Modeling and simulation of manufacture sector data in Malaysia with detection of outliers: An ARMA-GARCH approach

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Abstract. Manufacturing is one of the major sectors that contribute to the economy of Malaysia. The situation of manufacturing sales, especially rubber gloves received the attention of investors to forecast. However, the pattern of economics exposed to unexpected changes, which called outlier which occurred because of internal or external factors. Consequently, give shock to time series data. The main approach used is the hybrid of Autoregressive Moving Average (ARMA) model and Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model. The effectiveness of the volatility model with the existence of outliers are measured by Monte Carlo method. Besides, to find the best ARMA-GARCH model there are four models produced from different specifications in ARMA\((a,b)\) and GARCH\((g,h)\) models. In this paper, we used 216 monthly price data of Standard Malaysian Rubber Grade 20 (SMR 20) in Malaysia. The validity comparison of diagnostic checking is measured on AIC, AICc, SIC and HQIC. While the forecasting performance evaluated using MSE, RMSE and MAPE. The results of the empirical analysis indicate that the ARMA\((2,0)\)-GARCH\((1,2)\) model is the appropriate model to forecast the price of SMR 20 that were used to the manufacturing of rubber gloves in Malaysia.

1. Introduction

According to [1], about 23% from Gross Domestic Product are contributed by manufacturing sectors. One of the industries that contributed to manufacturing sectors are the rubber glove industry. The domestic consumption of natural rubber used in 2015 is 73.5% or 349,031 tonnes. However, the domestic consumption of natural rubber shows fluctuations from the period from 2008 to 2010; see Figure 1. These indicates that most of the time series data are influenced by heavy-tailed distribution and volatility clustering. The existing of both characteristics can give negative affect on volatility modelling as well as forecasting. Based on the previous research, Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model is used to accomplish the accuracy of modelling as well forecasting.

The GARCH model is highly recognized compared to Autoregressive Conditional Heteroscedasticity (ARCH) model. In recent years, there have been various amount of study on GARCH\((1,1)\) model to analyze time series data such as [2, 3, 4, 5, 6, 7, 8, 9]. Some references supports that GARCH\((1,1)\) model is popular among others specifications because it is fits many data series well [10] and sufficient to capture the volatility clustering in the data [11]. However, the phenomenon of outliers can give impacts to GARCH model.
The first serious discussion of outlier emerged during the 1970s by [12]. As highlighted by [13], the stock market volatility forecasts can be enhanced by revising the additive outlier. In 2005, [14] extended their investigation to innovative outlier. The GARCH model was preferred by both studies to forecast volatility and check out the effect of outlier. Several studies have revealed that the implications of outliers can tendency the parameters estimation of GARCH model [15, 16, 17], on estimation and identification of the GARCH-type models [18, 19], and also on forecasting [13, 17, 18]. Thus, previous research was tested the efficiency of the volatility model with hybrid ARMA\((a,b)\)-GARCH\((g,h)\) model.

Although the above investigations reported many interesting results, little work has examined on different specifications on ARMA\((a,b)\)-GARCH\((g,h)\) model. In particular, the effectiveness of volatility model in the presence of outliers via Monte Carlo method is less reported. The paper is planned as follows. The description of the ARMA\((a,b)\) model, GARCH\((g,h)\) model and additive outlier is explained in the next section. Then, the process of Monte Carlo simulation also presented. After that we applied to 216 monthly prices of SMR 20. Finally, the conclusion is summarized in the last section.

2. Materials and Methods

The time series models that will discussed in this section are Autoregressive Moving Average (ARMA) model and Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model. The formation of ARMA\((a,b)\) model is from the coupled of autoregressive (AR) model and moving-average (MA) model which can denoted in sigma notation as [20]

$$y_t = A + \sum_{i=1}^{d} \phi_i y_{t-i} + \sum_{j=1}^{b} \theta_j \varepsilon_{t-j} + \varepsilon_t$$  \hspace{1cm} (1)

where A is a constant term, \(\phi_i\) are the parameters of the AR term of order \(a\), \(\theta_j\) are the parameters of the MA term of order \(b\), and \(\varepsilon_t\) is the error term at time \(t\). The order \(a\) and \(b\) are positive integers.

In the recent decades, GARCH model which developed by [21] has been one of the major interesting in nonlinear time series model. This is due to the ARCH model utilize more parameters compared to GARCH model [22]. The conditional mean equation \((r_t)\) and conditional variance equation \((\sigma_t^2)\) in GARCH\((g,h)\) model formulated as in Eq.(2) and Eq.(4), respectively.

![Figure 1. The trend of SMR 20 (January 2008 – December 2010). Source: Malaysian Rubber Board.](image-url)
where \( r_t \) is a return series \((\ln(R_t/R_{t-1}))\), \( A \) is a constant term and \( \epsilon_t \) is residual term at time \( t \).

\[
r_t = A + \epsilon_t
\]

\( \epsilon_t = z_t \sigma_t, z_t \sim N(0,1) \)  

\[
\sigma_t^2 = \eta + \sum_{i=1}^{g} \beta_i \sigma_{t-i}^2 + \sum_{j=1}^{h} \alpha_j \epsilon_{t-j}^2
\]

where \( z_t \) is the standardized residual, \( \sigma_t^2 \) is the conditional variance at time \( t \), \( \eta \) is the constant parameter, \( \sigma_t^2 \) is the forecast variance for the current period (GARCH term) and \( \epsilon_t^2 \) is the recent information about volatility observed in the current period (ARCH term) with conditions \( \eta > 0, \beta_i \geq 0, i = 1, \ldots, g \) and \( \alpha_j \geq 0, j = 1, \ldots, h \).

In order to determine the persistence of GARCH(\( g,h \)) model, the non-negative constants can calculated as \( \sum \beta_i + \sum \alpha_j \). When the \( \sum \beta_i + \sum \alpha_j < 1 \), hence GARCH(\( g,h \))model is called covariance stationary. If the constant parameter, \( \eta \) combined with \( \sum \beta_i + \sum \alpha_j \), the level of unconditional variance (known as long term volatility) can be determined by

\[
\bar{\sigma}^2 = \text{var}(\epsilon_t) = \frac{\eta}{1 - (\sum \beta_i + \sum \alpha_j)}
\]

Since the general mathematical form of GARCH(\( g,h \)) model in Eq.(4), the GARCH(1,2) model can be written as follows

\[
\sigma_t^2 = \eta + \beta_1 \sigma_{t-1}^2 + \alpha_1 \epsilon_{t-1}^2 + \alpha_2 \epsilon_{t-2}^2
\]

where \( \sigma_t^2 \) is the conditional variance at time \( t \), \( \eta \) is the constant parameter, \( \sigma_{t-1}^2 \) is the forecast variance in the preceding period (GARCH term), \( \epsilon_{t-1}^2 \) is the information about volatility observed in the preceding period (ARCH term) and \( \epsilon_{t-2}^2 \) is the information about volatility observed in the two preceding period (ARCH term) with condition \( \eta > 0, \beta_1 \geq 0, \alpha_1 \geq 0 \) and \( \alpha_2 \geq 0 \).

Although there are various types of outliers that effect to time series data yet this research only focused to additive outliers (AO). The past forty years, [12] described AO in AR model. AO is also known as an external or exogenous change [23]. The recording errors, measurement errors or external factors are among the aspects that caused an AO.

From Eq.(4), GARCH(\( g,h \)) model can be written as an ARMA(\( a,b \)) model for \( \epsilon_t^2 \) [21] as

\[
\epsilon_t^2 = \eta + \sum_{i=1}^{a} (\alpha_j + \beta_i) \epsilon_{t-i}^2 + \kappa_t - \sum_{i=1}^{b} \beta_i \kappa_{t-j}
\]
with \( a = \max\{g, h\} \) and \( \kappa_i = \varepsilon_i^2 - \sigma_i^2; t = 1, 2, \ldots, n \) where \( \varepsilon_i^2 \) known as outlier free time series while \( \kappa_i \) known as outlier-free residuals. Equation (7) can be written

\[ \varepsilon_i^2 = \frac{\eta}{1 - \alpha(G) - \beta(G)} + \frac{1 - \beta(G)}{1 - \alpha(G) - \beta(G)} \kappa_i = \frac{\eta}{1 - \alpha(G) - \beta(G)} + \pi^{-1}(G) \kappa_i \]  

(8)

with \( \alpha(G) = \sum_{j=1}^{h} \alpha_j G^j, \beta(G) = \sum_{i=1}^{g} \beta_i G^i \) and \( \pi(G) = \frac{1 - \alpha_j(G) - \beta_i(G)}{1 - \beta_j(G)} \).

According to [24], the presence of AO in GARCH model turn into

\[ e_i^2 = \omega_{AO} \xi_{AO}(G) I_t(P) + e_i^2 \]  

(9)

From Eq.(9) can be interpreted as a regression model for \( e_i^2 \) and rewrite as

\[ e_i^2 = \omega_{AO} x_i + e_i^2 \]  

(10)

where

\( e_i^2 \) is an observed series \( e_i^2 \),

\( \omega_{AO} \) is the magnitude effect of AO, which is \( \omega_{AO}(P) = \frac{\sum_{i=1}^{n} \varepsilon_i^2 x_i}{\sum_{i=1}^{n} (x_i)^2} \),

\( x_i \) represent as \( x_i = \begin{cases} 0 & , t \n
\xi_{AO}(G) \) is the dynamic pattern of AO effect, where \( \xi_{AO}(G) = 1 \),

\( I_t(P) \) is an indicator function that explained the effect of outliers as

\[ I_t(P) = \begin{cases} 1 & , t = P \\
0 & , \text{otherwise} \end{cases} \]  

where \( P \) is the position of AO occurred.

2.1 Model Selection Criteria

The performance between different types of ARMA\((a, b)\)-GARCH\((g, h)\) models specification can be compared based on four model selection criteria: Akaike Information Criteria (AIC) [25], the corrected Akaike Information Criteria (AICc), Schwarz’s Bayesian Information Criterion (SIC) [26] and the Hannan-Quinn Information Criterion (HQIC) [27]. The AIC, AICc, SIC and HQIC can be computed as

\[ \text{AIC} = -2\ln(L) + 2k \]

\[ \text{AICc} = \text{AIC} + \frac{2(k + 1)}{N - k - 1} \]

\[ \text{SIC} = -2\ln(L) + \ln(N)k \]

\[ \text{HQIC} = -2\ln(L) + 2\ln(\ln(N))k \]

where \( L \) is the value of the likelihood function that evaluated at the parameter estimates, \( N \) is the number of observations, and \( k \) is the number of estimated parameters. When comparing among
ARMA\((a,b)\)-GARCH\((g,h)\) models, the smallest value of AIC, AICc, SIC and HQIC are chosen as the best model.

2.2 Model Goodness of Fit

In order to determine the model’s goodness of fit, the performance of forecasting model is evaluated using three measures: Mean Square Error (MSE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE).

\[
\text{MSE} = \frac{1}{T} \sum_{t=1}^{T} (\sigma_t^2 - \hat{\sigma}_t^2)^2 \\
\text{RMSE} = \sqrt{\frac{1}{T} \sum_{t=1}^{T} (\sigma_t^2 - \hat{\sigma}_t^2)^2} \\
\text{MAPE} = \frac{1}{T} \sum_{t=1}^{T} \left| \frac{\sigma_t^2 - \hat{\sigma}_t^2}{\sigma_t^2} \right| \times 100
\]

where \(T\) is the number of total observations and \(T_i\) is the first observation in out-of-sample part. The \(\sigma_t^2\) and \(\hat{\sigma}_t^2\) is the actual and predicted conditional variance at time \(t\), respectively. The ARMA\((a,b)\)-GARCH\((g,h)\) model that have minimum value of MSE, RMSE and MAPE was selected as the best forecast model.

2.3 Simulation Study

The GARCH model was generated by using tseries package [29] and fGarch package [30] in the statistical software environment R [28]. The effectiveness of the ARMA\((a,b)\)-GARCH\((g,h)\) models were compared in two scenarios: contaminated with 0% AO and contaminated with 10% AO. For each scenario, there are three types of time series length (T) which are 120, 360 and 480. The simulation process carried out in this study is summarized as the following algorithm:

1. The true value of coefficients were fixed as \(A = 1.0265, \varphi_1 = -0.3581, \varphi_2 = 0.0198, \eta = 31.0877, \alpha_1 = 0.0967, \alpha_2 = 0.3322, \beta_1 = 0.001821\) during specified ARMA\((2,0)\)-GARCH\((1,2)\) model in garchSpec function.
2. The GARCH process were simulated 120 series length with normal innovations.
3. The coefficients of the ARMA\((2,0)\)-GARCH\((1,2)\) model were estimated with normal innovations in garchFit function.
4. In the scenario of 0% AO, the efficiency of ARMA\((2,0)\)-GARCH\((1,2)\) model were calculated.
5. About 10% from time series length contaminated as AO. The positions and magnitudes of AO are recognized.
6. The coefficients of the ARMA\((2,0)\)-GARCH\((1,2)\) model were estimated with normal innovations during contamination 10% AO.
7. In the scenario of 10% AO, the efficiency of ARMA\((2,0)\)-GARCH\((1,2)\) model were calculated.
8. Step (1) to (7) repeated by setting time series length to 360 and 480.

3. Results and Discussion

3.1 Simulation Results

Table 1 presents the summary of the descriptive statistics during 0% AO and 10% AO. The kurtosis values in the scenario of 10% AO are 8.3639, 17.5987 and 17.0654 for time series length 120, 360 and 480, respectively. From this data we can revealed that there is leptokurtic distribution during contaminated.
Table 1. Summary of descriptive statistics for 0% and 10% additive outlier.

| Criteria      | 0% AO T=120 | 0% AO T=360 | 0% AO T=480 | 10% AO T=120 | 10% AO T=360 | 10% AO T=480 |
|---------------|-------------|-------------|-------------|-------------|-------------|-------------|
| Mean          | -0.0044     | 0.0140      | 0.0789      | -0.1252     | 0.0018      |
| Variance      | 1.0909      | 0.9922      | 1.0003      | 6.3115      | 6.9388      | 10.3543     |
| Standard deviation | 1.0445     | 0.9961      | 1.0001      | 2.5123      | 2.6342      | 3.2178      |
| Kurtosis      | -0.3047     | -0.2124     | -0.1377     | 8.3639      | 17.5987     | 17.0654     |
| Skewness      | -0.0062     | 0.0202      | -0.0310     | 1.9662      | -0.8984     | -1.1096     |

As shown in Table 2, the two scenarios were compared based on selection criteria. When simulated 120 observations with contaminated 10% AO, there were an increased of 47.12%, 47.21% and 46.09%, respectively in AIC, SIC and HQIC criteria. In addition, the AIC, SIC and HQIC criteria showed increased when the time series length increased to 360 and 480. These finding highlights that the value of three criteria’s during contamination AO is larger than without contamination AO.

Table 2. Selection criteria for 0% and 10% additive outlier.

| Percentage contamination | Criteria | T=120 | T=360 | T=480 |
|--------------------------|---------|-------|-------|-------|
| 0%                       | AIC     | 2.9782| 2.8587| 2.8393|
|                          | SIC     | 2.9719| 2.8580| 2.8389|
|                          | HQIC    | 3.0442| 2.8888| 2.8633|
|                          | AIC     | 4.3814| 4.8003| 5.1723|
| 10%                      | SIC     | 4.3751| 4.7996| 5.1719|
|                          | HQIC    | 4.4474| 4.8304| 5.1962|

Table 3 provides the comparison goodness of fit among contaminated 0% and 10% AO. The MSE value in time series length 120 during situation 0% AO and 10% AO displayed 1.0240 and 6.5103, respectively. This showed the percentage increment of 535.77%. While there was an increased of 152.15% in RMSE criteria. When the percentage of contamination increased, both criteria’s shows larger value. This situation is consistent when the time series length increased.

Table 3. Goodness of fit for 0% and 10% additive outlier.

| Percentage contamination | Criteria  | T=120 | T=360 | T=480 |
|--------------------------|-----------|-------|-------|-------|
| 0%                       | MSE       | 1.0240| 0.9836| 0.9731|
|                          | RMSE      | 1.0119| 0.9918| 0.9865|
| 10%                      | MSE       | 6.5103| 6.8454| 10.2186|
|                          | RMSE      | 2.5515| 2.6164| 3.1967|

3.2 Empirical Results

In this section, the monthly price data of Standard Malaysian Rubber Grade 20 (SMR 20) are investigated. These data consist of period from January 2000 to December 2017. All observations were taken from official portal of Malaysia Rubber Board. From 216 observations, about 151 observations were selected into in-sample part as model estimation while 65 observations were selected into out-of-sample part as model evaluation in forecasting.

There is a clear trend of 151 monthly observations prices of the SMR 20 in Malaysia from January 2000 to July 2012. When monthly prices converted to log returns, the plot in Figure 2 (right) illustrates there are large negative values especially on October 2008 and December 2008. Both figures can explained there exist volatility clustering in monthly returns on SMR 20.
Figure 2. In-sample results of monthly prices (left) and returns (right) of SMR 20.

The descriptive statistics of the monthly returns for SMR 20 are shown in Table 4. The kurtosis value displays 5.1872, which is greater than the value of normal distribution. From this value, we can state that there is a leptokurtic distribution during the model estimation part.

| Table 4. Summary of descriptive statistics of monthly returns of SMR 20. |
|-------------------|-------------------|-------------------|-------------------|-------------------|
| Mean | Variance | Standard deviation | Kurtosis | Skewness |
| 0.8070 | 60.6026 | 7.7848 | 5.1872 | -1.2846 |

The first step in time series data analysis is to test the stationarity. There are three tests that are considered in this paper: Phillips-Perron (PP) test [31], Augmented Dickey-Fuller (ADF) test [32], and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test [33]. The finding of ADF test is consistent with the PP test, which we reject the null hypothesis of a unit root at the 5 percent level of significance. These indicate that the series is stationary where there is no unit root. Meanwhile, we do not reject the null hypothesis of a unit root in KPSS test. This indicates that the series is stationary and there is no unit root. All three tests proved that the series is stationary and has no unit root, therefore we proceed to the next step.

After confirmed heteroscedastic exist in residuals, then we proceed to specify the model. We generate four models from different conditional mean and conditional variance specification in ARMA($a$, $b$)-GARCH($g$, $h$) models where $a$ and $b$ were 2 and 0, respectively. While $g$ and $h$ were either 1 or 2. The four different specification models was compared based on criteria such as AIC, AICc, SIC and HQIC to select the best model. The comparison among four models are highlighted in Table 5. The ARMA(2,0)-GARCH(1,2) model presents the minimum value for all selection criteria (AIC, AICc, SIC and HQIC). Therefore, we decided ARMA(2,0)-GARCH(1,2) model as the best model in-sample part.

| Table 5. Comparison of selection criteria for ARMA($a$, $b$)-GARCH($g$, $h$) models. |
|-------------------|-------------------|-------------------|-------------------|-------------------|
| Models | AIC | AICc | SIC | HQIC |
| ARMA(2,0)-GARCH(1,1) | 1030.8990 | 1031.4864 | 1048.9628 | 1038.2377 |
| ARMA(2,0)-GARCH(1,2) | 1022.2898 | 1023.0786 | 1043.3643 | 1030.8517 |
| ARMA(2,0)-GARCH(2,1) | 1034.8354 | 1035.1112 | 1046.8779 | 1039.7279 |
| ARMA(2,0)-GARCH(2,2) | 1034.8291 | 1035.1050 | 1046.8717 | 1039.7216 |

In Figure 3 (left) there is a clear trend of 65 monthly observations prices of the SMR 20 from August 2012 to December 2017. The plot in Figure 3 (right) illustrates there are large negative values especially on April 2017. Both figures can be explained that there exists volatility clustering in monthly prices and returns on SMR 20.
In out-of-sample part, the performance of forecasting was evaluated. The evaluation of ARMA(\(a, b\))-GARCH(\(g, h\)) models in out-of-sample are summarized in Table 6. As illustrated in Table 6, the accurate forecast for MSE and RMSE statistic is ARMA(2,0)-GARCH(1,1) model. While ARMA(2,0)-GARCH(1,2) model present more accurate in MAPE statistic. Therefore among four models, we decided ARMA(2,0)-GARCH(1,2) model as the best accurate model in out-of-sample part. This is supported by [34] which suggested that the selection of MAPE statistic is the best if there are different results between three statistics.

| Models            | MSE       | RMSE      | MAPE     |
|-------------------|-----------|-----------|----------|
| ARMA(2,0)-GARCH(1,1) | 34.3860   | 5.8640    | 812.5882 |
| ARMA(2,0)-GARCH(1,2) | 34.3939   | 5.8646    | 800.5116 |
| ARMA(2,0)-GARCH(2,1) | 34.3862   | 5.8640    | 813.7431 |
| ARMA(2,0)-GARCH(2,2) | 34.3862   | 5.8640    | 813.7431 |

For overall part, there is a clear trend of 216 monthly observations prices of the rubber SMR 20 in Malaysia from January 2000 to December 2017 depicted in Figure 4. When monthly prices converted to log returns, plotted of monthly returns of rubber SMR 20 clearly show exhibit volatility clustering.

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

\[
\hat{y}_t = 1.0265 - 0.3581y_{t-1} + 0.0198y_{t-2}
\]
\[ \sigma_i^2 = 31.0877 + 0.001821 \sigma_{i-1}^2 + 0.0967 \epsilon_{i-1}^2 + 0.3322 \epsilon_{i-2}^2 \]

The outliers in monthly price of SMR 20 were detected automatically by using X12 procedure. During this process, the best ARIMA model selection which is \((1,1,0) \times (0,0,0)_{12}\) was automatic identify based on [35]. The default initial critical values used for additive outlier (AO) and level change outlier (LC) detection is 3.971414. It appears that, the LC on June 2002 was identified as potential outliers. While there are two types of outliers that included in the regression model. There are LC and AO which located on October 2008 and December 2008, respectively. This is due to the fact that the global economic recession happened in the second half of the year. In addition, when the critical value decreases to 3.3, there are two additional outliers detected. These includes LC on June 2002 and AO on March 2011. As it happens on 11 March 2011, the Earthquake and Tsunami hit Japan which triggered panic selling.

4. Conclusion

This paper presents the modeling and numerical simulation of SMR 20 return price that used in manufacturing rubber gloves. The following conclusions were obtained. 1) Based on the modelling result shows that ARMA(2,0)-GARCH(1,2) model is the best model for the period of in-sample part and out-of-sample part compared to three different specifications of ARMA\((a,b)\)-GARCH\((g,h)\) model. These findings of this paper suggest that GARCH(1,2) model is suitable used to model the current SMR 20 rubber price compared to GARCH (1,1) model. 2) One of the more significant findings to emerge from this paper is that the efficiency of ARMA(2,0)-GARCH(1,2) model were decreased when outliers were present. The outliers that we have identified therefore assists in our understanding of the influence of outlier in time series data. more research is required on the modelling of rubber gloves by using latex price. Considerably more work will need to be done to determine the outlier types of outliers that effects on the behavioural time series data such as level change outliers and temporary change outliers based on different specification of ARMA\((a,b)\)-GARCH\((g,h)\) model.

References

[1] Department of Statistics Malaysia Retrieved from http://www.dosm.gov.my/v1/ 28 February 2019
[2] Pham H T and Yang B S 2010 Estimation and forecasting of machine health condition using ARMA/GARCH model Mechanical Systems and Signal Processing 24 546–558
[3] Wang Y and Wu C 2012 Forecasting energy market volatility using GARCH models: Can multivariate models beatunivariate model Energy Economics 34 2167–2181
[4] Hickey E, Loomis D G and Mohammad H 2012 Forecasting hourly electricity prices using ARMAX-GARCH models: An application to MISO hubs Energy Economics 34 307–315
[5] Salisu A A and Fasanya I O 2013 Modelling oil price volatility with structural breaks. Energy Policy 52 554–562
[6] Huq M M, Rahman M M, Rahman M S, Shahin A and Ali A 2013 Analysis of Volatility and Forecasting General Index of Dhaka Stock Exchange American Journal of Economics 3(5) 229–242
[7] Joukar A and Nahmens I 2015 Volatility Forecast of Construction Cost Index Using General Autoregressive Conditional Heteroskedastic Method Journal of Construction Engineering and Management 142(1) 04015051
[8] Goh H H, Tan K L, Khor C Y and Ng S L 2016 Volatility and Market Risk of Rubber Price in Malaysia: Pre- and Post-Global Financial Crisis Journal of Quantitative Economics 14(2) 323–344
[9] Epaphra M 2017 Modeling Exchange Rate Volatility: Application of the GARCH and EGARCH Models *Journal of Mathematical Finance* 7 121–143
[10] Hill R C, Griffiths W E and Lim G C 2011 *Principles of Econometrics* ed Fourth (United States of America: John Wiley & Sons, Inc) chapter 14 pp 526
[11] Brooks C 2014 *Introductory Econometrics for Finance* ed Third (New York: Cambridge University Press) chapter 9 pp 430
[12] Fox A J 1972 Outlier in time series *Journal of the Royal Statistical Society. Series B (Methodological)* 34(3) 350–363
[13] Franses P H and Ghysels H 1999 Additive outliers, GARCH and forecasting volatility *International Journal of Forecasting* 15(1) 1–9
[14] Charles A and Darné O 2005 Outliers and GARCH models in financial data *Economics Letters* 86(3) 347–352
[15] Sakata S and White H 1998 High breakdown point conditional dispersion estimation with application to S&P 500 daily returns volatility *Econometrica* 66(3) 529–567
[16] Melo Mendes B V D 2000 Assessing the bias of maximum likelihood estimates of contaminated GARCH models *Journal of Statistical Computation and Simulation* 67(4) 359–376
[17] Charles A 2008 Forecasting volatility with outliers in GARCH models *Journal of Forecasting* 27(7) 551–565
[18] Carnero M A, Peña D and Ruiz E 2007 Effects of outliers on the identification and estimation of GARCH models *Journal of Time Series Analysis* 28(4) 471–497
[19] Carnero M A, Peña D and Ruiz E 2012 Estimating GARCH volatility in the presence of outliers *Economics Letters* 114(1) 86–90
[20] Box G E P, Jenkins G M, Reinsel G C and Ljung G M 2015 *Time series analysis: Forecasting and control* ed Fifth (Hoboken, New Jersey: John Wiley & Sons, Inc)
[21] Bollerslev T 1986 Generalized autoregressive conditional heteroskedasticity *Journal of Econometrics* 31(3) 307–327
[22] Poon S H and Granger C W 2003 Forecasting volatility in financial markets: A review *Journal of Economic Literature* 41(2) 478–539
[23] Urooj A and Asghar Z 2017 Analysis of the performance of test statistics for detection of outliers (additive, innovative, transient and level shift) in AR (1) processes *Communications in Statistics Simulation and Computation* 46(2) 948–979
[24] Chen C and Liu L-M 1993 Joint estimation of model parameters and outlier effects in time series *Journal of the American Statistical Association* 88(421) 284–297
[25] Akaike H 1974 A new look at the statistical model identification *IEEE Transactions on Automatic Control* AU-19 716–722
[26] Schwarz G 1978 Estimating the dimension of a model *The Annals of Statistics* 6(2) 461–464
[27] Hannan E J and Quinn B G 1979 The determination of the order of an autoregression *Journal of the Royal Statistical Society. Series B (Methodological)* 41(2) 190–195
[28] The R project for statistical computing Retrieved from http://www.r-project.org/ 11 June 2019
[29] tseries: Time series analysis and computational finance Retrieved from http://cran.r-project.org/web/packages/tseries 11 June 2019
[30] fGarch: Rmetrics – Autoregressive conditional heteroskedastic modelling Retrieved from http://cran.r-project.org/web/packages/fGarch 11 June 2019
[31] Phillips P C B and Perron P 1988 Testing for a unit root in time series regression *Biometrika* 75(2) 335–346
[32] Dickey D A and Fuller W A 1979 Distribution of the estimators for autoregressive time series with a unit root *Journal of the American Statistical Association* 74(366a) 427–431
[33] Kwiatkowski D, Phillips P C B, Schmidt P and Shin Y 1992 Testing the null hypothesis of stationarity against the alternative of a unit root *Journal of Econometrics* 54(1–3) 159–178
[34] Makridakis S 1993 Accuracy measures: Theoretical and practical concerns *International Journal of Forecasting* 9(4) 527–529
[35] Gómez V and Maravall A 2001 *Automatic modeling methods for univariate series* In: Peña D, Tiao GC and Tsay RS *A course in time series* (New York: Wiley) p 171-201