage change for each risk factor. The formula provided below is the percentage change of periodic daily return, r , using the continuous compounding method.

$$\begin{aligned} \text{Today's Stock Price} &= \text{Yesterday's Stock Price} * e^r \\ \text{Periodic Daily Return, } r &= \ln \frac{\text{Today's Stock Price}}{\text{Yesterday's Stock Price}} \\ r &= \ln \frac{S_{t+\Delta t}}{S_t} \end{aligned} \quad (3)$$

This method has been applied to forecast Volatility Index (VIX) (Jiang & Lazar, 2020) and predict the share market (Arthini et al., 2012). Besides that, historical simulation has many derivatives, such as age-weighted and volatility-weighted (Mohamed Rozali et al., 2015). The formula for age-weighted historical simulation is provided below:

$$VaR = p_{t-1} - (p_{t-1} - p_t) \left(\frac{(1 - k_{t-1}) - (1 - \alpha)}{(1 - k_{t-1}) - (1 - k_t)} \right), \quad (4)$$

where p_t is the return for time t , k_t is the cumulative value for time t , and α is the significance level. Meanwhile, the volatility-adjusted return formula for volatility-weighted historical simulation is illustrated below:

$$r_{t,i}^* = \frac{\sigma_{T,i}}{\sigma_{t,i}} r_{t,i}, \quad (5)$$

where $r_{t,i}$ is the historical return on asset i and time t and σ is the volatility. The historical simulation is based on the real history prices. Therefore, parameter estimators or assumptions are unnecessary (Flodman & Karlsson, n.d.). The advantage of historical simulation is that it does not depend on parametric assumptions on the portfolio and is very simple to implement (Abad et al., 2014).

The limitation of historical simulation is that it depends on the volatility of historical data, where there is no guarantee that the same profitable condition will occur. This method will also produce misleading results when calculating VaR in emerging markets. For instance, a report suggests that the backtest on basic historical simulation is accepted in developed markets at 90%, 95%, and 99% confidence levels. However, it is rejected in emerging markets at a 99% confidence level (Naimy & Zeidan, 2019).

Alternatively, the Monte Carlo simulation and Bootstrapping method can replace the historical simulation in terms of the non-parametric approach. The next section discusses with regard to the Monte Carlo simulation in VaR calculations.

Monte Carlo simulation

A Monte Carlo simulation models the probability of various outcomes in a complicated prediction process due to random variables. The Monte Carlo simulation, also identified as the Monte Carlo method, is currently a widely utilised scientific method. It can solve analytically

intractable issues that would be too time-consuming, expensive, or impracticable (Harrison, 2009).

There are several advantages and disadvantages of Monte Carlo simulation in real situations. This method's primary function is to generate a considerable amount of accurate data that may be utilised to calculate VaR. Furthermore, the simulation captures convexity, which is frequently employed in nonlinear instruments such as options (Flodman & Karlsson, n.d.). However, the most significant disadvantage of this method is that it is time-consuming (Neira-Castro et al., 2021; Todorov, 2018; Walia, 2022). Besides that, this method is often underestimated, and it is challenging to determine the sensitivity of the data (Todorov, 2018). The Monte Carlo simulation will be employed with Geometric Brownian Motion (GBM) as the algorithm generate randomness. In solving VaR, the asset returns serve as the input, and the output is the 5% VaR return (Mohamed Rozali et al., 2015).

The GBM approach simulates the future stock price in the Monte Carlo simulation. Louis Bachelier is the first author to model stock prices with the Brownian motion (David, 2002). Application GBM assumes stock prices are log-normally distributed, with a particular component's mean and an uncertain component's standard deviation (Mohamed Rozali et al., 2015; Reddy & Clinton, 2016).

Bootstrapping Simulation

Bootstrapping is another derivative of historical simulation. This method repeatedly draws sample data with replacement (resampling) to estimate a population parameter from a data source.

Bootstrapping combined three steps:

1. Make a Bootstrapped dataset from the original database. Here, we can generate a randomisation function more than several times from the initial amount of data.
2. The VaR will be calculated based on the new Bootstrapped dataset.
3. Repeat steps 1 to 2 many times, and a mean of VaR can be obtained. The population has many possible outcomes, and the sample is small enough. Bootstrapping usually only creates a subset to estimate the entire distribution.

The advantages of the Bootstrapping method are clearly revealed at the beginning: it improves the weakness of a small dataset from historical simulation. It allows cost reduction in repeating the experiment. Other than that, this method does not require making assumptions about the data since it derives from historical data. However, Bootstrap will be inaccurate if the samples do not represent the entire population.

REVIEW OF COMPARISON BETWEEN MATHEMATICAL METHODS IN ANALYSING VAR

Bootstrapping simulation vs Monte Carlo simulation

Various studies have been conducted to compare methods, especially in the asymmetry test. For example, according to Acquah (2013), in a small sample of Houck's model and Granger and Lee's asymmetry model, the results revealed that the Bootstrap method was more powerful than the Monte Carlo simulation (Acquah, 2013). Another research regarding the financial sector share in Malaysia suggested that the result of these two methods was almost the same when calculating the VaR of those finance companies (Mohamed Rozali et al., 2015). According to Pažický (2017), the most accurate approach for stock price simulation was the Bootstrap experiment with a heteroscedastic error term (blocked Bootstrap). Note that the key difference between both methods is that the Monte Carlo simulation utilises a GBM algorithm, while the Bootstrap method employs the Bootstrap algorithm. Secondly, randomness is applied in the algorithm of the Monte Carlo simulation, whereas Bootstrapping simulation method randomises the selected data from actual historical data.

Historical Simulation vs Monte Carlo Simulation

Arthini et al. (2012) analysed the risk of a smoking company's share in Indonesia. They discovered that the Monte Carlo simulation provided better results than the historical simulation since it could do more iteration than the historical simulation. The result revealed the value of VaR of Gudang Garam Tbk. (GGRM.JK), shares with the historical method are 3.28%. However, it increased to 3.52% when using the Monte Carlo simulation (Arthini et al., 2012). Even if historical data is unavailable, the Monte Carlo simulation allows a researcher to evaluate as many options as feasible (Kaczmarczyk,

2019). In addition, Oppong et al. (2016) also compared these methods in calculating VaR for 10 stocks traded in Ghana Stock Exchange and discovered that Monte Carlo Simulation provided a better result for VaR estimation.

Meanwhile, Jones et al. (2018) concluded that the historical simulations provide a good estimate if VaR is calculated for a stable risk source and in the presence of real historical data. However, Monte Carlo simulations are better when historical data is volatile and non-stationary, with uncertain normality assumptions.

Parametric Method vs Monte Carlo Simulation vs Historical Simulation

Dalbudak (2017) conducted research on Istanbul Stock Index 30 futures (ISE-30) by comparing VaR among parametric method, Monte Carlo simulation, and Historical simulation. The results revealed that the historical simulation was preferable since the VaR results were higher than the other two methods (Dalbudak et al., 2017). When normal assumptions were doubtful over long periods, Šime Ćorkalo supported his opinion that historical simulation was the best of the three approaches after backtesting (Ćorkalo, 2011).

Since these methods are commonly discovered in financial analysis, we incorporate all four methods for comparison.

METHODOLOGY

The core objective of this paper is to determine the value of VaR in M-REITs and to compare the parametric method, historical simulation, Bootstrapping simulation, and Monte Carlo simulation methods. Before we conducted the formulation and analysis, several assumptions had been set in the beginning as follows:

- i. The one-tail confidence interval of VaR calculated will be set at 95% only.
- ii. The two-tail confidence interval at which we choose to reject or fail to reject the VaR model will be set as at 95% only.
- iii. The time horizon will only include the previous five years for each M-REIT.
- iv. All calculations will utilise the built-in MS EXCEL functions and macro-Excel only.

- v. The final results at the end of the simulation include VaR only.
- vi. The number of historical price data is fixed according to the minimum amount of data for one REIT. For example, if one of the REITs only has 1230 data after data cleaning for the previous five years, then all other REITs' history price data will only have a maximum of 1230 data.
- vii. The outcome of VaR is always positive since the value implies a possible loss.
- viii. Only 17 listed REITs in Bursa Malaysia are involved.

Overall, 18 local M-REITs are still active in trading. However, only 17 M-REITs are considered in this work since one of the REITs does not have complete five years of historical price data.

This methodology will be conducted in three phases, which consist of:

Phase 1 : Data collection and cleaning.

Phase 2 : The calculation of VaR on REITs using historical simulation, parametric method, Monte Carlo simulation and Bootstrapping simulation method.

Phase 3 : Backtesting for all four methods.

Phase 1: Data Collection and Cleaning

Data Collection and Cleaning

Actual previous five-year history raw price data for each REIT in Malaysia are extracted from Yahoo Finance (<http://www.finance.yahoo.com>) and Refinitiv Eikon & DataStream via University Utara Malaysia's (UUM) e-resources database. The historical data consisted of 17 M-REITs actively trading listed on Bursa Malaysia from 27 April 2017 until 22 April 2022. Consequently, data cleaning is performed to eliminate invalid or missing data. Besides that, we only involve the daily adjusted price. Therefore, the open, high, low, close, and volume of stock data will be eliminated.

Selection of Sample Interval

Since the VaR calculation and backtest require the utilisation of two sets of data besides the VaR model calculation and backtest timeline, this work ultimately chose the following two-time periods as the choice of historical data.

Table 1

The Dataset for Phase 2 and Phase 3

Dataset 1(for Phase 2)	27 April 2017 - 29 October 2019	617 data
Dataset 2 (for Phase 3)	30 October 2019 – 22 April 2022	612 data
Total		1229

Therefore, the first dataset calculates the predicted VaR values, and the second dataset will be set as the actual exceptions observed. Correspondingly, the VaR values from the first dataset were forwarded to backtesting in the second dataset.

Phase 2: The calculation of VaR on REITs using historical simulation, parametric method, Monte Carlo simulation, and Bootstrapping simulation method

The progress of the four methods in Phase 2 will be applied to the first dataset only. Every method has a different step in determining VaR. For example, we only discuss the processes for historical simulation and parametric methods. Basically, for these two methods, Step 1 and Step 2 are similar as follows:

Step 1. The historical price data is obtained, and the periodic daily return is calculated using the formula:

$$\text{Periodic Daily Return, } r(\%) = \ln \left(\frac{\text{Today's Stock Price}}{\text{Yesterday's Stock Price}} \right), \quad (6)$$

where “ln” is the natural logarithm to calculate the periodic daily return.

Step 2. The rank of the return is made ascending using the SORT Excel formula, and the rank number, can be set using the RANK Excel formula.

Rank = SORT (array, [sort_index], [sort_order], [by_col])
return = SORT(D4: D1235,1,1, FALSE)

Rank = RANK (number, ref, [order])
number = ROUND(H4, \$H\$4: \$H\$1235,1), 0)

Subsequently, for Step 3, under the historical simulation method, the VLOOKUP formula is used to draw out the VaR value according to the sequence/ranking of rank return.

Meanwhile, for the parametric method, an extension to two steps is made as follows:

Step 3. The average and standard deviation of the historical price change is calculated.

Average of historical price change, μ $= AVERAGE$

Standard deviation, σ $= STDEV. S$

Step 4. The value of VaR is calculated using the formula $VaR(95) = \mu - 1.64485\sigma$.

Phase 3: Model Validation by Backtesting

The model validation process is the general process of testing whether a model is adequate. Backtesting is a classic model validation method used to check whether the actual losses are consistent with the predicted value from the VaR model. If a VaR model were completely accurate, we would expect the VaR loss limit to be exceeded (exception). For example, if we utilise a 99% confidence level, we expect to find exceptions in 1% of instances. When we compare the predicted value of VaR (before a fixed time) and the actual value (after a set time), we can refer to the result outside the range of certainty as an exception. If there are too many exceptions, the number of actual exceptions observed is more than the predicted number of losses. Note that the number of actual losses is a Bernoulli trial. In this case, the model will underestimate the risk. Therefore, this model is inaccurate and needs some adjustment.

In the Backtesting method, several steps are conducted to verify a model based on exceptions or failure rates.

Step 1: Set the null hypothesis and the alternative hypothesis.

H0: Observed number of exceptions is not significantly different from expected number of exceptions. Model passes Backtesting.

H1: Observed number of exceptions is significantly different from expected number of exceptions. Model fails Backtesting

Step 2: Compute the test statistic.

The probability of actual exceptions observed can be set as a Binomial distribution.

Step 3: Find the critical value.

If the confidence level is set as 1%, therefore the critical value in a normal distribution is -2.57583 or 2.57583 .

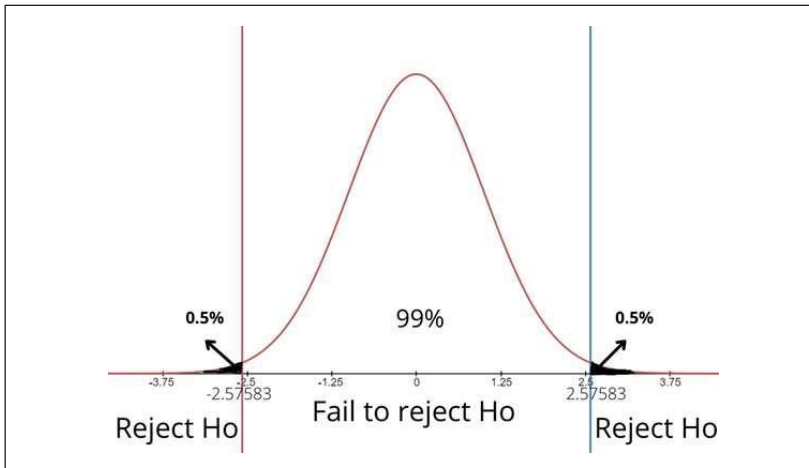
Step 4: Determine the number of exceptions that can fail to reject the null hypothesis within the range $-2.57583 < z < 2.57583$.

Step 5: Compare the critical value and the number of exceptions in Step 4 and conclude it.

If the number of exceptions is beyond the range $-2.57583 < z < 2.57583$, the model rejects the null hypothesis and will fail to backtest. If the number of exceptions is within the range of $-2.57583 < z < 2.57583$, the model does not reject the null hypothesis and will pass backtesting. In this work, the backtesting method will only utilise the second dataset from 30 October 2019 to 22 April 2022 (612 data). The results of VaR values from Phase 2 are applied in Phase 3. After that, the ascending order of the returns in the second dataset will be ranked to get the number of actual exceptions observed, f . In other words, the number of returns in Phase 3 is worse than the value VaR in Phase 2.

Figure 2

The Conclusion of Model Validation Can Be Made According to the Calculated Z Values



Now, we need to calculate the critical value for the number of exceptions observed, x . Based on the backtesting formula:

$$x = Z\sqrt{T * p * (1 - p)} + pT, \quad (7)$$

when $z = -2.57583$ $\{P(X < -2.57583) = 0.005\}$,

where $p = 0.05$ (because VaR confidence level is 95%),
and

$T = 612$ (total number of trading days in 2nd dataset is 612 days)
 $x = -2.57583\sqrt{612 * 0.05 * (1 - 0.05)} + (0.05)612 = 16.71$.

When $z = 2.57583$ $\{P(X > 2.57583) = 0.005\}$,

where $p = 0.05$ (because VaR confidence level is 95%),
and

$T = 612$ (total number of trading days in 2nd dataset is 612 days)
 $x = 2.57583\sqrt{612 * 0.05 * (1 - 0.05)} + (0.05)612 = 44.49$.

When $-2.57583 < z < 2.57583$, the range of critical value of the number of exceptions is $16 < x < 45$ under 95% confidence level.

The model passed backtesting if the number of exceptions is within the range $16 < x < 45$, and we would not reject the null hypothesis. The observed number of exceptions is not significantly different from the expected number of exceptions. Otherwise, the model is considered as failed.

Remark: The confidence level at which we choose to reject or fail to reject the VaR model is not related to the confidence level at which VaR was calculated.

The list of VaR values obtained for 17 M-REITs using the above-mentioned four methods will be displayed in the next section.

RESULT AND ANALYSIS

Table 2 highlights the VaR of all REITs using the historical simulation, parametric method, Monte Carlo simulation, and Bootstrapping simulation method. According to the historical simulation, SENTRAL's share is the least risky since it has the lowest VaR, which is -0.995%, implying that a 5% probability of the returns will likely be more than 0.995% lost. By applying the Monte Carlo simulation approach, the riskiest share is CapitaLand Malaysia Trust's (CLMT) shares. CLMT's VaR value is -3.094%, implying a 5% chance that the investor will lose more than -3.094% of their money.

Table 2

The REITs' VaR uses Historical Simulation, Parametric Method, Monte Carlo Simulation, and Bootstrapping Simulation Method

M-REIT company	Parametric method	Historical simulation	Monte Carlo simulation	Bootstrapping simulation
ALAQAR	0.02170	0.02072	0.02177	0.02282
ALSREIT	0.02438	0.02469	0.02451	0.02319
AMFIRST	0.01521	0.01036	0.01525	0.01040
ARREIT	0.01157	0.01183	0.01164	0.01213
ATRIUM	0.01471	0.01004	0.01472	0.01022
AXREIT	0.02005	0.02007	0.02021	0.01775
CLMT	0.03063	0.01905	0.03094	0.01902
HEKTAR	0.01918	0.01754	0.01921	0.01469
IGBREIT	0.02022	0.01482	0.02025	0.01709
KIPREIT	0.01540	0.01258	0.01544	0.01534
KLCC	0.01878	0.01567	0.01880	0.01497
PAVREIT	0.02408	0.01846	0.02412	0.01811
SENTRAL	0.01537	0.00995	0.01546	0.01253
SUNREIT	0.01900	0.01316	0.01893	0.01281
TWRREIT	0.01649	0.01653	0.01662	0.01887
UOAREIT	0.01722	0.01575	0.01729	0.01476
YTLREIT	0.01613	0.01639	0.01625	0.01583

The shares of the companies have given a very close VaR for the parametric method and the Monte Carlo simulation. This situation happens due to one thousand iterations of the Monte Carlo simulation, making its result closer to the parametric method. Both sample data are large enough. Table 3 below provides some statistics values by REITs.

Table 3
Statistics Analysis of REITs' VaR

	N	Mean	Std. Error of Mean	Median	Mode	Std. Deviation	Skewness	Kurtosis	Range	Minimum	Maximum
Valid											
ALAQAR	4	0.0217525	0.00042902	0.021735	0.02072 ^a	0.00085804	0.122	1.475	0.00210	0.02072	0.02282
ALSREIT	4	0.0241925	0.00034016	0.024445	0.02319 ^a	0.00068031	-1.791	3.348	0.00150	0.02319	0.02469
AMFIRST	4	0.0128050	0.00140012	0.012805	0.01036 ^a	0.00280024	0.000	-5.998	0.00489	0.01036	0.01525
ARREIT	4	0.0117925	0.00012519	0.011735	0.01157 ^a	0.00025038	1.017	0.043	0.00056	0.01157	0.01213
ATRIUM	4	0.0124225	0.00132409	0.012465	0.01004 ^a	0.00264817	-0.004	-5.977	0.00468	0.01004	0.01472
AXREIT	4	0.0195200	0.00059107	0.020060	0.01775 ^a	0.00118214	-1.978	3.931	0.00246	0.01775	0.02021
CLMT	4	0.0249100	0.000339253	0.024840	0.01902 ^a	0.000678506	0.002	-5.989	0.01192	0.01902	0.03094
HEKTAR	4	0.0176550	0.00106255	0.018360	0.01469 ^a	0.00212510	-1.303	0.971	0.00452	0.01469	0.01921
IGBREIT	4	0.0180950	0.00131957	0.018655	0.01482 ^a	0.00263915	-0.600	-2.643	0.00543	0.01482	0.02025
KIPREIT	4	0.0146900	0.00070363	0.015370	0.01258 ^a	0.00140727	-1.995	3.983	0.00286	0.01258	0.01544
KLCC	4	0.0170550	0.00101185	0.017225	0.01497 ^a	0.00202370	-0.102	-5.410	0.00383	0.01497	0.01880
PAVREIT	4	0.0211925	0.00168019	0.021270	0.01811 ^a	0.00336037	-0.009	-5.945	0.00601	0.01811	0.02412
SENTRAL	4	0.0133275	0.00131539	0.013950	0.00995 ^a	0.00263077	-0.762	-1.766	0.00551	0.00995	0.01546
SUNREIT	4	0.0159750	0.00172781	0.016045	0.01281 ^a	0.00345563	-0.009	-5.947	0.00619	0.01281	0.01900
TWRREIT	4	0.0171275	0.00058147	0.016575	0.01649 ^a	0.00116294	1.987	3.955	0.00238	0.01649	0.01887
UOAREIT	4	0.0162550	0.00061186	0.016485	0.01476 ^a	0.00122372	-0.532	-2.983	0.00253	0.01476	0.01729
YTLREIT	4	0.0161500	0.00011916	0.016190	0.01583 ^a	0.00023833	-0.884	0.865	0.00056	0.01583	0.01639

a. Multiple modes exist.
The smallest value is shown

According to Table 3, YTLREIT has the lowest standard deviation (0.00023833) and CLMT has the largest standard deviation (0.00118214). Using four different methods, this result reveals that the data in YTLREIT are clustered closely around the mean. As a result, it may be employed in any of the four approaches. However, in the instance of CLMT, the difference in outcomes obtained by the four approaches is significant (range = 1.192%). As a result, it must utilise the most appropriate approach, or else the VaR will be affected, or a large gap between the actual VaR and the observed VaR will occur.

Thus, for validation purposes, any method is considered a good method that gives the number of results under the expected number of exceptions range $16 < x < 45$ with the most frequency. Table 4 provides the number of exceptions, x , for each M-REIT. If the number of exceptions is within $16 < x < 45$, the model passes backtesting.

Table 4 lists that for some of the REIT, when historical simulation and Bootstrapping simulation pass the backtesting, parametric method and Monte Carlo simulation will also pass the backtesting. Examples are ALAQAR, AXREIT, KIPREIT, KLCC, PAVREIT, and UOAREIT. This observation demonstrates that the Monte Carlo simulation and parametric method will cover the result in historical simulation and Bootstrapping simulation. Note that 12 REIT companies, including ALAQAR, AMFIRST, ATRIUM, AXREIT, CLMT, IGBREIT, KIPREIT, KLCC, PAVREIT, SENTRAL, SUNREIT, and UOAREIT, are within the required range for both the parametric technique and the Monte Carlo simulation which more than historical modelling (six companies) and Bootstrapping simulation (seven companies).

Table 4

The Number of Exceptions under Backtesting

Company	Short Name	Historical simulation		Parametric Method		Monte Carlo simulation		Bootstrapping simulation	
								Method	
ALAQAR		38	Accept H_0	37	Accept H_0	37	Accept H_0	22	Accept H_0
ALSREIT		68	Reject H_0	68	Reject H_0	68	Reject H_0	71	Reject H_0
AMFIRST		151	Reject H_0	26	Accept H_0	26	Accept H_0	146	Reject H_0
ARREIT		66	Reject H_0	66	Reject H_0	66	Reject H_0	66	Reject H_0
ATRIUM		59	Reject H_0	35	Accept H_0	35	Accept H_0	59	Reject H_0
AXREIT		32	Accept H_0	32	Accept H_0	30	Accept H_0	36	Accept H_0
CLMT		11	Reject H_0	32	Accept H_0	32	Accept H_0	11	Reject H_0
HEKTAR		68	Reject H_0	62	Reject H_0	62	Reject H_0	84	Reject H_0
IGBREIT		53	Reject H_0	25	Accept H_0	25	Accept H_0	44	Accept H_0
KIPREIT		23	Accept H_0	19	Accept H_0	19	Accept H_0	19	Accept H_0
KLCC		32	Accept H_0	22	Accept H_0	22	Accept H_0	33	Accept H_0
PAVREIT		39	Accept H_0	26	Accept H_0	26	Accept H_0	39	Accept H_0
SENTRAL		82	Reject H_0	43	Accept H_0	43	Accept H_0	60	Reject H_0
SUNREIT		87	Reject H_0	44	Accept H_0	44	Accept H_0	91	Reject H_0
TWRREIT		81	Reject H_0	84	Reject H_0	81	Reject H_0	58	Reject H_0
UOAREIT		33	Accept H_0	19	Accept H_0	19	Accept H_0	33	Accept H_0
YTLREIT		58	Reject H_0	59	Reject H_0	59	Reject H_0	64	Reject H_0
Total H_0 accepted		6		12		12		7	

CONCLUSION AND FUTURE RESEARCH

This paper performed the VaR calculation for 17 M-REITS using four methods and a comparison among the parametric method, historical simulation, Monte Carlo simulation, and Bootstrapping simulation in determining the best method to analyse the VaR in Malaysia. The parametric method and Monte Carlo simulation are better techniques for M-REITS' VaR calculation compared with historical simulation and Bootstrapping simulation due to the number of models for 17 companies that passed backtesting more for the former than the latter. For future research, we can construct the same analysis by adding more methods, such as the Generalised Autoregressive Conditional Heteroskedasticity (GARCH) model and the Autoregressive Conditionally Heteroscedastic (ARCH) model. Additionally, the age-weighted and volatility-weighted historical simulations also can be applied in VaR calculations. Further investigation is needed for the type of portfolio in REITs such as healthcare, diversified, office, industrial, retail, and hotel/resorts of REIT, which are not affected by the hypothesis test.

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