Journal of Statistics & Management Systems
ISSN 0972-0510 (Print), ISSN 2169-0014 (Online)
Vol. 28 (2025), No. 2, pp. 355–374
DOI : 10.47974/JSMS-1391

Randow walk classifications and market risk evaluations of Malaysian stock market

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Abstract

This study delves into the characterization of random walks in the Malaysian stock market, specifically focusing on FTSE Bursa Malaysia KLCI. The examination of different types of random walks has been conducted through a battery of tests. The analysis takes into account the impact of the COVID-19 pandemic and divides the data into two distinct periods: before COVID-19 (from December 1, 2015, to May 1, 2019) and during COVID-19 (from December 1, 2015, to December 31, 2021). Subsequently, forecasting and risk determination are carried out using the ARMA-GJR model and ARMA-GARCH model. The empirical results reveal a substantial influence of COVID-19 on both the return and volatility of FTSE Bursa Malaysia KLCI.

Subject Classification: *91G15, 91G70, 62M10.*

Keywords: *Random walk hypothesis, Weak form efficiency, FTSE bursa Malaysia KLCI, GARCH*

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1. Introduction

The Efficient Market Hypothesis (EMH) claims that security prices accurately reflect all available information [1], originating from the research of Paul A. Samuelson and Eugene F. Fama in the 1960s. According to EMH, stocks consistently trade at their fair market value, and the changes in stock prices become unpredictable when all relevant information, such as stock analysis or market strategies, is fully incorporated. Consequently, investors face the challenge of being unable to consistently identify the precise value of the stocks, encouraging a focus on riskier investments for higher returns.

EMH comprises three levels of hypotheses: weak form, semi-strong form, and strong form. The weak form, often referred to as the Random Walk Theory, posits that security prices reflect all available information, with past prices and volumes being independent of future prices [2]. This suggests that the current stock price fully encompasses all historical information, aligning closely with the empirical results of the random walk hypothesis (RWH). The random walk data series suggests weak form efficiency, where past prices cannot be used to forecast future stock price movements. Consequently, methods like technical analysis, which forecast future stock prices based on historical price changes, are deemed less useful, and fundamental analysis may be inaccurate at times.

The RWH extends the concept, asserting that the market is efficient, and security prices move unpredictably. This theory [3] suggests that buying and holding a portfolio is a superior investment strategy. However, objections to the RWH highlight factors such as the diverse number of investors in a stock market, each spending different amounts of time in the market. This variability could lead to short-term trends influencing stock prices, enabling investors to perform well by capitalizing on buying and selling opportunities within a brief timeframe. Critics also argue that, in the long run, stock prices may indeed follow patterns or trends influenced by factors like interest rates or government regulations. The study recognizes uncertainties that may hinder the public from clearly identifying patterns or trends, emphasizing that the absence of clear identification does not negate their existence.

This study undertakes an examination of the weak form efficiency of the Malaysian stock market, specifically the FTSE Bursa Malaysia KLCI (KLSE), during the COVID-19 period from 2015 to 2021. The investigation aims to determine whether the KLSE index adheres to a random walk and explores potential violations of the random walk hypothesis through modeling and forecasting techniques.

Numerous studies on the RW behavior of the KLSE index have been conducted, presenting mixed findings on the efficiency of the Malaysian stock market. For instance, Barnes [4] demonstrated a high degree of weak form efficiency. The study by Muhammad Fadhil Marsani and Ani Shabri [5] revealed that growth and crisis series followed a RW, but the recovery series did not due to the presence of autocorrelations in returns. In 2022, a study [6] investigated extreme stock returns using KLSE index data, revealing that extreme stock returns in Malaysia did not follow a random walk, with weak-form market efficiency observed only during crisis and recovery periods. A study on the Nepalese stock market [7] found weak-form inefficiency, supporting this conclusion with various tests of random walk. Another study [8] proposed weak-form inefficiency in selected leading crypto markets, favoring a non-random walk hypothesis due to persistent volatility. Further studies [9] explored specific economic impacts, such as the study on Standard Malaysian Rubber Grade 20 (S.M.R 20) prices, which aimed to determine the best ARMA-GARCH model for price forecasting. Besides KLCI, the ARMA-GARCH model aslo implemented in other stock market [10]. In 2015, a study [11] on FTSE Bursa Malaysia KLCI using GARCH models identified volatility clustering and persistent effects on volatility. Investigating the influences of COVID-19 pandemic on the volatility of KLCI and other sectoral indices, a 2023 study [12] employed the ARCH test and GARCH model, indicating a significant ARCH effect during COVID-19.

A study [13] examining the impacts of pandamic on the Malaysian stock market have employed regression analysis, demonstrating the significant influence of factors like the number of pandemic cases, Brent oil price, and volatility index on market performance. Another study used the ARIMA method [14] to forecast future stock prices under the impact of COVID-19.

In conclusion, the main objective of this research is to comprehensively examine the weak-form efficiency of the Malaysian stock equity market during the pandemic period, providing valuable insights into the adherence of the KLSE index to a random walk. The study employs various statistical tests, including the variance ratio test, serial correlation test, unit root test, and ARMA-GARCH model, offering a thorough analysis of market efficiency. The Box-Jenkins Methodology is applied for modeling, encompassing model identification, parameter estimation, diagnostic tests, and forecasting. The study recognizes the unique context of the

COVID-19 period and contributes nuanced insights into market behavior during this critical timeframe.

The principle aim of this study is to assess the weak form efficiency of the Malaysian stock equity market, specifically focusing on the KLSE index, and ascertain whether it adheres to a random walk pattern during the COVID-19 period spanning from 2015 to 2021. Additionally, the study seeks to investigate potential violations of the Random Walk Hypothesis (RWH) by employing modeling and forecasting techniques amid the COVID-19 context. The analysis incorporates various statistical tests, including the variance ratio test, serial correlation test, unit root test, and the implementation of an ARMA-GARCH model.

As mentioned earlier, the RWH manifests in three forms, with the run test, assuming Independent and Identically Distributed (IID) increments, being a well-known test for RWH. The study [15] excludes consideration of RW2, as it involves methods that lack statistical inference, such as filter rules and technical analysis. To model the data, the Box-Jenkins Methodology is employed, encompassing three key phases: model identification and selection, parameter estimation and diagnostic tests, and forecasting. For empirical data analysis, the chosen index is divided into training and validation data, with a dedicated segment for forecasting spanning one month.

During the initial stage of the Box-Jenkins Methodology, the stationarity of the data series is scrutinized to determine the necessity for differencing in the presence of non-stationarity patterns. Serial correlation and the ARCH effect are examined to provide insights into potential ARMA or GARCH models. The subsequent parameter estimation phase involves estimating various ARMA-GARCH models with distinct orders, utilizing MATLAB software. Model selection is based on the Akaike Information (AI) and Bayesian Information (BI) criteria. Following this, diagnostic tests are conducted to assess the consistency of the estimated model residuals with white noise.

In the final stage, forecast evaluation is carried out, incorporating metrics such as Mean Absolute (MA) and and Root Mean Squared Error (RMS) errors. The model demonstrating the lowest values of these metrics is selected for practical application, including forecasting and value at risk considerations. This meticulous methodology provides a comprehensive framework for examining weak form efficiency, assessing adherence to a random walk, and identifying potential violations of the RWH within the Malaysian stock market during the specified COVID-19 period.

2.0 Methodology

2.1 *Random Walk Classifications*

RWH states that the market is efficient, and security prices move unpredictably. RWH also suggests that buying and holding a portfolio is a better investment strategy. RWH can be expressed as follows:

$$p_t = \mu + p_{t-1} + \varepsilon_t, \text{ where } \varepsilon_t \sim iid\ N(0,\sigma^2) \quad (1)$$

where p_t is the natural logarithm of stock price at time t, μ is the expected price change or drift and ε_t's are IID random variables or strict white noise. In 1998, Campbell, Lo & MacKinlay [16] illustrated three forms of RWH. RW1, the fundamental version of random walk, states that the returns are IID. The IID returns indicate that the upcoming price fluctuations are not based on the past price movements. Consider a random walk such that $p_t = p_{t-1} + \varepsilon_t$ and define increments as $r_t = p_t - p_{t-1} = \varepsilon_t$, with the IID increments. Independence not only indicates that the increments in any other forms are uncorrelated. The distributional assumption will lead to violation of limitation liability. Hence, the study applies natural logarithm of prices that follows a random walk process with normally distributed increments.

RW2 states that increments are independent but not identically distributed (INID). In addition, RW2 allows unconditional heteroscedasticity in the increments. Independence not only indicates that the disjoint increments are uncorrelated, but any nonlinear functions of increments are also uncorrelated e.g. $Cov(f(\varepsilon_t),\ g(\varepsilon_{t+k})) = 0$, where $f(\varepsilon_t)$ and $g(\varepsilon_{t+k})$ are two arbitrary functions, ε_t and ε_{t+k} are asset's returns at t and t + i, for all i and for $k \neq 0$.

The weakest version of RWH is RW3 which states that increments are dependent and uncorrelated. RW3 allows conditional heteroscedasticity in the increments. It contains both RW1 and RW2 as a special case. In this case, every pair of distinct increments are uncorrelated such that $Cov(\varepsilon_t,\ \varepsilon_{t-k}) \neq 0$. But the functions of increments may not be zero e.g. $Cov(\varepsilon_t^2, \varepsilon_{t-k}^2) \neq 0$.

2.2 *ARMA-GARCH Models*

The ARMA (AutoRegressive Moving Average) model serves as a forecasting method for future values in a stationary time series. It is constructed by merging an AR model with a MA model. In general,

$$r_t = \phi_0 + \sum_{i=1}^{p} \phi_i r_{t-1} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-1} + \varepsilon_t \quad (2)$$

where

- p and q are the order of AR and MA models.
- ϕ_0 is a constant term.
- ϕ_i are the AR coeffecients of order p.
- θ_i are the MA coefficients of order q.
- ε_t are identically distributed random errors with mean zero.

The asymmetric GJR-GARCH model [17] has an additional leverage effect to measure the effect of bad news and good news. The GJR-GARCH(r, k) is expressed as

$$\sigma_t^2 = \omega_0 + \sum_{i=1}^{k} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{r} \beta_i \sigma_{t-i}^2 + \sum_{i=1}^{k} \gamma_i \varepsilon_{t-i}^2 d_{t-i} \quad (3)$$

$$d_{t-i} = \begin{cases} 1 & \text{if } \varepsilon_{t-i} < 0 \\ 0 & \text{otherwise} \end{cases}$$

where

- k and r represent the order of ARCH and GARCH terms respectively.
- $\omega_0 > 0$ is a constant.
- $\alpha_i \geqslant 0$, $\beta_i \geqslant 0$.
- d_{t-i} is a dummy variable which is a functional index. d_{t-i} worth one when ε_{t-i} is negative, indicating bad news while d_{t-i} worth zero when ε_{t-i} is positive, indicating good news.
- γ_i measures the leverage effect. If $\gamma_i > 0$, the impact of bad news will be greater than the effect of good news.
- The stationary condition satisfies when $\sum_{i=1}^{k} \alpha_i + \sum_{i=1}^{r} \beta_i + \sum_{i=1}^{k} \gamma_i < 1$.

2.4 *Value-at-Risk Determination*

Value-at-Risk (VaR) is a statistical metric that forecasts the highest possible amount and probability of loss over a period. It is a traditional method for investors to measure the risk in a portfolio. VaR is commonly used by banks or large corporations to assess the potential loss in a portfolio. There are several methods for calculating VaR which include

Historical Simulation, Monte Carlo simulation, and the ARMA-GARCH model.

2.4.1 Historical Simulation method

Historical simulation calculates VaR from historical returns. The historical returns are sorted from lowest to highest. The VaR in a one-day time horizon is calculated based on the confidence level. If the confidence level is 99%, VaR is estimated to correspond to the 1% quantile of daily returns. There is a 99% confidence level that the loss will not exceed the VaR in the next day.

2.4.2 ARMA-GARCH model

The conditional mean and variance equation are defined can be expressed as

$$r_t = \phi_0 + \sum_{i=1}^{p} \phi_i r_{t-1} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-1} + \varepsilon_t$$

$$\sigma_t^2 = \omega_0 + \sum_{i=1}^{k} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{r} \beta_i \sigma_{t-i}^2 + \sum_{i=1}^{k} \gamma_i \varepsilon_{t-i}^2 d_{t-i} \tag{7}$$

A one day ahead forecast conditional mean and variance equation are expressed as

$$\hat{r}_t(1) = \hat{\phi}_0 + \sum_{i=1}^{p} \hat{\phi}_i r_{t-1} + \sum_{i=1}^{q} \hat{\theta}_i \varepsilon_{t-1}$$

$$\hat{\sigma}_t^2 = \hat{\omega}_0 + \sum_{i=1}^{k} \hat{\alpha}_i \varepsilon_{t-i}^2 + \sum_{i=1}^{r} \hat{\beta}_i \sigma_{t-i}^2 + \sum_{i=1}^{k} \hat{\gamma}_i \varepsilon_{t-i}^2 d_{t-i} \tag{8}$$

If the standardized residuals, $\tilde{\varepsilon}_t \sim t_v(100 - X)$ with mean 0 and variance $\frac{v}{v-2}$, VaR is calculated as

$$VaR = \hat{r}_t(1) + t_v^*(100 - X)\hat{\sigma}_t(1) \tag{9}$$

where $t_v^*(100 - X) = \frac{t_v(100-X)}{\sqrt{v/(v-2)}}$ and X is the confidence level.

2.4.3 Expected Shortfall

Expected Shortfall (ES) is the anticipated loss over an N-day period under the condition that the loss exceeds the Value at Risk (VaR) during that period. ES can be calculated by using the average the portfolio's returns that are worse than the VaR at a confidence level. For single asset, the one-day expected shortfall is given by

$$1-dayES=\frac{\mu+\exp(-N^{-1}(X))^2/2}{\sqrt{2\pi}(1-c)} \tag{10}$$

where μ is the mean of returns, σ is the standard deviation of returns, c is the confidence level and $N^{-1}(X)$ is the inverse normal cumulative probability function. The expected shortfall over N-day period is calculated by

$$N-dayES=1-dayES\times\sqrt{N} \tag{11}$$

where the returns are normally distributed, $r_t \sim N(\mu,\sigma^2)$.

3.0 Empirical Study

3.1 *Preliminary Analysis*

In Figure 1, there is an obvious trend with seasonality on the daily closing price of KLSE. The price series is converted into return series to achieve stationarity. It is found that the return series exhibits a phenomena of volatility clustering during COVID-19 period (1 December 2015 to 31 December 2021).

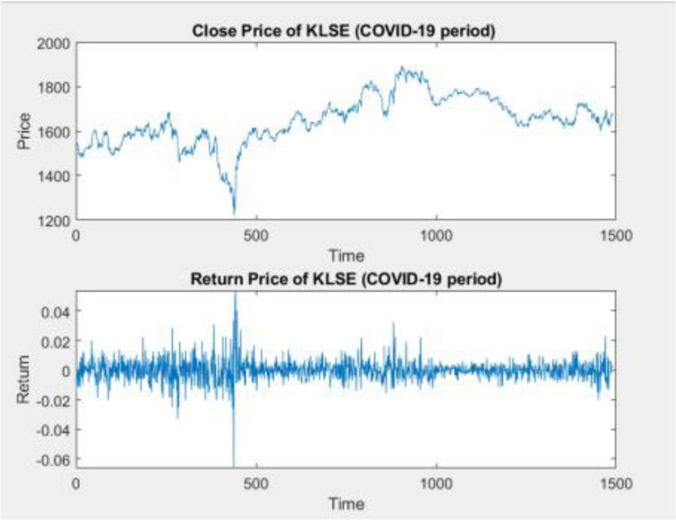

Figure 1

Prices and Returns of KLSE

Table 1

Numerical Statistics of KLSE returns

KLSE	Mean	Median	Variance	Std.dev	Skewness	Kurtosis
pre-COVID-19	0.00003	−0.00008	0.00003	0.00543	0.58269	5.94665
COVID-19	0.00005	−0.0003	0.0005	0.00718	0.25529	13.30564

Table 1 indicates the descriptive statistics of daily KLSE returns before COVID-19 and during COVID-19. From Table 1, the mean daily returns of KLSE increases from 0.00003 to 0.00005, indicating that the market gained some profit even with the presence of COVID-19. Additionally, KLSE shows a higher standard deviation during COVID-19 than before COVID-19, suggesting that volatility increases due to the pandemic. In other words, the return series during COVID-19 fluctuates more rapidly and is less stable. Furthermore, KLSE returns have positive skewness in both periods, implying small losses and a few large returns. Also, the kurtosis for both periods are found to be significantly higher than 3, showing that the return series possesses heavy tails. In comparison, the kurtosis is higher during COVID-19, indicating price fluctuation and increased risk in that period.

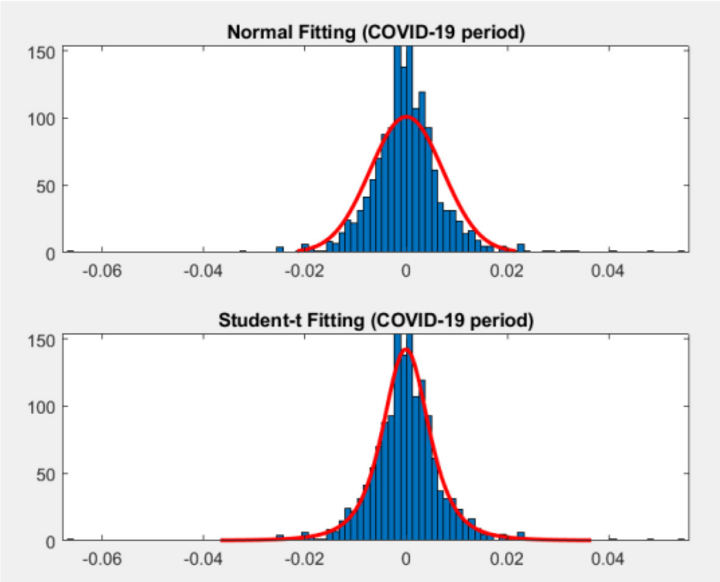

Figure 2

Normal and Student-*t* Fitting Histograms of KLSE Daily Returns

Figure 2 shows histograms with normal distribution fitting and Student-*t* distribution fitting of KLSE daily returns over the COVID-19 period. It is found that the Student-*t* distribution fits better than the normal distribution.

3.2 *Randomness Tests*

First, variance-ratio test is applied to examine the linearity of variance of increments and randomness of return series in RW1. The hypotheses of variance-ratio test are given by

$$H_0 : VR(q) = 1;$$
$$H_a : VR(q) \neq 1.$$

Table 2

Variance Ratio Test Before and During COVID-19

Period (*q*)	**Hypothesis**	**pre-COVID-19 *P*-value**	**COVID-19 *P*-value**
2	0	0.34692	0.51439
4	0	0.90999	0.23880
8	0	0.92774	0.06554

Table 2 shows the results of variance ratio test before and during COVID-19. The null hypothesis was not rejected for periods 2, 4 and 8 at the 5% significance level. Except for period 8 during COVID-19, the rejection is most likely due to the test not accounting for the heterosccedasticity effect in the return series.

Table 3 indicates the results of runs test before and during COVID-19. The null hypothesis was not rejected at 5% significance level, indicating negative serial correlation. Hence, the finding shows that KLSE daily returns follow RW1 and experience weak-form efficiency before and during pandemic.

Table 3

Runs Test Before and During COVID-19

Runs Test	Hypothesis	*P*-value
pre-COVID-19	0	0.43699
COVID-19	0	0.54547

Next, serial correlation test which is Ljung-Box Q-test was applied to examine RW3. The null hypothesis is the first *m* autocorrelations are jointly zero which means that the data are independently distributed, $H_0 : \rho_1 = \rho_2 = ... = \rho_m = 0$.

Table 4 shows the results of Ljung-Box Q-test before and during COVID-19. The findings show that *P*-values for lags tested are statistically significant at 5% significance level, except for lag 15 during COVID-19. These indicate the presence of autocorrelations in the return series. The null hypothesis was rejected and it can be concluded that returns are not independently distributed. Hence, the results suggest that return series does not follow RW3.

Table 4

Ljung-Box Q-test of KLSE Daily Return Before and During COVID-19

Period (*q*)	**pre-COVID-19 *P*-value**	**COVID-19 *P*-value**
5	0.03057	0.03547
10	0.03676	0.02622
15	0.04345	0.09597

The Augmented Dickey-Fuller (ADF) test is employed for this purpose, with the null hypothesis stating the presence of a unit root in the series. The results of the ADF test, presented in Table 5, indicate statistically significant P-values at a 5% significance level. Consequently, the null hypothesis is rejected, suggesting that the return series is stationary both before and during COVID-19.

In cases where the return series exhibits white noise characteristics, the price series is considered to follow a RW, indicating unpredictability in returns. However, based on the outcomes of the Ljung-Box Q-test, the return series demonstrates autocorrelation, which is inconsistent with white noise. Therefore, the results imply that the return series do not adhere to a RW pattern.

Table 5

ADF Test of Daily KLSE Returns

ADF	Hypothesis	P-value
pre-COVID-19	1	0.001
COVID-19	1	0.001

To summarize, ADF test and Ljung-Box Q-test rejected the RWH of KLSE return series. However, variance ratio test and runs test show that KLSE return series follows a random walk and exhibits weak form efficiency. This study was further investigated by using GARCH model with time-varying properties approach.

Finally, the Engle's ARCH test was used to check the heteroscedastic effect on the residuals. The results are shown in Table 6. Based on the results, assuming the significance level is 5%, the null hypothesis was rejected since all the *P*-values were less than 5% significance level. These findings suggested the presence of heteroscedastic effect and concluded the existence of RW3. Therefore, the squared residuals of KLSE return series are serially correlated, suggesting the use of ARCH(r, s) or GARCH(r, s) model. In short, ARMA-GARCH model is recommendeded for the returns and volatility modelling.

Table 6

ARCH test of KLSE Daily Returns Before and During COVID-19

Period (q)	**pre-COVID-19 *P*-value**	**COVID-19 *P*-value**
5	0.00142×10^{-9}	0.00000
10	0.01626×10^{-9}	0.00000
15	0.10508×10^{-9}	0.00000

3.3 *Model Estimation*

After testing for the serial correlation and ARCH effect, the next step is to seek for appropriate models. The return series was fitted to models with different orders by the trial and error method. AIC and BIC values were computed to select the best model. Ideally, the built-up models are expected to have all significant parameter coefficients but this is unlikely to happen in real life practice. Hence, the model proposed in this study is not a perfect model. 11 models, presented in Table 7, with different orders and distributions were proposed based on the daily returns during COVID-19 (1 December 2015 to 31 December 2021).

From Table 7, ARMA(2,2)-GJR(1,1) with student-*t* distribution provides the smallest AIC and BIC values. Hence, it is selected as the best model for KLSE return series in both periods. This confirms the conclusion in the previous section where the series is student-*t* distributed. For comparisons, the best three student-t models ARMA(2,2)-GJR(1,1),

Table 7

Comparison of Models Based on AIC and BIC

No.	Models	Distribution	AIC	BIC	Rank AIC	Rank BIC
1	ARMA(1,1)-GARCH(1,1)	normal	−10983	−10945	9	7
2	ARMA(2,2)-GARCH(1,1)	normal	−10974	−10927	10	10
3	ARMA(3,3)-GARCH(1,1)	normal	−10973	−10914	11	11
4	ARMA(1,1)-GJR(1,1)	normal	−11003	−10961	6	4
5	ARMA(2,2)-GJR(1,1)	normal	−11005	−10952	7	5
6	ARMA(3,3)-GJR(1,1)	normal	−10994	−10930	8	9
7	ARMA(1,1)-GARCH(1,1)	student-t	−11014	−10972	4	2
8	ARMA(2,2)-GARCH(1,1)	student-t	−11017	−10964	3	3
9	ARMA(3,3)-GARCH(1,1)	student-t	−11008	−10944	5	8
10	ARMA(2,2)-GJR(1,1)	student-t	−11031	−10973	1	1
11	ARMA(3,3)-GJR(1,1)	student-t	−11018	−10949	2	6

ARMA(1,1)-GARCH(1,1) and ARMA(2,2)-GARCH(1,1), are selected in the discussion of estimation and forecasting.

3.4 *Impact of COVID-19 and Weak Efficiency Form on KLSE index*

Table 8: Parameter Estimation for ARMA(2,2)-GJR(1,1) Fitting to KLSE Daily Returns Before COVID-19.

The fitted model equation is given by

$$\hat{r}_t = -0.00028 - 0.78248 r_{t-2} + 0.76383 \varepsilon_{t-2} + \varepsilon_t$$

$$\hat{\sigma}_t^2 = 4.97640 \times 10^{-7} + 0.04034 \varepsilon_{t-1}^2 + 0.90005 \sigma_{t-1}^2 + 0.10292 \varepsilon_{t-1}^2 d_{t-1}$$

Table 9

Parameter Estimation for ARMA(2,2)-GJR(1,1) Fitting to KLSE Daily Returns During COVID-19

Parameter	Coefficients	P-value
ϕ_0	-8.23114×10^{-6}	0.72181
ϕ_2	0.85021	0
θ_2	−0.82977	0
ω_0	4.96254×10^{-7}	0.28565
α_1	0.03687	0.01289
β_1	0.90323	0
γ_1	0.11194	0
v	8.32573	0
$\alpha_1 + \beta_1 + \frac{\gamma_1}{2}$	0.99607	

The fitted model equation is given by

$$\hat{r}_t = -8.23114\times10^{-6} + 0.85021 r_{t-2} - 0.82977\varepsilon_{t-2} + \varepsilon_t$$

$$\hat{\sigma}_t^2 = 4.96254\times10^{-7} + 0.03687\varepsilon_{t-1}^2 + 0.90323\sigma_{t-1}^2 + 0.11194\varepsilon_{t-1}^2 d_{t-1}$$

From Table 8 and 9, all parameter coefficients are statistically significant at 5% significance level except for the constant term, ϕ_0 and ω_0. The stationary condition of the model in both periods is satisfied with the values 0.99185 and 0.99607 ($\alpha_1 + \beta_1 + \frac{\gamma_1}{2}$) being less than 1. The results during COVID-19 revealed that ARCH coefficient, α_1 is positive and significant, suggesting that today's important news are impacted by the events of previous day. There is also a positive and statistically significant GARCH coefficient, β_1, which indicates that the parameter has conditional variance and caused a larger impact on volatility. Since the GARCH coefficient is higher than ARCH coeffcient during COVID-19, it can be said that volatility is highly persistent and clustering. In addition, the GARCH coefficient has increased while ARCH coefficient has decreased during COVID-19, suggesting that volatility increases its persistence but reacts slower towards the new information of COVID-19 pandemic. Moreover, the value of leverage, γ_1 during COVID-19 is positive and significant. The presence of leverage effect suggests that the volatility in KLSE return series is more likely impacted by bad news compared to good news.

The best forecast model is selected by using forecast accuracy metrics including MAE and MSE. In Table 10, 3 models that passed the diagnostics tests were evaluated by ranking the values of MAE and MSE from lowest to highest. Based on the results, the student-t ARMA(2,2)- GJR(1,1) will be used to forecast 30 one days ahead return and volatility forecast in the study. From Figure 3, the forecasted contiditional return plot illustrates that the daily returns will be consistent over the next 30 days. The red line represents the predicted points while the green line represents the 95% confidence interval of returns. With 95% confidence, the daily returns of KLSE will decrease as much as 1.37% and will increase up to 1.36% in the next 30 days, indicating that the price fluctuation will occur over the periods. In addition, the forecasted conditional volatility plot illustrates that there is a slight increase of volatility over the next 30 days, suggesting a higher risk. By comparing to the actual returns in the future, it is found that there is a large deviation between actual returns and predicted returns. The possible reason is the uncertainty impacts of COVID-19 pandemic.

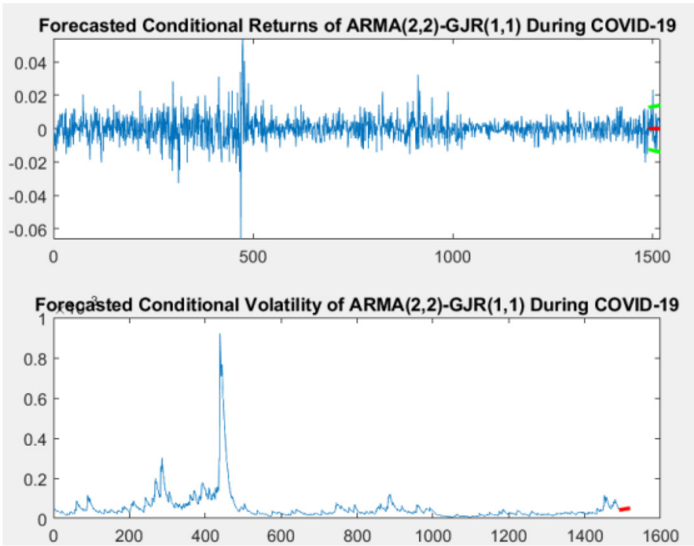

Figure 3

30 One Days Ahead Return and Volatility Forecast

Table 10

Forecast Evaluation During COVID-19

Models	Distribution	MAE	MSE
ARMA(1,1)-GARCH(1,1)	student-t	0.005273	4.08354×10^{-5}
ARMA(2,2)-GARCH(1,1)	student-t	0.00530	4.12292×10^{-5}
ARMA(2,2)-GJR(1,1)	student-t	0.00529	4.10694×10^{-5}

3.5 *Value-at-Risk Determination*

VaR is used as a method to determine the market risk by measuring the maximum loss from the investment that will be exceeded in the next *N*-days at a given confidence level. The calculation of VaR can help investors to assess the risk and determine the risk management strategy. In this study, two methods which are Historical Simulation and ARMA-GARCH model were applied to calculate the VaR. The VaR in one-day time horizon was measured based on an investment capital amount of RM100,000 at 95% and 99% confidence level.

- Historical Simulation

  The 95% percentile of the daily returns is 75th which corresponds to a loss of 1.07% while the 99% percentile of the daily returns is 15th which corresponds to a loss of 1.87% after ranking the returns from highest to lowest.

  95% 1–day VaR = RM100, 000 × 1.07% = RM1,070.00

  99% 1–day VaR = RM100, 000 × 1.87% = RM1,870.00

- ARMA-GARCH

  The conditional mean and conditional variance equations of ARMA(2,2)-GJR(1,1) is given by

$$\hat{r}_t = -8.23114 \times 10^{-6} + 0.85021 r_{t-2} - 0.82977 \varepsilon_{t-2} + \varepsilon_t$$

$$\hat{\sigma}_t^2 = 4.96254 \times 10^{-7} + 0.03687 \varepsilon_{t-1}^2 + 0.90323 \sigma_{t-1}^2 + 0.11194 \varepsilon_{t-1}^2 d_{t-1}$$

  By using MATLAB software, VaR at 95% and 99% confidence level are calculated as

  95% 1–day VaR = RM100, 000 × 1.0417% = RM1,041.70

  99% 1–day VaR = RM100, 000 × 1.6156% = RM1,615.60

  In short, by using Historical Simulation, it is with 95% confident that the loss in investment of capital RM100,000 will not exceed RM1,070.00 in the next trading day while with 99% confident that the loss will not be exceeded RM1,870.00. By using ARMA-GARCH on the other hand, it is with 95% confident that the loss in investment of capital RM100,000 will not exceed RM 1,041.70 in the next trading day while with 99% confident that the loss will not be exceeded RM 1,615.60.

- Expected Shortfall

  ES on an investment of capital RM100,000 is calculated at 95% and 99% confidence level. The 95% percentile of the daily returns is 75th while the 99% percentile of the daily returns is 15th. The expected shortfall is calculated by taking the average from 1st to 75th returns at 95% confidence level and 1st to 15th returns at 99% confidence level.

  95% 1–day ES = RM100, 000 × 1.5305% = RM1,530.50

  99% 1–day ES = RM100, 000 × 2.5139% = RM2,513.90

There are 95% confidence that the expected shortfall of investment of capital RM100,000 will be RM1,530.50 in the next trading day when the loss is worse than 95% VaR. There are 99% confidence that the expected shortfall of investment of capital RM 100,000 will be RM2,513.90 in the next trading day when the loss is worse than 99% VaR.

4.0 Conclusion

This study sought to explore the Random Walk Hypothesis and market efficiency of the FTSE Bursa Malaysia KLCI using daily returns spanning from December 1, 2015, to December 31, 2021. To evaluate the impact of COVID-19 and market efficiency during this period, the data underwent segregation into two distinct periods: pre-COVID-19 (December 1, 2015, to May 1, 2019) and during COVID-19 (December 1, 2015, to December 31, 2021). Both timeframes were subjected to a battery of statistical tests, including the unit root test, serial correlation test, variance ratio test, Augmented Dickey-Fuller (ADF) test, and ARMA-GARCH model.

Descriptive statistics revealed notable trends. The mean daily returns of the KLSE index increased amid the existence of COVID-19, indicating the market earned some profit. Simultaneously, heightened volatility, evidenced by an increased standard deviation, pointed to swift price fluctuation. Skewness decreased, and KLSE returns consistently skewed to the right before and during COVID-19, suggesting minor losses and sporadic substantial returns. Kurtosis, exceeding 3 in both periods, underscored a substantial investment risk, indicating that KLSE returns did not follpw to a normal distribution.

The examination of RWH involved various statistical assessments. The unit root test, specifically the ADF test, indicated stationarity in the KLSE index returns both before and during COVID-19, refuting the presence of a unit root. Contrarily, the serial correlation test (Ljung-Box Q-test) revealed significant autocorrelation between return series and lagged returns, challenging the assumption of independence crucial to RWH.

Conversely, a non-parametric runs test was implemented to assess the randomness of the return series, examining the sequence of consecutive return series with positive, negative, or no change. The findings indicated that the KLSE return series both before and during COVID-19 exhibited non-random patterns, revealing a negative serial correlation. Despite this, the variance ratio test, probing into the linearity of variance increments, suggested a homoscedastic random walk. Consequently, the KLSE return series was deemed to follow a random walk, indicating weak-form efficiency. To delve deeper into volatility and ascertain adherence to a random walk, the GARCH model was employed. The choice of the ARMA model was propelled by the dependence observed in the Ljung-Box Q-test, while the GARCH model was prompted by the presence of the ARCH effect in Engle's ARCH test. Employing the Box-Jenkins Methodology, the study operated under the assumption that the KLSE index does not conform to a random walk, and future stock movements are predictable.

Regarding RWH, the model selection favored the ARMA(2,2)-GARCH(1,1) model for fitting the KLSE return series both before and during COVID-19. Examination of the estimated parameters revealed a sum close to one for coefficients on previous ARCH and GARCH, indicating a high persistence of volatility clustering. This outcome signified that the KLSE index is weak form inefficient. Among the selected models ranked by AIC and BIC values, the ARMA(2,2)-GJR(1,1) outperformed other GARCH(1,1) models. Parameter estimation of ARMA(2,2)-GJR(1,1) applied to the KLSE index during COVID-19 showcased statistically significant parameters, signifying high persistence of volatility clustering. The significant and positive leverage value indicated that negative news has a more pronounced impact on volatility than positive news. Forecasting and risk determination were executed using ARMA(1,1)-GJR(1,1) and ARMA(2,2)-GJR(1,1), with only the ARMA(1,1)-GJR(1,1) results being illustrated. The forecasted outcomes substantiated the predictability of the KLSE index, thereby refuting the RWH.

In summary, the variance ratio test and runs test suggested the presence of a random walk and weak form efficiency in the KLSE index, particularly during the COVID-19 period. Conversely, the serial correlation test, unit root test, and GARCH model indicated a rejection of the RWH and weak form inefficiency in the KLSE index. These conflicting results render the research on the RWH of the KLSE index inconclusive over the period from December 1, 2015, to December 31, 2021. It is plausible that there are predictable components in the KLSE index, indicating that it is neither purely weak form efficient nor inefficient during the specified periods.

Given the inconclusive nature of this study, it is recommended that future research endeavors focus on investigating the RWH and weak form efficiency using major indices under the KLSE index, such as Genting Malaysia Berhad, Hong Leong Bank Berhad, Maxis Berhad, and others. Further exploration could involve examining whether Malaysian stock markets follow a random walk pattern using weekly and monthly data across different indices. Alternatively, research centered on large and liquid stocks may provide more robust insights into the presence of a RW in Malaysian stock markets. Additionally, future studies could move beyond statistical tests and explore the testing of RWH using technical analysis and fundamental analysis, given the potential limitations of statistical tests with weak theoretical foundations.

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Received January, 2024