Journal of Statistics & Management Systems
ISSN 0972-0510 (Print), ISSN 2169-0014 (Online)
Vol. 28 (2025), No. 6, pp. 1133–1149
DOI : 10.47974/JSMS-1456

Analyzing market risk forecasting of asymmetric GARCH model for stock volatility during the Malaysian general election period

Tan Yu Heng [§]
Tan Xiao Xian [†]
Chin Wen Cheong *
Koh Siew Khew [‡]
Lim Min [@]
Department of Mathematics
Xiamen University Malaysia
43900 Sepang
Selangor Darul Ehsan
Malaysia

Abstract

This study applies the ARMA-GARCH model to analyze the return and volatility of FTSE Bursa Malaysia KLCI, before and after the 14th General Election Malaysia (GE14). On May 9, 2018, this election was the first in Malaysian history to have the reigning party overthrown. In this scenario, we are interested in the effect of the GE14 towards the market index of Malaysia, KLCI. The sample is selected from the period May 10, 2013 until February 20, 2020. Throughout the process of model selection, we found that the ARMA(20,20)-GJR(1,1) model and ARMA(20,20)-GARCH(1,1) model with student's t-distribution are more appropriate for our dataset. After fitting the appropriate ARMA-GARCH models to our dataset, we perform a 100-period one-day-ahead forecasts and then determine the value-at-risk for a long position of RM 1 million investment in KLCI with different confidence levels.

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

Keywords: *ARMA-GARCH, KLCI, GE14, Forecasting, Value-at-risk.*

[§] *E-mail:* **mat2109752@xmu.edu.my**
[†] *E-mail:* **mat2109751@xmu.edu.my**
* *E-mail:* **wcchin@xmu.edu.my (Corresponding Author)**
[‡] *E-mail:* **siewkhew.koh@xmu.edu.my**
[@] *E-mail:* **limmin@xmu.edu.my**

Introduction

In financial stock market, stock composite index is an indicator used to evaluate the performance of a certain stock market. A composite index is built by the stocks that are chosen to represent a specific market or industry. Market participants can refer to these indices as benchmarks to evaluate the performance of the market as a whole or of segments within it. They represent a quick overview of the state of the economy, investor sentiment, and market trends. Some of the most well-known indices in the world include the Nikkei 225 in Japan, the FTSE 100 (U.K)., and the Dow Jones Industrial Average, S&P 500, and Nasdaq Composite in the U.S. Bursa Malaysia is the main stock exchange of Malaysia, listing the top 30 businesses that make up the Kuala Lumpur Composite Index (KLCI), which serves as an economic barometer of Malaysia's performance. The KLCI was first introduced in 1986 and is an essential indicator for analyzing market performance in Malaysia. Meanwhile, it also reflects the investor confidence and the overall performance of the economy. In Malaysia financial market, the KLCI plays an important role. It is commonly used by investors, fund managers and analysts to track the market trends, compare the performance of different industries, and make appropriate financial decisions. Economists and policy makers also keep a close eye on the KLCI's performance since it provides information on the country's growth prospects and overall economic health. Moreover, the KLCI acts as a benchmark for various financial instruments, which seek to mirror its performance. In this study, we aim to measure volatility, which is a statistical estimation of the variance of returns for our KLCI dataset.

Volatility refers to the level of fluctuation of a price series over a period. High volatility indicates that an asset's price can change rapidly in a short period in either direction, which is often referred to as instability. On the other hand, a low level of volatility indicates that the asset's price is still relatively stable. Not only domestic and foreign investors, but also several lawmakers, and economists closely tracked and studied KLCI's price volatility. As a result, it's critical to build an appropriate GARCH model to predict and estimate future price volatility. This section contains some research on developing various models for various indices in different countries. Some of the study also indicates that the GE14 in Malaysia have had a great impact on the volatility of KLCI during those times. Among the research, Cheian, et al. [1] apply the GARCH model to adjust for volatility clustering and it is statistically proven that there is an unusual volatility during the 12th Malaysian general election. As mentioned, this study is solely concerned with Malaysia's 12th general election. As a result, all the findings of this study are only applicable to the 12th Malaysian general election. Similar study has been conducted by Cheong et al. [2] which including GE13 and GE14. Choong, Kun and Theng [3] discuss eight Malaysian sector stocks. The primary goal is to compare stock performance across sectors using CAPM theory. The TGARCH model is used to capture the leverage effect of news and to model stock return volatility using the modified CAPM model. This article has concluded that these sectors' indices are less volatile than the KLCI stock market. Febrian and Herwany [4] examine the performance evaluations of three significant South-east Asian capital markets, namely the STI, KLSE, and JKSE. As a result, it was discovered that the best volatility forecasting models are all GARCH model with different specifications. On the other hand, Yunita [5] estimates the volatility model of Asia Pacific Indices and found that the ARIMA models fitted well in the aforementioned Asia Pacific indices. Furthermore, the volatility determinations are also constructed under GARCH models. Cheong, Mohd Nor, and Zaidi [6] examine the asymmetry long-memory volatility behavior of daily data from the Malaysia stock market spanning from 1991 to 2005. Their study employs asymmetric GARCH models to capture leverage effects, volatility clustering, and long-memory characteristics. The findings indicate that, compared to the standard GARCH model, both long-memory GARCH models more effectively represent the persistent volatility patterns in the Malaysian stock market. In a separate study, Cheong [7] analyzes the rapid changes in volatility in the KLSE using a abrupt-jump FIGARCH model. Their results showed several abrupt jumps in volatility, especially during the financial crises. This approach has overcome the overestimation issue of standard FIGARCH models in the study of Malaysian stock indices.

With the involvement of 14th General Election, this study has conducted volatility analysis to observe the influence of general election towards the KLCI during the selected period. The structure of this study is as follows: Introduction presents a literature review related to the study. Methodology describes the dataset information, and the methodology used. Empirical study presents the empirical results of the study and summarizes the overall results of the study.

Methodology

In this study, our dataset is FTSE Bursa Malaysia KLCI, which is the primary index of the Malaysian stock market. The data is collected from

Yahoo Finance by daily KLCI spot price. To observe the effect of GE14 on KLCI, we have selected the data from two different periods. One is before the GE14, from 10 May 2013 to 8 May 2018, and the other one includes GE14 and the days afterwards, from 10 May 2013 to 20 February 2020. For the first group, namely pre-GE14 period, we have 1227 observations. While for the second group, we have a total of 1661 observations. The currency of the data is in MYR. The methodology used in the following analysis is the so-called Box-Jenkins Methodology, which is a five-step process including model identification, parameter estimation, model selection, model diagnosis and forecasting. This methodology makes use of regression analysis on time series data. It is based on the idea that events in the past have an impact on events in the future. The Box-Jenkins Model performs well for forecasting periods of no more than 18 months. The rate of return measures the profitability of an investment over a period. Log return, r_t assumes that returns are compounded constantly instead of at discrete time intervals. The natural log return is defined as $r_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$, where P_t is the price at time t and r_t is the log return between time $t-1$ and t.

Return and Volatility Model Specifications

The return series is captured by the ARMA model. The ARMA model combines both the AR and MA parts to provide a more flexible approach to time series modelling. Compared to a single MA or AR model, it is usually more parameter-efficient when fitting to data. An ARMA model of order (s,r) can be written as:

$$r_t = \phi_0 + \sum_{i=1}^{s} \phi_i r_{t-i} + \sum_{j=1}^{r} \theta_j \varepsilon_{t-j} + \varepsilon_t$$

where s and r are non-negative integers, and ε_t is a white noise with mean zero and constant variance σ_ε^2.

For conditional volatility, the GARCH model is used. GARCH allows past conditional variances to affect the current conditional variance. It gives a more flexibility and capturing longer-term volatility patterns. The GARCH (p,q) model has the form:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2$$

where $\alpha_0 > 0$ and $\alpha_i \geq 0$ are constant, and the coefficient of the lagged squared residual ε_{t-i}^2 where i = 1,2,...,q, $\beta_j \geq 0$ is the coefficient of the lagged conditional variances σ_{t-j}^2 where j = 1,2,...,p, and

$\sum_{i=1}^{q}\alpha_i + \sum_{j=1}^{p}\beta_j < 1$. The $\sum_{i=1}^{q}\alpha_i\varepsilon_{t-i}^2$ is the ARCH term and the $\sum_{j=1}^{p}\beta_j\sigma_{t-j}^2$ is the GARCH term.

The GJR-GARCH model is a variant of GARCH model by adding a new term to take volatility asymmetries into consideration. With the same magnitude, bad news tends to increase future market volatility more than good news. Hence, this model is helpful for capturing the leverage effect which commonly referred as bad news impart on market volatility. For GJR-GARCH (p,q) model, it is defined as:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q}(\alpha_i\varepsilon_{t-i}^2 + \gamma_i\varepsilon_{t-i}^2 D_{t-i}) + \sum_{j=1}^{p}\beta_j\sigma_{t-j}^2$$

where α_0, α_i and β_j have the same interpretations as in the GARCH model, the γ_i is the coefficient of asymmetry, while D_{t-i} is a dummy variable were

$$D_{t-i} = \begin{cases} 1, & \varepsilon_{t-i} < 0 \\ 0, & \text{otherwise} \end{cases}.$$

D_{t-i} is the indicator variable that equals 1 if $\varepsilon_{t-i} < 0$, which indicates bad news and equals 0 if $\varepsilon_{t-i} \geq 0$, which indicates good news.

After fitting an ideal model for our data, we are interested in the forecasting accuracy of the model. The forecast evaluation process involves the comparison between the forecasting values estimated by the model and the actual observed values. In this study, we use Mean Absolute Error and Mean Squared Error to measure the error of the forecasting value. The general formula of MAE and MSE are respectively:

$$MAE = \sum_{i=1}^{n}\frac{|\hat{y}_i - y_i|}{n}$$

$$MSE = \sum_{i=1}^{n}\frac{(\hat{y}_i - y_i)^2}{n}$$

where y_i is the actual value and $\hat{y}_i$ is the forecast value. With financial data, we usually denote the actual return and forecast return at time *t* as rt and $\hat{r}_t$. Without considering direction, MAE calculates the average of absolute forecast errors. For MSE, it calculates the average of the squares of the errors and is more error-sensitive than MAE. Since both of them are measuring errors, thus the lower the MAE and MSE, the better the model is.

Market Risk determination using Value-at-Risk

The Value-at-Risk (VaR) concept was first introduced in the early 1990s by J.P. Morgan. It is mainly used to estimate the maximum potential losses of a portfolio at a certain confidence level over a specific time period. There are three key components of computing VaR: time horizon, confidence level and loss amount. Firstly, the time horizon. The length of time that the risk is measured, usually in days, weeks or months. Secondly is the confidence level. The VaR estimation probability usually is 95% and 99%. For example, a 95% confidence level means that there is a 5% chance that the loss will exceed the estimated VaR amount. Thirdly, the loss amount. The amount of potential loss. In this study, we consider three methods to estimate the VaR, namely the Historical Simulation method, Variance-Covariance method and ARMA-GARCH method. A brief description of each method is as follows:

Historical Simulation method

Among these three methods, the Historical Simulation method is the simplest because it just simulates potential losses using historical market data. The historical return is applied to the current portfolio to create a distribution of possible outcomes. We generate a histogram of historical return and estimate the VaR at different confidence levels. However, there is a limitation that this method depends on historical data, which might not perform well in forecasting future risks.

Variance-Covariance method

Variance-Covariance method assumes that the returns of assets are normally distributed and use the mean and variance of the returns to calculate the VaR. To quote an example, the formula of a 5% VaR is defined as:

$$5\%\text{VaR} = \$\text{Capital} \times 5\% \text{ quantile}$$

where the 5% quantile is calculated as

$$5\% \text{ quantile} = \mu + Z_{5\%}\,\sigma$$

and under the standard normal distribution assumption, we have a mean 0 and standard deviation 1. Hence, we simplify the equation above to $5\%\text{-}VaR = \$Capital \times Z_{5\%}$.

ARMA-GARCH method

Similar to Variance-Covariance method, ARMA-GARCH method applies the forecasted GARCH values to estimate the VaR of a portfolio. The differences are that ARMA-GARCH method allows for non-normality and the variances are time-varying instead of constant over time. Recall the ARMA-GARCH model from

$$r_t = \phi_0 + \sum_{i=1}^{s} \phi_i r_{t-i} + \sum_{j=1}^{r} \theta_j \varepsilon_{t-j} + \varepsilon_t$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2$$

Then, we obtain the forecasted value $\hat{r}_i$ and $\hat{\sigma}_t^2$. For convenience, we use the same example from above. The 5% VaR using ARMA-GARCH method is:

$$5\% - VaR = \$\ Capital \times (\hat{r}_t + Z_{5\%} \hat{\sigma}_t)$$

If our ARMA-GARCH model follows a student's t-distribution with specific degrees of freedom (dof), then the formula of VaR is:

$$5\% - VaR = \$Capital \times \left(\hat{r}_t + \frac{\hat{t}_{dof}}{\sqrt{\frac{dof}{dof-2}}} \hat{\sigma}_t \right)$$

Empirical Study

This session focuses on modeling and forecasting, including the losses estimation using Value-at-Risk that we introduced in the previous chapter. To avoid confusion and repetition, we perform the process for the second group of data (1661 observations) in the following sections. Then, we compare the best model for the two groups of data in the final stage. To build a model for the return, we use Equation 3.1 to find the log return from the daily price. Hence, the return series will have 1660 observations. The Box-Jenkins methodology suggests a forecasting period within 18 months or less. Therefore, we have chosen to perform 100 period of forecasting. To compare the forecasting value with the actual value, we divide the data into two groups. One group is used for modeling, comprising 1560 return observations. The other group is for comparing forecasted value to actual value, consisting of 100 return observations.

Preliminary Study

Table 1

Descriptive statistics of KLCI Return Series

	Mean	Median	Variance	Skewness	Kurtosis
Percentage (%)	–0.0087	0.0070	0.3122	–0.4322	5.4244

From Table 1, the descriptive statistics of daily return of KLCI are shown. It can be seen that the KLCI has a negative mean of return -0.0087%, showing that it has experienced losses on average over the period. The median of return is 0.0070%, implying that half of the returns are greater than 0.007%. Furthermore, the variance of return is 0.3122, and it is equivalent saying that the return has a standard deviation of 0.5587. For the measurement of skewness, the KLCI return series has a skewness of –0.4322, which means that the distribution is moderately skewed to the left. Lastly, the kurtosis of the return is 5.4244, which is greater than 3. We conclude that the return series has distribution with heavier tails, indicating that there is a higher chance of extreme return or extreme loss over the period.

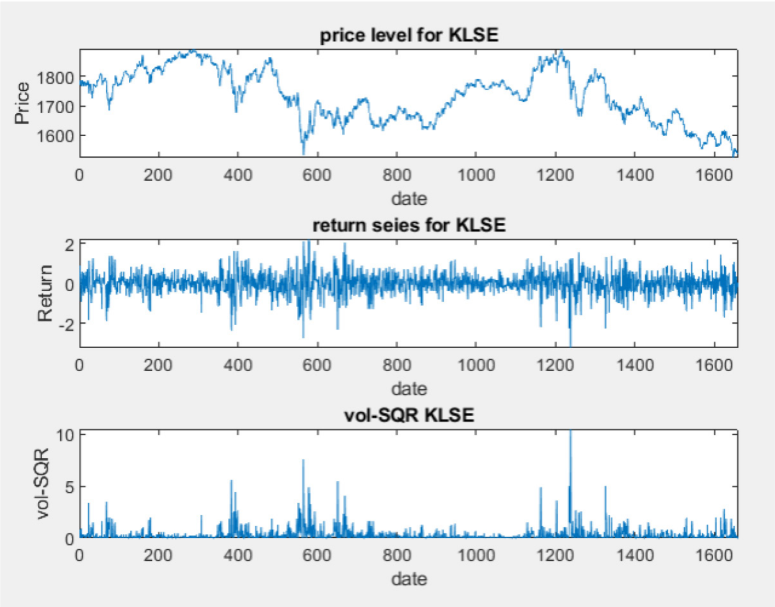

Figure 1

Plot of KLCI daily prices, return and volatility

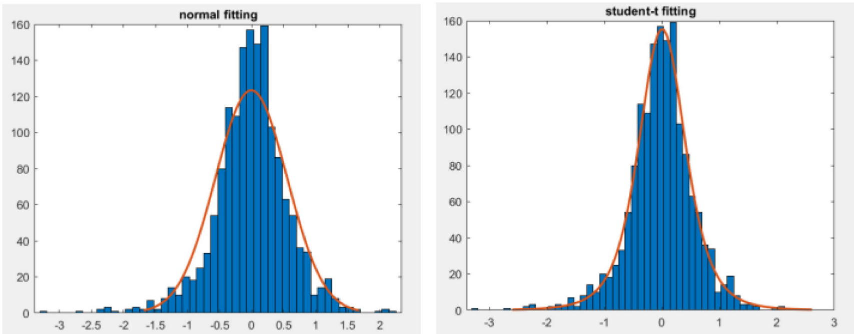

Figure 2

Normal fitting and student-t fitting for KLCI Return Series

Figure 1 shows the daily prices, return and volatility of KLCI over the chosen period. By looking at these three plots, we may observe that when there is a decline in the price, the return fluctuates in a larger magnitude and the volatility is higher. This is consistent with the assumptions of GJR-GARCH model that "bad news tends to increase future market volatility more than good news." Hence, we may consider the GJR-GARCH model for our data in the following section.

Figure 2 shows the normal approximation of the probability histogram for the KLCI Return Series. By comparing the normal fitting and student-t fitting, we may see that there are some outliers that are not covered by the normal distribution, while the student-t fitting distribution perfectly covers all the outliers. Therefore, we conclude that student-t distribution is a better fit for our KLCI Return Series compare to normal fitting.

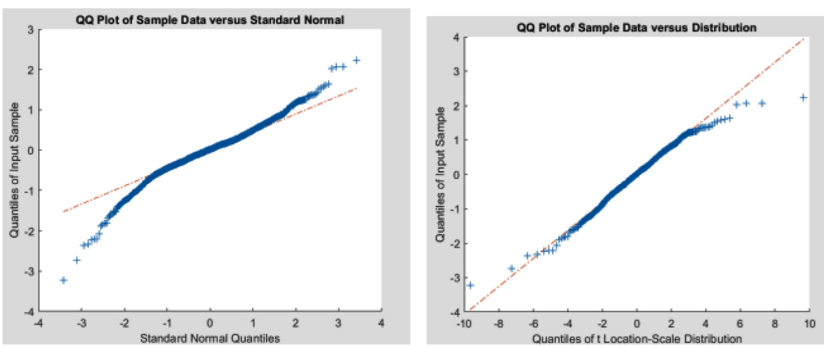

Figure 3

Normal probability plot (Quantile-quantile plot) for KLCI Return Series

Figure 3 shows the Q-Q plot for KLCI Return Series. By comparing both plots, we may observe that the center part of data points fall closely on the straight line. However, the tails of normal Q-Q plot deviate from the straight line more than the student-t Q-Q plot. Hence, we draw the same conclusion as above.

Model Selection and Diagnostic test

We use AIC and BIC to evaluate the quality of the potential models. We will rank them up by comparing their AIC and BIC values. The table 2 shows all the potential models with their AIC and BIC values:

Table 2

Potential models for KLCI Return Series

Model	Distribution	AIC	BIC	AIC Rank	BIC Rank
ARMA(1,1)-GARCH(1,1)	normal	2363.27	2395.39	15	15
ARMA(1,20)-GARCH(1,1)	normal	2361.50	2393.62	13	13
ARMA(20,1)-GARCH(1,1)	normal	2362.06	2394.17	14	14
ARMA(20,20)-GARCH(1,1)	normal	2365.17	2397.29	16	16
ARMA(1,1)-GJR(1,1)	normal	2352.36	2389.83	11	11
ARMA(1,20)-GJR(1,1)	normal	2349.78	2387.24	9	9
ARMA(20,1)-GJR(1,1)	normal	2350.58	2388.05	10	10
ARMA(20,20)-GJR(1,1)	normal	2355.02	2392.49	12	12
ARMA(1,1)-GARCH(1,1)	student-t	2314.43	2351.89	8	8
ARMA(1,20)-GARCH(1,1)	student-t	2310.70	2348.17	6	5
ARMA(20,1)-GARCH(1,1)	student-t	2310.84	2348.31	7	6
ARMA(20,20)-GARCH(1,1)	student-t	2306.91	2344.38	4	2
ARMA(1,1)-GJR(1,1)	student-t	2307.15	2349.97	5	7
ARMA(1,20)-GJR(1,1)	student-t	2303.35	2346.17	2	3
ARMA(20,1)-GJR(1,1)	student-t	2303.55	2346.37	3	4
ARMA(20,20)-GJR(1,1)	student-t	2292.80	2335.61	1	1

Table 2 lists the ranking of the potential models based on a comparison of their AIC and BIC values. We can see a slight difference in ranking by comparing their AIC and BIC values. In this table, the top four rankings were chosen among the models, ARMA (20,20)-GJR (1,1), ARMA (1,20)-GJR (1,1), ARMA (20,1)-GJR (1,1) and ARMA (20,20)- GARCH (1,1) with student-t distribution to perform the diagnostic test. Under the serial correlation and ARCH test, for ARMA (20,20)-GJR (1,1) model and ARMA (20,20)-GARCH (1,1) model, although they have captured the heteroskedasticity in the data, they fail to capture the serial correlation in the data. On the other hand, ARMA (1,20)-GJR (1,1) model and ARMA (20,1)- GJR (1,1) model have successfully captured both serial correlation and heteroskedasticity in the data. Therefore, we only have two models that pass the diagnostic test, which are ARMA (1,20)-GJR (1,1) model and ARMA (20,1)-GJR (1,1) model.

The impact of GE14

Comparison of the fitted models between pre-GE14 period and overall period at the same time, we perform the exact same processes for our first data set, which is the pre-GE14 dataset. Then, we have the following fitted models for the two groups of data. Here, we first compare the fitted ARMA (1,20) - GJR (1,1) model between the pre-GE14 period and during GE14 period.

ARIMA(20,0,1) Model (t Distribution):

	Value	StandardError	TStatistic	PValue
Constant	-0.0063908	0.013395	-0.47709	0.6333
AR{20}	0.058919	0.027592	2.1354	0.032727
MA{1}	0.065372	0.030632	2.1341	0.032834
DoF	9.2131	2.3289	3.956	7.6201e-05

GJR(1,1) Conditional Variance Model (t Distribution):

	Value	StandardError	TStatistic	PValue
Constant	0.0063243	0.002446	2.5856	0.0097207
GARCH{1}	0.88246	0.023632	37.342	3.3702e-305
ARCH{1}	0.042681	0.023446	1.8204	0.068694
Leverage{1}	0.1057	0.036402	2.9037	0.0036872
DoF	9.2131	2.3289	3.956	7.6201e-05

Figure 4

ARMA(20,1)-GJR(1,1) model for KLCI Return Series pre-GE14 period

In Figure 4, the fitted ARMA (20,1) - GJR (1,1) model for KLCI Return Series pre-GE14 period:

$$r_t = -0.0063908 + 0.058919 r_{t-20} + 0.065372 \varepsilon_{t-1}$$
$$\sigma_t^2 = 0.0063242 + 0.88246 \sigma_{t-1}^2 + 0.042681 \varepsilon_{t-1}^2 + 0.1057 \varepsilon_{t-1}^2 d_{t-1}$$

ARIMA(20,0,1) Model (t Distribution):

	Value	StandardError	TStatistic	PValue
Constant	-0.0046132	0.012252	-0.37653	0.70652
AR{20}	0.047068	0.023686	1.9871	0.046906
MA{1}	0.060123	0.025764	2.3336	0.019617
DoF	8.1523	1.4607	5.5812	2.3881e-08

GJR(1,1) Conditional Variance Model (t Distribution):

	Value	StandardError	TStatistic	PValue
Constant	0.0086257	0.0027165	3.1753	0.0014968
GARCH{1}	0.87881	0.02102	41.808	0
ARCH{1}	0.048809	0.021428	2.2779	0.022734
Leverage{1}	0.087915	0.029776	2.9525	0.0031521
DoF	8.1523	1.4607	5.5812	2.3881e-08

Figure 5

ARMA(20,1)-GJR(1,1) model for KLCI Return Series during GE14 period

In Figure 5, the fitted ARMA (20,1) - GJR (1,1) model for KLCI Return Series overall period:

$$r_t = -0.0046132 + 0.047068 r_{t-20} + 0.060123 \varepsilon_{t-1}$$
$$\sigma_t^2 = 0.0086257 + 0.87881 \sigma_{t-1}^2 + 0.048809 \varepsilon_{t-1}^2 + 0.087915 \varepsilon_{t-1}^2 d_{t-1}$$

For comparisons, we observe that there are small changes in the coefficients in return and volatility equations. Hence, we may conclude that there is small significant impact of GE14 event towards the KLCI return and volatility. It is found that the inclusion of GE-14 period indicated a volatility shift in term of long run volatility from 0.0063242 to 0.0086257. Some volatility is observed during or after the GE14 due to the new government led by Pakatan Harapan. Investors still lack confidence in the newly form government which may lead to possibility of short-term capital outflow due to new cabinets might implemented new policy in investments. Besides the policy uncertainty, fiscal policy and foreign exchange rate may indicate additional volatility during this period.

Table 3

MAE and MSE of ARMA (1,20) - GJR (1,1) and ARMA (20,1) - GJR (1,1)

Model	MAE	MSE
ARMA(1,20)-GJR(1,1)	0.4071	0.2923
ARMA(20,1)-GJR(1,1)	0.4070	0.2922

As previously mentioned, we perform a 100-one-day-aheads forecasts for KLCI Return Series. Since the ARMA (1,20)-GJR (1,1) model and ARMA (20,1)-GJR (1,1) model passed the diagnostic test, we use them for forecasting. Afterward, we use MAE and MSE to check the accuracy of model forecasting.

Table 3 shows that both MAE and MSE of the ARMA (20,1) - GJR (1,1) model are smaller than those of the ARMA (1,20) - GJR (1,1) model. This indicates that the ARMA (20,1) - GJR (1,1) model has higher forecasting accuracy compared to ARMA (1,20) - GJR (1,1) model.

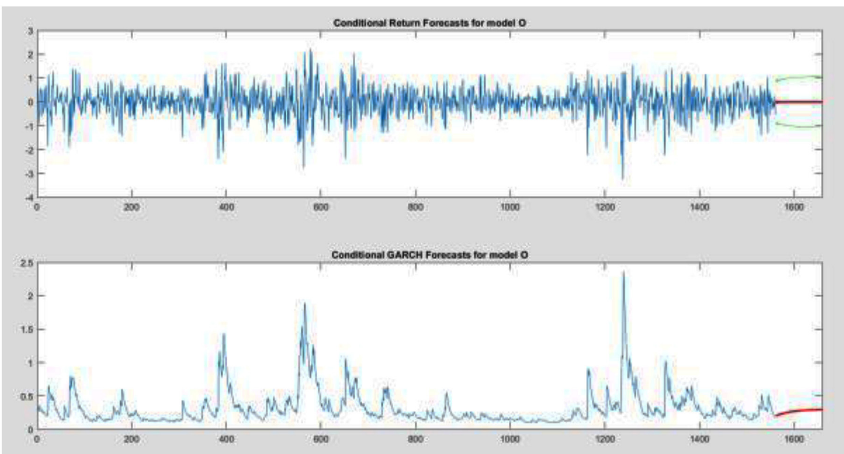

Figure 6

100 days ahead forecasting return and volatility of KLCI by ARMA (20,1) - GJR (1,1) model

From Figure 6, we can see that the red line, which is the forecasting return will remain constant at the future 100 days. While the forecasting volatility has an upward trend in both plots, indicating that the volatility might be higher over the next 100 days.

Value-at-Risk during GE14

In this section, we calculate a 1-day horizon VaR of KLCI Return Series. In previous chapter, we have introduced three methods to estimate VaR. Now, these three methods will be used to evaluate KLCI Return Series. Assume that we hold a long position of RM 1 million in KLCI.

For Historical Simulation method, the histogram that was shown previously:

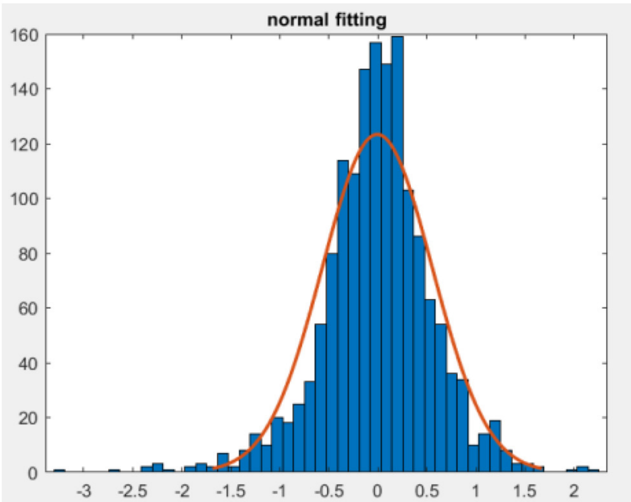

Figure 7

Normality fitting to KLCI index

From Figure 7, we can roughly estimate the 5%, 2.5% and 1% one-day VaR are respectively -RM 9,518.97, -RM 12,406.83 and -RM 16,231.5.

For Variance-covariance method, the VaR at different significance level are as follows:

$$95\%\text{ 1-day VaR} = \text{RM 1 million} \times -1.6449\% = -\text{RM}16,449$$
$$97.5\%\text{ 1-day VaR} = \text{RM 1 million} \times -1.96\% = -\text{RM}19,600$$
$$99\%\text{ 1-day VaR} = \text{RM 1 million} \times -2.3263\% = -\text{RM}23,263$$

The VaR estimated by Variance-Covariance method may have underestimated issue. However, it still provides a higher VaR compared to historical simulation method at different significant levels.

For the third approach, the ARMA-GARCH method is based on the ARMA (20,1)-GJR (1,1) model with a degree of freedom 8.1523. The 5%, 2.5% and 1% t value are -1.8551, -2.2985 and -2.8836. The different confidence levels quantiles are as follows:

$$5\% - Quantile = -0.0401 + \frac{-1.8551}{\sqrt{\frac{8.1523}{8.1523-2}}}(0.2020) = -0.7644\%$$

$$2.5\% - Quantile = -0.0401 + \frac{-2.2985}{\sqrt{\frac{8.1523}{8.1523-2}}}(0.2020) = -0.9376\%$$

$$1.0\% - Quantile = -0.0401 + \frac{-2.8836}{\sqrt{\frac{8.1523}{8.1523-2}}}(0.2020) = -1.1660\%$$

Thus, the associated VaR with RM1,000,000 investments are

$$5\% - VaR = RM1,000,000 \times -0.7644\% = -RM7,644$$
$$2.5\% - VaR = RM1,000,000 \times -0.9376\% = -RM9,376$$
$$1.0\% - VaR = RM1,000,000 \times -1.3362\% = -RM10,660$$

As a conclusion, we say that with 5% VaR of this long position, we have 95% confidence that the maximum loss will not exceed RM 7,644 the next day. To make a comparison, we apply the ARMA-GARCH method to estimate the VaR for the first group of datasets, which is the one without including GE14 period. The table 4 shows the results:

Table 4

VaR of two datasets at different significance level

Significance level	5%	2.5%	1%
VaR (with GE14)	-RM 7,644	-RM 9,376	-RM 11,660
VaR (without GE14)	-RM 5,736.50	-RM 7,013.50	-RM 8,673.70

As a result, we can see that the VaR after GE14 is higher than the VaR before GE14 at every significance level. This indicates that after GE14, the maximum potential loss of our position is higher and we may experience greater losses with the same probability.

Conclusion

In this study, we are interested in modeling and forecasting the return and volatility of index market. We choose to analyze the KLCI that has 1661 observations, from 10 May 2013 to 20 February 2020. Based on the descriptive statistics of KLCI, we found out that the KLCI has suffered small losses on average over the chosen period since it has a negative mean. The skewness -0.4322 shows that the distribution of KLCI is moderately left-skewed. The 5.4244 kurtosis also indicates that the distribution of the return series has heavy tails. We then performed the normality test for KLCI Return Series. We found that the student-t distribution for KLCI has a better fit in both probability histogram and Q-Q plot compared to the normal distribution. Then, we perform Ljung Box Test for the serial correlation test and the Engle's ARCH test for ARCH effect test. By testing at lag 7, with 5% significance level, we conclude that there are serial correlations and ARCH effects in the KLCI Return Series, showing that ARMA-GARCH model is suitable. To suggest an appropriate model for our return series, we use the autocorrelation function (ACF) and partial autocorrelation function (PACF) to find the potential models. The result suggests that ARMA (1,1), ARMA (1,20), ARMA (20,1) and ARMA (20,20) models combined with GARCH (1,1) and GJR (1,1) models may be appropriate for the KLCI Return Series. To determine which model is more suitable, we introduce Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). As a result, we choose model ARMA (20,20)-GJR (1,1), ARMA (1,20)-GJR (1,1), ARMA (20,1)-GJR (1,1) and ARMA (20,20)- GARCH (1,1) with student-t distribution as they have a lower AIC and BIC values compared to other models. A diagnostic test is performed to confirm that the models have captured the serial correlation and heteroskedasticity in the data. From the finding, there are two models that pass the diagnostic test at lag 7, which are ARMA(1,20)-GJR (1,1) model and ARMA (20,1)-GJR (1,1) model. 29 For the models that passed the diagnostic test, we use them to forecast, and we choose to forecast 100-one-day-ahead. After forecasting, we evaluate the accuracy using mean absolute error (MAE) and mean squared error (MSE). By comparing the MAE and MSE of both models, we conclude that ARMA (20,1)-GJR (1,1) model has higher accuracy in forecasting since it has lower value in MAE and MSE values. Lastly, we use three methods to calculate 5%, 2.5% and 1% VaR, if holding a long position of RM 1 million. By using Variance-Covariance method, the potential loss of next day is the largest at every significant level. At the same time, by using the historical simulation method, the potential loss of the next day has a moderate risk, which has a smaller amount than that estimated by Variance-Covariance method but has a larger amount than ARMA-GARCH method. On the other hand, the ARMA-GARCH gives the smallest potential loss of next day, which may be the most realistic estimate. At the end, we compared the VaR with two different period. We have the result that the VaR after GE14 is higher than the VaR before GE14. Due to the GE14, Malaysia was politically unstable during GE14. Because of the uncertainty about the result of GE14, the KLCI is more volatile and riskier than usual. Therefore, we conclude that there is an impact of GE14 towards the VaR of KLCI.

References

[1] A. C. R. Cheian, B. M. Siang, C. L. Woon, C. L. Chiang, and L. C. Hoong, Efficient market hypothesis: Impact of 12th Malaysian general election on the stock market, Final Year Project, Universiti Tunku Abdul Rahman (UTAR), Malaysia (2013).

[2] C. W. Cheong, L. M. Cherng, L. C. Zhi, and Z. Y. Huai, “Do general elections affect fractal structure of stock market?” *Journal of Statistics and Management Systems*, vol. 24, no. 5, pp. 951–964 (2021), doi: 10.1080/09720510.2020.1776943.

[3] C. L. Choong, S. S. Kun, and T. Y. Theng, A sectorial performance analysis of Kuala Lumpur stock exchange (KLSE Bursa Malaysia), MPRA Paper (2018). [Online]. Available: https://mpra.ub.uni-muenchen.de/

[4] E. Febrian and A. Herwany, “Volatility forecasting models and market cointegration; a study on South-East Asian markets,” *The Indonesian Capital Market Review,* vol. 1, no. 1, Article 3 (2009).

[5] I. Yunita, “Volatility modeling using Arch/Garch method: Application on Asia Pacific index,” in Proc. 3rd Int. Seminar and Conference on Learning Organization (ISCLO 2015), Atlantis Press, pp. 182–189 (2016).

[6] C. W. Cheong, A. B. S. Mohd Nor, and I. Zaidi, “Asymmetry and long-memory volatility: Some empirical evidence using GARCH,” *Physica A: Statistical Mechanics and its Applications*, vol. 373, no. 1, pp. 651–664 (2007).

[7] C. W. Cheong, “Time-varying volatility in Malaysian stock exchange: An empirical study using multiple-volatility-shift fractionally integrated model,” *Physica A: Statistical Mechanics and its Applications,* vol. 387, no. 4, pp. 889–898 (2008).

Received September, 2024