Modeling and Forecasting of Volatility using ARMA-GARCH: Case Study on Malaysia Natural Rubber Prices

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Abstract. Malaysia is one of the largest producers of natural rubber in the world. Among the various types of natural rubber which contribute to the country’s agricultural sector is the Standard Malaysian Rubber Grade 20 (S.M.R 20). Since 2008, the rubber price has received attention of investors and Malaysia Rubber Board due to price fluctuation. The price of rubber is characterized by the existence of heavy tails and volatility clustering. These properties play a significant impact on parameter estimation and forecasting performance resulting from S.M.R 20 rubber price data. The approach used in modeling S.M.R 20 rubber price data, is Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model. The aims of this paper are to find the best ARMA-GARCH model by using different specifications structures and to forecast the daily price for 20 days ahead. There are 20 models produced from different specifications in ARMA(R,M) dan GARCH(p,q) models. In this study, 1953 daily price data of S.M.R 20 are taken into consideration. The validity comparison of diagnostic checking and forecasting performance are based on AIC, AICC, SBC, HQC, MSE, RMSE and MAPE. The results reveals that ARMA(1,0)-GARCH(1,2) model is the best volatility modeling in S.M.R 20 rubber price. Based on the implications of the results, the scope of the future research directions has been widen.

1. Introduction

Financial time series usually include of floating and volatility models. The floating component always modelled using mean models such as ARIMA, moving average and many other models. The volatility of financial time series will be model when the series have stylized facts. It can be modelled using ARCH/GARCH. Several studies investigating volatility have been carried out on rubber price [1], oil price [2], electricity price [3] and petroleum [4]. Furthermore, most volatility in business and economic data influenced by stylized facts.

The stylized facts that give significant impact on modeling financial time series are fat tails, volatility clustering and nonlinear dependence. With the existing of volatility clustering in economic data, it can affect the forecasting performance of the mean models. In order to achieve accurate forecast, most researchers applied Generalized Autoregressive Conditional Heteroscedasticity (GARCH) to model volatility.

More recent studies have selected GARCH(1,1) model to analyze time series data. Some references consensus that GARCH(1,1) model is popular among others specifications because it is the simplest and most robust among volatility models [6], fits many data series well [7] and sufficient to capture the volatility clustering in the data [8]. Furthermore, Olson and Wu [9] mentioned that analysis can adequate with only one lag for each variable.

The research to date has tended to focus an exchange rate rather than production and prices from agricultural data. Goh et al. [1] and Isa and Jamil [10] investigated on the Standard Malaysia Rubber 20 (S.M.R 20) price. Both studies was selected GARCH(1,1) model in modeling and forecasting. ¹⁰found that GARCH(1,1) model is appropriate in modeling S.M.R 20 and Ribbed...
Smoked Sheet Grade I (RSS 1) price during the period of 1980 to 2002. In another study, one examined the comparison between symmetry and asymmetry GARCH model during pre and post-global financial crisis in 15 years. According to both studies, whereby preferred GARCH(1,1) model in analysis S.M.R. 20 rubber price, one unresolved question is whether GARCH(1,1) model accurate in current S.M.R 20 rubber price. Therefore, in this study S.M.R 20 rubber price using GARCH model with combination ARMA model based on different specifications. Adding to that, the study indicated daily forecasted for S.M.R 20 for 20 days ahead. The GARCH model [1] is one of the furthermost statistical technique applied in volatility. A large and growing body of literature has investigated using GARCH(1,1) model [1-2, 12-17]. However not all of these literature reported GARCH(1,1) is more appropriate in analyzing. Only [12] shown that GARCH(1,1) has predictive power in modeling daily exchange rate in the nation of Tanzania. Another study by [14] found that ARMA(1,1) with GARCH(1,1) and GARCH(2,1) is applicable in Dhaka Stock Exchange.

The paper is organized as follows. In the next section, few models are briefly described which are the ARMA model, ARCH model and GARCH model. Third session will be the result and discussion of ARMA-GARCH model based on S.M.R 20 from the duration 4th January 2010 to 29th December 2017. Last but not least are the summarized conclusion of the research.

2. Materials and Methods

2.1. Data
In this section, 1953 daily price data of Standard Malaysia Rubber 20 (S.M.R 20) are used. These data consist of period from 4th January 2010 to 29th December 2017. All observations were taken from official portal of Malaysia Rubber Board. Based on the observations, the data are split into two parts which is the in-sample part (4th January 2010 to 4th August 2015) and the out-of-sample part (5th August 2015 to 29th December 2017).

2.2. Methods
There are three types of time series models such as Autoregressive Moving Average (ARMA) model, Autoregressive Conditional Heteroscedasticity (ARCH) model and Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model.

In 1976, Box and Jenkins [18], proposed ARIMA(m,D,n) models where m is the number of autocorrelation terms, D is the number of differencing elements and n is the number of moving average terms. The letter "I" in ARIMA used to differentiate when the series are not stationary. However, when the time series is stationary, we can model it using three classes of time series process: autoregressive (AR), moving-average (MA) and mixed autoregressive and moving-average (ARMA).

An autoregressive model of order m, denoted as AR(m), can be expressed as
\[ y_t = \mu + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_m y_{t-m} + u_t \] (1)

The moving average of order n which denoted as MA(n) can be expressed as follows
\[ y_t = \mu + u_t + \theta_1 u_{t-1} + \theta_2 u_{t-2} + \cdots + \theta_n u_{t-n} \] (2)

where \( u_t( t = 1,2,3,\ldots) \) is a white noise disturbance term with \( E(u_t) = 0 \) and \( \text{var}(u_t) = \sigma^2 \).
The combination of AR(m) model and MA(n) model formed of ARMA(m,n) model which expressed as
\[ y_t = \mu + \phi_1 y_{t-1} + \cdots + \phi_m y_{t-m} + \theta_1 u_{t-1} + \cdots + \theta_n u_{t-n} + \varepsilon_t \]  
(3)
or in sigma notation
\[ y_t = C + \sum_{i=1}^{m} \phi_i y_{t-i} + \sum_{j=1}^{n} \theta_j \varepsilon_{t-j} \]  
(4)
where \( y_t \) is the daily rubber S.M.R 20 prices, \( C \) is a constant term, \( \phi_i \) are the parameter of the autoregressive component of order \( m \), \( \theta_j \) are the parameters of the moving average component of order \( n \), and \( \varepsilon_t \) is the error term at time \( t \). The order \( m \) and \( n \) are non-negative integers.

There are two time-varying volatility models that popular among researchers: ARCH model and GARCH model. The aims of ARCH model that developed by Engle [6] is to predict the conditional variance of return series.
\[ y_t = C + \varepsilon_t \]  
(5)
\[ \varepsilon_t = z_t \sigma_t \]  
(6)
Where \( y_t \) is an observed data series, \( C \) is a constant value, \( \varepsilon_t \) is residual, \( z_t \) is the standardized residual with independently and identically distributed with mean equal to zero and variance equal to one and \( \sigma_t \) is the square root of the conditional variance with non-negative process. The general form of ARCH(q) model with the first q past squared innovations can be expressed as follows [6]:
\[ \sigma_t^2 = \eta + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 \]  
(7)
The constraints of parameters are \( \eta > 0 \) and \( \alpha_j \geq 0 (j = 1, \ldots, q) \), which to ensure the conditional variance, \( \sigma_t^2 \) is non-negative. Although the ARCH model is simple model and widely used among researchers, but it has weakness. When modeling volatility using ARCH, there might be a need for a large value of the lag \( q \), hence a large number of parameters to be estimated. This may result the difficulties to estimate parameters.

After four years an extension from ARCH model was developed by [11] namely GARCH model. The GARCH model is more parsimonious (use fewer parameters) than ARCH model [19]. There are two part that consist in GARCH model which are mean equation, \( y_t \); see Equation (4) and variance equation, \( \sigma_t^2 \); see Equation (8). The general form for GARCH(p,q) model can be written as follows:
\[ \sigma_t^2 = \eta + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 \]  
(8)
where $\eta$ is the long-run volatility with condition $\eta > 0$, $\beta_i \geq 0; i = 1, ..., p$ and $\alpha_j \geq 0; j = 1, ..., q$. If $\beta_i + \alpha_j < 1$, then GARCH(p,q) model is covariance stationary. The unconditional variance of the error terms

$$\text{var}(\epsilon_t) = \frac{\eta}{1 - \beta - \alpha}$$

(9)

From the general form of GARCH(p,q) model, the GARCH(1,1) model can be defined as

$$\sigma_t^2 = \eta + \beta \sigma_{t-1}^2 + \alpha \epsilon_{t-1}^2$$

(10)

### 2.3. Model Selection

When comparing among different specification of ARMA-GARCH models, then we select an appropriate model based on Akaike Information Criteria (AIC) [20], the corrected Akaike Information Criteria (AICC), Schwarz's Bayesian Information Criterion (SBC) [21] and the Hannan-Quinn Information Criterion (HQC). The AIC, AICC, SBC and HQC can be computed as

$$AIC = -2 \ln (L) + 2k$$

$$\text{AICC} = \text{AIC} + 2 \frac{k(k + 1)}{N - k - 1}$$

$$SBC = -2 \ln (L) + \ln(N)k$$

$$\text{HQC} = -2 \ln (L) + 2 \ln(\ln(N))k$$

Where $L$ is the value of the likelihood function evaluated at the parameter estimates, $N$ is the number of observations, and $k$ is the number of estimated parameters. The minimum value of AIC, AICC, SBC and HQC was selected as the better model when comparing among models.

### 2.4. Model Evaluations

The performance of forecasting models are evaluated using three measures: Mean Square Error (MSE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE).

$$\text{MSE} = \frac{1}{T} \sum_{t=T_1}^{T} (\sigma_t^2 - \hat{\sigma}_t^2)^2$$

$$\text{RMSE} = \sqrt{\frac{1}{T} \sum_{t=T_1}^{T} (\sigma_t^2 - \hat{\sigma}_t^2)^2}$$

$$\text{MAPE} = \frac{1}{T} \sum_{t=T_1}^{T} \left| \frac{\sigma_t^2 - \hat{\sigma}_t^2}{\sigma_t^2} \right| \times 100$$

Where $T$ is the number of total observations and $T_1$ is the first observation in out-of-sample. The $\sigma_t^2$ and $\hat{\sigma}_t^2$ is the actual and predicted conditional variance at time $t$, respectively. When comparing among ARMA-GARCH models, the smallest value of MSE, RMSE and MAPE are chosen as the best accurate forecast model.

### 3. Results and Discussion

#### 3.1. In-Sample Part

In Fig. 1 (left panel) there is a clear trend of 1367 daily observations prices of the S.M.R 20 in Malaysia from 4th January 2010 to 4th August 2015. When daily prices converted to log returns, the plot in Fig. 1 (right panel) illustrates there are large negative values especially on March and October 2011. Both Fig.s can explained there exist volatility clustering in daily returns on S.M.R 20.
Fig. 1. In-sample results of daily prices (left panel) and daily returns (right panel) of S.M.R 20

The descriptive statistics of the daily returns for S.M.R 20 are shown in Table 1. There is excess kurtosis in daily returns, which is 5.5298 larger than the normal value of 3. This can explain that there exist heavier tails in the data and distribute as leptokurtic.

Table 1. Descriptive Statistics of Daily Returns of S.M.R 20

| Mean  | Variance | Standard Deviation | Kurtosis | Skewness |
|-------|----------|--------------------|----------|----------|
| -0.0469 | 1.3963   | 1.1817             | 5.5298   | -0.6102  |

Source: Author’s calculation using data S.M.R 20

The first step in time series data is to test the stationarity. The SAS output based on Phillips-Perron (PP) test [22], Augmented Dickey-Fuller (ADF) test [23] and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test [24] are shown in Table 2, 3 and 4, respectively. As Table 2 shows, we reject the null hypothesis of a unit root for the three cases (Zero mean, Single mean and Trend) at the 5 percent level of significance. This is because the “Pr<Tau” values are <.0001. These indicates that the series is stationary where there is no unit root.

Table 2. SAS output based on the PP test

| Type        | Lags | Rho    | Pr<Rho | Tau   | Pr<Tau |
|-------------|------|--------|--------|-------|--------|
| Zero mean   | 7    | -817.1034 | <.0001 | -24.2783 | <.0001 |
| Single mean | 7    | -816.8883 | 0.0019 | -24.2876 | <.0001 |
| Trend       | 7    | -817.0899 | 0.0008 | -24.2994 | <.0001 |

Source: Author's calculation using data S.M.R 20

In addition, at the 5 percent level of significance the Tau test in Table 3 also rejects the null hypothesis of a unit root in the three cases. The finding of ADF test is consistent with the PP test. Therefore, both PP test and ADF test results imply that the returns are stationary and the series has no unit root. Meanwhile in Table 4, the Eta test do not reject the null hypothesis of a unit root in the two cases (Single mean and Trend) at 5 percent level of significance. These indicates that the series is stationary and there is no unit root. Because all three tests proved the series is stationary and has no unit root, therefore we proceed next step.
Table 3. SAS output based on the ADF test

| Type          | Lags | Rho       | Pr<Rho | Tau      | Pr<Tau | F          | Pr>F   |
|---------------|------|-----------|--------|----------|--------|------------|--------|
| Zero mean     | 0    | -830.9948 | <.0001 | -24.3937 | <.0001 | 298.0640   | <.0010 |
| Single mean   | 0    | -832.3303 | <.0001 | -24.4155 | <.0001 | 298.5766   | <.0010 |
| Trend         | 0    | -833.6864 | <.0001 | -24.4367 | <.0001 | 298.5766   | <.0010 |

Source: Author's calculation using data S.M.R 20

Table 4. SAS output based on the KPSS test

| Type          | Lags | Eta       | Pr<Eta |
|---------------|------|-----------|--------|
| Single mean   | 23   | 0.1963    | 0.2754 |
| Trend         | 23   | 0.0861    | 0.2298 |

Source: Author's calculation using data S.M.R 20

When the series are stationary, the next testing is done on the statistical independence. In this step two models were tested: AR(1) model and MA(2) model. Both models were selected by using SCAN option in SAS software. The autocorrelation check of residuals for AR(1) model and MA(2) model are illustrated in Table 5 and 6, respectively. It appears from both tables that the Pr > ChiSq values are greater than 0.05 for all lag order, which implying that we cannot reject the null hypothesis of white noise and the estimated residuals are white noise. Therefore the identified model AR(1) and MA(2) passed the diagnostic test.

Table 5. Autocorrelation Check For Residuals of AR(1) Model

| To Lag | Chi-Square | DF | Pr > ChiSq | Autocorrelations |
|--------|------------|----|------------|------------------|
| 6      | 7.98       | 5  | 0.1571     | 0.020            |
| 12     | 13.05      | 11 | 0.2903     | -0.039           |
| 18     | 18.11      | 17 | 0.3817     | 0.014            |
| 24     | 24.70      | 23 | 0.3658     | -0.040           |
| 30     | 30.01      | 29 | 0.4137     | 0.017            |
| 36     | 34.05      | 35 | 0.5139     | 0.000            |
| 42     | 42.26      | 41 | 0.4164     | 0.027            |
| 48     | 45.33      | 47 | 0.5419     | 0.014            |

Source: Author's calculation using data S.M.R 20

Table 6. Autocorrelation Check For Residuals of MA(2) Model

| To Lag | Chi-Square | DF | Pr > ChiSq | Autocorrelations |
|--------|------------|----|------------|------------------|
| 6      | 3.39       | 4  | 0.4954     | -0.000           |
| 12     | 8.26       | 10 | 0.6031     | -0.036           |
| 18     | 13.19      | 16 | 0.5990     | 0.016            |
| 24     | 19.72      | 22 | 0.6005     | -0.039           |
| 30     | 25.53      | 28 | 0.5991     | 0.018            |
| 36     | 29.06      | 34 | 0.7083     | 0.001            |
| 42     | 37.39      | 40 | 0.5884     | 0.025            |
| 48     | 40.42      | 46 | 0.7045     | 0.018            |

Source: Author's calculation using data S.M.R 20
Table 7. In-Sample Analysis of Testing an ARCH Effect For S.M.R 20

| Order | Q    | Pr > Q | LM   | Pr > LM | LK   | Pr > |WL| Pr >WL |
|-------|------|--------|------|---------|------|------|---|--------|
| 1     | 166.1245 | <.0001 | 165.9043 | <.0001 | 25.0250 | <.0001 | 175.8346 | <.0001 |
| 2     | 227.7188 | <.0001 | 178.7377 | <.0001 | 24.5244 | <.0001 | 243.5460 | <.0001 |
| 3     | 422.5273 | <.0001 | 297.4051 | <.0001 | 30.6907 | <.0001 | 311.7386 | <.0001 |
| 4     | 518.0371 | <.0001 | 308.9287 | <.0001 | 27.8513 | <.0001 | 370.6685 | <.0001 |
| 5     | 529.9433 | <.0001 | 309.1092 | <.0001 | 26.9007 | <.0001 | 415.0158 | <.0001 |
| 6     | 556.9039 | <.0001 | 309.7842 | <.0001 | 26.5255 | <.0001 | 443.5837 | <.0001 |
| 7     | 589.8222 | <.0001 | 311.7765 | <.0001 | 24.8546 | <.0001 | 494.9318 | <.0001 |
| 8     | 594.9220 | <.0001 | 312.4701 | <.0001 | 23.0565 | <.0001 | 535.6105 | <.0001 |
| 9     | 596.8305 | <.0001 | 312.4006 | <.0001 | 21.8958 | <.0001 | 572.0933 | <.0001 |
| 10    | 597.1771 | <.0001 | 313.8788 | <.0001 | 20.7063 | <.0001 | 624.4816 | <.0001 |
| 11    | 597.5316 | <.0001 | 313.8788 | <.0001 | 19.7216 | <.0001 | 635.2950 | <.0001 |

Source: Author’s calculation using data S.M.R 20

Table 7 provides the result of ARCH effect using four tests which are Q test, LM test, LK test and WL test. The p-value of four tests indicate that we rejected the null hypothesis of no ARCH effect at the 5 percent level of significance. From Table 7, the results show that the presence of ARCH effect in S.M.R 20. This can be explained that heteroscedastic appeared in residuals.

Table 8. Comparison Model of Selection Criteria ARMA-GARCH Model

| Models          | AIC    | AICC   | SBC    | HQC    |
|-----------------|--------|--------|--------|--------|
| ARMA(0,1)       | 4124.7460 | NA     | 4135.1850 | NA     |
| ARMA(0,2)       | 4108.7360 | NA     | 4124.3950 | NA     |
| ARMA(1,0)       | 4110.6460 | 4110.6550 | 4121.0850 | 4114.5530 |
| ARMA(1,1)       | 4109.1410 | NA     | 4124.8000 | NA     |
| ARMA(1,2)       | 4110.7340 | NA     | 4131.6130 | NA     |
| ARMA(2,0)       | 4109.2020 | 4109.2190 | 4124.8610 | 4115.0620 |
| ARMA(2,1)       | 4111.1220 | NA     | 4132.0000 | NA     |
| ARMA(2,2)       | 4112.7330 | NA     | 4138.8310 | NA     |
| GARCH(1,1)      | 4034.7170 | 4034.7460 | 4055.5960 | 4042.5310 |
| GARCH(1,2)      | 4016.4990 | 4016.5430 | 4042.5970 | 4026.2670 |
| GARCH(2,1)      | 4329.4060 | 4329.4150 | 4339.8450 | 4333.3130 |
| GARCH(2,2)      | 4327.1800 | 4327.1890 | 4337.6200 | 4331.0880 |
| ARMA(1,0)-GARCH(1,1) | 3836.9930 | 3837.0370 | 3863.0910 | 3846.7610 |
| ARMA(1,0)-GARCH(1,2) | 3831.8580 | 3831.9200 | 3863.1760 | 3843.5800 |
| ARMA(1,0)-GARCH(2,1) | 4109.9150 | 4109.9330 | 4125.5740 | 4115.7760 |
| ARMA(1,0)-GARCH(2,2) | 4107.7620 | 4107.7790 | 4123.4210 | 4113.6230 |
| ARMA(2,0)-GARCH(1,1) | 3837.7330 | 3837.7950 | 3869.0510 | 3849.4540 |
| ARMA(2,0)-GARCH(1,2) | 3831.7290 | 3831.8120 | 3868.2670 | 3845.4050 |
| ARMA(2,0)-GARCH(2,1) | 4110.9660 | 4110.9960 | 4131.8450 | 4118.7810 |
| ARMA(2,0)-GARCH(2,2) | 4110.7770 | 4110.8060 | 4131.6550 | 4118.5910 |

NA = Not applicable

After confirmed heteroscedastic exist in residuals, then we proceed to specify the model. We generates 20 models from different conditional mean ad conditional variance specification in ARMA(m,n)-GARCH(p,q) models where m and n were either 0,1 or 2 while p and q were either 1 or 2. The 20 different specification models was compared based on criteria such as AIC, AICC, SBC and HQC to select the best model. The comparison among 20 models are highlighted in Table 8. The ARMA(2,0)-GARCH(1,2) model presents the minimum value of AIC and AICC.
ARMA(1,0)-GARCH(1,1) and ARMA(1,0)-GARCH(1,2) model shows minimum in SBC and HQC value, respectively. As Table 9 indicates, the ARMA(1,0)-GARCH(1,2) model and ARMA(2,0)-GARCH(1,2) model are the lowest in total rank. From both models, we decided ARMA(1,0)-GARCH(1,2) model as the best model in-sample part.

| Table 9. Comparison of ARMA-GARCH Model Based on Ranking |
|-----------------|-----------------|----------|----------|----------|----------|
| Models          | Rank AIC        | Rank AICC| Rank SBC | Rank HQC | Total rank |
| ARMA(0,1)       | 18              | 20       | 17       | 19       | 74        |
| ARMA(0,2)       | 8               | 15       | 9        | 15       | 47        |
| ARMA(1,0)       | 12              | 10       | 7        | 8        | 37        |
| ARMA(1,1)       | 9               | 16       | 10       | 16       | 51        |
| ARMA(1,2)       | 13              | 17       | 13       | 17       | 60        |
| ARMA(2,0)       | 10              | 8        | 11       | 9        | 38        |
| ARMA(2,1)       | 16              | 18       | 16       | 18       | 68        |
| ARMA(2,2)       | 17              | 19       | 18       | 20       | 74        |
| GARCH(1,1)      | 6               | 6        | 6        | 6        | 24        |
| GARCH(1,2)      | 5               | 5        | 5        | 5        | 20        |
| GARCH(2,1)      | 20              | 14       | 20       | 14       | 68        |
| GARCH(2,2)      | 19              | 13       | 19       | 13       | 64        |
| ARMA(1,0)-GARCH(1,1) | 3         | 3       | 1        | 3        | 10        |
| ARMA(1,0)-GARCH(1,2) | 2        | 2       | 2        | 1        | 7         |
| ARMA(1,0)-GARCH(2,1) | 11       | 9       | 12       | 10       | 42        |
| ARMA(1,0)-GARCH(2,2) | 7        | 7       | 8        | 7        | 29        |
| ARMA(2,0)-GARCH(1,1) | 4         | 4       | 4        | 4        | 16        |
| ARMA(2,0)-GARCH(1,2) | 1         | 1       | 3        | 2        | 7         |
| ARMA(2,0)-GARCH(2,1) | 15       | 12      | 15       | 12       | 54        |
| ARMA(2,0)-GARCH(2,2) | 14       | 11      | 14       | 11       | 50        |

3.2. Out-of-Sample Part

In Fig. 2 (left panel) there is a clear trend of 586 daily observations prices of the S.M.R 20 from 5th August 2015 to 29th December 2017. The plot in Fig. 2 (right panel) illustrates there are large negative values especially on 28th September 2017. Both Figures can be explained that there exists volatility clustering in daily prices and returns on S.M.R 20.

In out-of-sample part, the performance of forecasting was evaluated. The evaluation of ARMA-GARCH models in out-of-sample are summarized in Table 10. As illustrated in Table 10, the accurate forecast for MSE and RMSE statistic are ARMA(2,0)-GARCH(2,1) model and ARMA(2,0)-GARCH(2,2) model. While ARMA(1,0)-GARCH(1,2) model present more accurate in MAPE statistic. Therefore among 14 models, we decided ARMA(1,0)-GARCH(1,2) model as the best accurate model in out-of-sample part. This is supported by25 which suggested that the selection of MAPE statistic is the best if there are different results between three statistics. In addition, based on the SCAN option during in-sample part analysis, only AR(1) model and MA(2) model selected for forecasting.
Fig. 2: Out-of-sample results of daily prices (left panel) and daily returns (right panel) of S.M.R 20

Table 10: Comparison Model Evaluation of ARMA-GARCH Models

| Models                        | MSE     | RMSE   | MAPE   |
|-------------------------------|---------|--------|--------|
| ARMA(1,0)                    | 4.4771  | 2.1159 | 99.7326|
| ARMA(2,0)                    | 4.4845  | 2.1177 | 99.7914|
| GARCH(1,1)                   | 4.4650  | 2.1131 | 99.9117|
| GARCH(1,2)                   | 4.4727  | 2.1149 | 100.4053|
| GARCH(2,1)                   | 4.4650  | 2.1131 | 99.8665|
| GARCH(2,2)                   | 4.4650  | 2.1131 | 99.8665|
| ARMA(1,0)-GARCH(1,1)         | 4.4620  | 2.1123 | 99.8477|
| ARMA(1,0)-GARCH(1,2)         | 4.4620  | 2.1123 | 99.6798|
| ARMA(1,0)-GARCH(2,1)         | 4.4618  | 2.1123 | 99.7328|
| ARMA(1,0)-GARCH(2,2)         | 4.4618  | 2.1123 | 99.7328|
| ARMA(2,0)-GARCH(1,1)         | 4.4638  | 2.1128 | 100.3370|
| ARMA(2,0)-GARCH(1,2)         | 4.4664  | 2.1134 | 100.2446|
| ARMA(2,0)-GARCH(2,1)         | 4.4615  | 2.1122 | 99.7919|
| ARMA(2,0)-GARCH(2,2)         | 4.4615  | 2.1122 | 99.7919|

Source: Author’s calculation using SAS

3.3. Overall Part

For overall part, there is a clear trend of 1953 daily observations prices of the rubber S.M.R 20 in Malaysia from 4\textsuperscript{th} January 2010 to 29\textsuperscript{th} December 2017 depicted in Fig. 3. When daily prices converted to log returns, plotted of daily returns of rubber S.M.R 20 clearly show exhibit volatility clustering.
Table 11 provides the result of ARCH effect using four tests which are Q test, LM test, LK test and WL test. The p-value of four tests indicate that we reject the null hypothesis of no ARCH effect at the 5 percent level of significance. Table 11 shows that the presence of ARCH effect in S.M.R 20. This can be explained that heteroscedastic appeared in residuals.

| Order | Q       | Pr > Q | LM       | Pr > LM | LK     | Pr > |LK| | WL       | Pr > WL |
|-------|---------|--------|----------|---------|--------|-------|---|---|---------|---------|
| 1     | 150.624 | <.0001 | 150.410  | <.0001  | 19.838 | <.0001|   | | 6800.491 | <.0001  |
| 2     | 217.600 | <.0001 | 175.112  | <.0001  | 20.691 | <.0001|   | | 10690.557 | <.0001  |
| 3     | 335.227 | <.0001 | 235.213  | <.0001  | 23.911 | <.0001|   | | 14325.307 | <.0001  |
| 4     | 416.569 | <.0001 | 251.162  | <.0001  | 24.831 | <.0001|   | | 16981.035 | <.0001  |
| 5     | 451.437 | <.0001 | 251.959  | <.0001  | 23.986 | <.0001|   | | 19081.184 | <.0001  |
| 6     | 489.096 | <.0001 | 254.964  | <.0001  | 23.673 | <.0001|   | | 21779.230 | <.0001  |
| 7     | 567.360 | <.0001 | 276.011  | <.0001  | 24.629 | <.0001|   | | 24279.598 | <.0001  |
| 8     | 590.339 | <.0001 | 276.195  | <.0001  | 23.927 | <.0001|   | | 27379.125 | <.0001  |
| 9     | 654.523 | <.0001 | 296.258  | <.0001  | 24.501 | <.0001|   | | 30696.639 | <.0001  |
| 10    | 680.825 | <.0001 | 296.770  | <.0001  | 24.111 | <.0001|   | | 33706.437 | <.0001  |
| 11    | 701.056 | <.0001 | 296.961  | <.0001  | 23.648 | <.0001|   | | 36433.951 | <.0001  |
| 12    | 733.562 | <.0001 | 299.649  | <.0001  | 23.607 | <.0001|   | | 38825.800 | <.0001  |

Source: Author’s calculation using data S.M.R 20

Since the best model in estimation part and forecasting part are consistent, then the parameter estimation of ARMA(1,0)-GARCH(1,2) model summarized in Table 12. From Table 12, the estimated conditional mean and conditional variance of ARMA(1,0)-GARCH(1,2) model can expressed as

\[
\hat{y}_t = 0.043 - 0.312y_{t-1}
\]

\[
\sigma_t^2 = 0.011 + 0.913\sigma_{t-1}^2 + 0.224\epsilon_{t-1}^2 - 0.136\epsilon_{t-2}^2
\]

Finally we used ARMA(1,0)-GARCH(1,2) model to forecast the daily S.M.R 20 rubber price for 20 days ahead (2\textsuperscript{nd} January 2018 to 30\textsuperscript{th} January 2018) which presented in Table 13. From this data there is a clear trend forecasting of rubber price and returns, visible in Fig. 4.
Table 12. Estimation Result of ARMA(1,0)-GARCH(1,2) Model For Rubber S.M.R 20

| Parameter | Estimate | Standard error | t-value | Approx. Pr > |t| |
|-----------|----------|----------------|---------|---------------|---|
| Intercept | 0.043    | 0.035          | 1.24    | 0.2158        |   |
| $\phi_1$  | -0.312   | 0.025          | -12.49  | <.0001        |   |
| $\eta$    | 0.011    | 0.003          | 4.18    | <.0001        |   |
| $\alpha_1$| 0.224    | 0.030          | 7.4     | <.0001        |   |
| $\alpha_2$| -0.136   | 0.030          | -4.49   | <.0001        |   |
| $\beta_1$ | 0.913    | 0.008          | 109.26  | <.0001        |   |

Forecast performance

|       |       |               |          |               |
|-------|-------|---------------|----------|---------------|
| AIC   | 6396.60874 |               |          |               |
| AICC  | 6396.65193 |               |          |               |
| SBC   | 6430.0684  |               |          |               |
| HQC   | 6408.90953 |               |          |               |
| MSE   | 2.28525   |               |          |               |
| MAPE  | 122.27325 |               |          |               |

Table 13. Forecast Prices for Rubber S.M.R 20 (sen/kg)

| Date      | Actual Price RM (sen/kg) | Forecast Price RM (sen/kg) | L95     | U95     | Returns |
|-----------|--------------------------|----------------------------|---------|---------|---------|
| 2/1/2018  | 582.00                   | 580.85                     | 543.581 | 618.122 | -0.29172|
| 3/1/2018  | 576.00                   | 573.75                     | 527.962 | 619.538 | -0.07991|
| 4/1/2018  | 571.00                   | 572.77                     | 504.148 | 641.392 | -0.04130|
| 5/1/2018  | 572.00                   | 567.49                     | 485.423 | 649.55  | -0.03427|
| 8/1/2018  | 572.50                   | 565.55                     | 464.742 | 666.359 | -0.03299|
| 9/1/2018  | 580.00                   | 561.39                     | 446.294 | 676.489 | -0.03276|
| 10/1/2018 | 588.50                   | 558.99                     | 427.973 | 690.012 | -0.03273|
| 11/1/2018 | 590.50                   | 555.49                     | 410.962 | 700.009 | -0.03273|
| 12/1/2018 | 595.50                   | 552.91                     | 394.67  | 711.139 | -0.03273|
| 15/1/2018 | 603.00                   | 549.79                     | 379.34  | 720.233 | -0.03274|
| 16/1/2018 | 603.00                   | 547.17                     | 364.827 | 729.504 | -0.03274|
| 17/1/2018 | 597.50                   | 544.30                     | 351.104 | 737.488 | -0.03275|
| 18/1/2018 | 602.00                   | 541.70                     | 338.142 | 745.263 | -0.03276|
| 19/1/2018 | 595.00                   | 539.01                     | 325.857 | 752.154 | -0.03277|
| 22/1/2018 | 600.50                   | 536.47                     | 314.241 | 758.702 | -0.03277|
| 23/1/2018 | 590.00                   | 533.91                     | 303.211 | 764.601 | -0.03278|
| 24/1/2018 | 584.50                   | 531.44                     | 292.756 | 770.132 | -0.03279|
| 25/1/2018 | 585.50                   | 528.99                     | 282.812 | 775.16  | -0.03279|
| 26/1/2018 | 591.50                   | 526.60                     | 273.362 | 779.839 | -0.03280|
| 29/1/2018 | 580.50                   | 524.24                     | 264.357 | 784.116 | -0.03281|
| 30/1/2018 | 580.50                   | 521.93                     | 255.778 | 788.077 | -0.03281|

L95 = Lower 95, U95 = Upper 95
4. Conclusion

In this paper, the aim was to model the S.M.R. 20 rubber price using 20 different specification of ARMA-GARCH models. The results of this paper shows that ARMA(1,0)-GARCH(1,2) model is the best model for the period of in-sample part and out-of-sample sections. The ARMA(1,0)-GARCH(1,2) model was used to estimate and forecast the daily S.M.R 20 rubber price for 20 days ahead in the future market effectively. The findings of this study suggest that GARCH(1,2) model is suitable used to model and forecast the current S.M.R 20 rubber price compared to GARCH(1,1) model. Future research should therefore concentrate on the investigation of excess kurtosis on S.M.R 20 rubber price which caused by outlier effect.

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Fig. 4. Forecast of daily prices of S.M.R 20 (left panel) and Forecast of daily returns of S.M.R 20 (right panel)
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