THE IMPACT OF STRUCTURAL BREAK TO PERMANENT AND TRANSITORY COMPONENTS OF MALAYSIAN STOCK MARKET

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Abstract

This article studied the time-varying volatility, components features of volatility, non-normality and leverage effect of Malaysian stock market under the structural breaks. A modified threshold two-components autoregressive conditional heteroscedasticity (ARCH) model with sudden structural changes is developed to account for all the possible stylized facts simultaneously. Our empirical results have shown that the permanent components are substantially reduced or eliminated when the structural break effects are included in the transitory and permanent components for the conditional variance models separately. With this finding, we concluded that the structural breaks have created the spurious long-persistence volatility in the Malaysian stock market.

Keywords: financial time series, structural break, long-persistence volatility, component GARCH.

JEL Classification: C5, C32, G12

1. Introduction

Long-persistence time varying volatility and occasional structural breaks are the two salient features in the financial asset pricing studies. Especially in volatility modelling, the occasional breaks often caused overestimation problem in long-persistence volatility models such as fractionally integrated in Brownian motion, ARCH and autoregressive-moving average (ARMA) models respectively. The preciseness of volatility estimations played an important role in controlling the financial risks as well as the portfolio strategy. Particularly in risk management, the immediate application of volatility estimation is the determination of value-at-risk [1], which has been widely used as a tool to control the risk in financial industry.

The common approaches to take into account the structural breaks in return and volatility can be found in the GARCH-jump models [2], regime-switching models [3,4], mixture of normal

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distributions model [5] and continuous-time volatility with jump effect [6,7]. In general, disregard for the presence of structural breaks might cause model misspecification problem and spurious statistical inference. Consequently, wrong conclusions might be used to explain the actual financial market behaviour. In addition, empirical studies by Diebold and Inoue [3] and Granger and Hyung [8] have shown that the structural breaks can create additional volatility persistence and possibily lead to the spurious long-memory volatility. Besides the long persistence time-varying volatility and occasional breaks issues, other stylized empirical facts such as leverage effect [9,10] and heavy-tailed property are also important in constructing the correct model specifications.

In this specific study, we concentrated on the Malaysian stock markets namely the Kuala Lumpur Stock Exchange (KLSE) composite index (CI). As an emerging stock market, the KLSE has received great attentions from researchers and investors as a source of case studies and potential investment alternatives. Studies [11-14] focused on long-persistence volatility, structural changes and important stylized facts in the KLSE especially during the Asian financial crisis, changes in currency policy, stock market liberalization, etc. With the empirical evidence, we strongly believed that all the mentioned stylized facts occurred in the Malaysian stock market. In this paper, we have selected the recovery period of the KLSE after the drastic Asian Financial crisis. During this period, the Malaysian stock market is speculated by mixtures of good and bad news such as the implementation of RM-USD un-pegged regulation where the RM is estimated to be undervalued by approximately 6.5%; the merged of MESDAQ (http://www.bursamalaysia.com.my) in the KLSE besides the Main board and Second board previously started in year 2002, regular hiking of petrol prices, etc.

For model specification, we have modified the threshold two-components GARCH model [15,16] with heavy tail innovation to take into account the long-persistence time-varying volatility, leverage effect, non-normality and structural break effect of the model specifications. Without the inclusion of the structural break, our results demonstrated the presence of non-normally distributed innovations (student-t with degree of freedom approximately 7), leverage effect and permanent and transitory components volatilities. However, the empirical evidence has shown that the permanent component are substantially reduced and eliminated when the structural break effects are included in the transitory and permanent components of the conditional variance models separately. This implies that the spurious long-persistence volatility may occur due to the structural break effects.

2. Data Source

The data for our empirical study consisted of the KLSE index prices during the period 1st January 2001 to 30th June 2005 (1100 observations). This price index is weighted by market capitalisation with the base year 1977 of 100 listed companies. The interday return series, r_t is defined as the close-to-close prices on consecutive trading days. The percentage interday returns can be expressed as:

$$r_t = 100\left(\ln P_{t,close} - \ln P_{t-1,close}\right) \qquad \ldots (1)$$

3. Methodology

3.1 Structural break identifications

There are voluminous alternatives of unknown break location tests [17-19], among others. Due to the simplicity and efficiency, we have selected an ordinary least squares (OLS) approach. The linear regression coefficients ($\theta_1,\ldots,\theta_{k+1}$) are obtained using the White heteroskedasticity consistent [20] estimator which remained the point estimates but changed the estimated standard errors for possible unknown heteroscedasticity. Instead of using the overall data, we divided them into different time-windows[4] (25, 50 and 100 days) in order to improve the sensitivity breaks identification. Consider a time series with sample size, T and let $\boldsymbol{x}_t$ be a vector of factors in a linear regression of p_t on $\boldsymbol{x}_t$ which changes at k discrete (break) points in time:

$$r_t = x_t'\varphi_1 + u_t \qquad t=1,\ldots,T_1;$$

$$r_t = x_t'\varphi_2 + u_t \qquad t=T_1+1,\ldots,T_2;$$

$$\vdots$$

$$r_t = x_t'\varphi_{k+1} + u_t \qquad t=T_k+1,\ldots,T; \qquad \ldots (2)$$

where T_k represents the possible breakpoints with the condition $T_1 < T_2 <\ldots< T_k < T$ and u_t is a disturbance term. The parameters' stability between the sub-periods is examined using the CUSUM test [21] based on the cumulative sum of the recursive residuals, w_t. The statistic w_t can be written in the form of

$$w_t = \sum_{t=k+1}^{n} \frac{w_n}{s} \quad \text{with } n = k+1, \ldots, T \text{ and } s \text{ is the White standard error.} \qquad \ldots (3)$$

The structural break point is detected when the w_t departed from the pair of 5% critical lines with the restriction of $|w_t| > 0.948\ (1+2\frac{n-k}{T-k})\sqrt{T-k}$. These procedures are used to identify both the returns and volatility structural break points.

3.2 Volatility models

3.2.1 GARCH-break

The conditional mean equation of the KLSE stock return is formulated as below:

$$r_t = \theta_0 + \sum_{i=1}^{k} DUM_i\theta_i r_{t-1} + a_t, \qquad a_t = \sigma_t\varepsilon_t,\ \varepsilon_t \sim t(v) \qquad \ldots (4)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1\sigma_{t-1}^2 + \phi_c a_{t-1}^2 I_{t-1} + \sum_{j=1}^{h} DUM_j\mu_j\sigma_{t-1}^2 \qquad \ldots (5)$$

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[4] We only illustrated the empirical results of time-window 50 days. The 25 and 100 time windows are somewhat too sensitive or less sensitive to detect the presence of structural breaks.

where the a_t is serially uncorrelated, but depend on its lag values or the conditional variance components. A *student-t* distribution with degree of freedom, v>2, is used in order to account for the fat-tailed property. On the other hand, the negative news impact is determined by a dummy variable, I.

3.2.2 Two Components GARCH-break

Ding and Granger [15] and Engle and Lee [16] introduced the CGARCH that can capture the high persistence in volatilities. Similar long-persistence volatility models can be found in [22-24], among others. Specifically, the CGARCH is decomposed into two components with one component capturing the short-run innovation impact and the other, the long-run impact of an innovation as follows:

$$\sigma_t^2 = \sigma_{t,q}^2 + \sigma_{t,s}^2; \quad \ldots (6)$$

$$\sigma_{t,q}^2 = \omega + \gamma_{1q}\sigma_{t-1,q}^2 + \gamma_{2q}(a_{t-1}^2 - \sigma_{t-1}^2) + \sum_{j=1}^{k} DUM_j \lambda_j \sigma_{t-1}^2 \quad \ldots (7)$$

$$\sigma_{t,s}^2 = \gamma_{1s}\sigma_{t-1,s}^2 + \gamma_{2s}(a_{t-1}^2 - \sigma_{t-1}^2) + \phi_c(a_{t-1}^2 - \sigma_{t-1}^2)I_{t-1} + \sum_{j=1}^{k} DUM_j \lambda_j \sigma_{t-1}^2 \quad \ldots (8)$$

where I is the dummy variable indicating negative innovation in the transitory component. The break features are added either in the permanent or transitory components to study the possible impact and implications. In the absence of permanent component, the CGARCH become a standard GARCH because the CGARCH is actually a restricted GARCH model.

For both the models, the initial values of innovation and conditional variance are obtained from the backcasting methodology. Next, the maximum likelihood estimation under the errors of student's distribution is used to estimate the desired parameters. Due to the nature of non-linearity of conditional variance, the parameter estimations are based on first derivative[5] Marquardt iterative optimization algorithm with the convergence criterion of 1×10^{-5}.

3.2.3 Diagnostic Tests

The adequacy of the models is tested using the Ljung-Box statistics for both standardized and squared residuals. The acceptance of the test statistics indicated no significant autocorrelation in the conditional mean and variance equations. The Engle LM ARCH test is also implemented to check the presence of ARCH effects. In addition, the adequacy test is further examined using Engle and Ng [25] test to determine the non-detected asymmetry volatility models' response to news.

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5 The first derivative approach is preferable due to the fast computational speed and accuracy as compared to second derivative of the Hessian matrix determination.

4. Empirical study

4.1 Descriptive statistics

Figure 1 illustrated the price index, returns and absolute returns of the Malaysian stock market where there are evidences of potential breaks in several dates. For return series, the clustering volatility is indicated in the second plot. Finally, the absolute return (as the volatility proxy) demonstrated long persistence spikes, which implied possible long-memory trend components in the volatility.

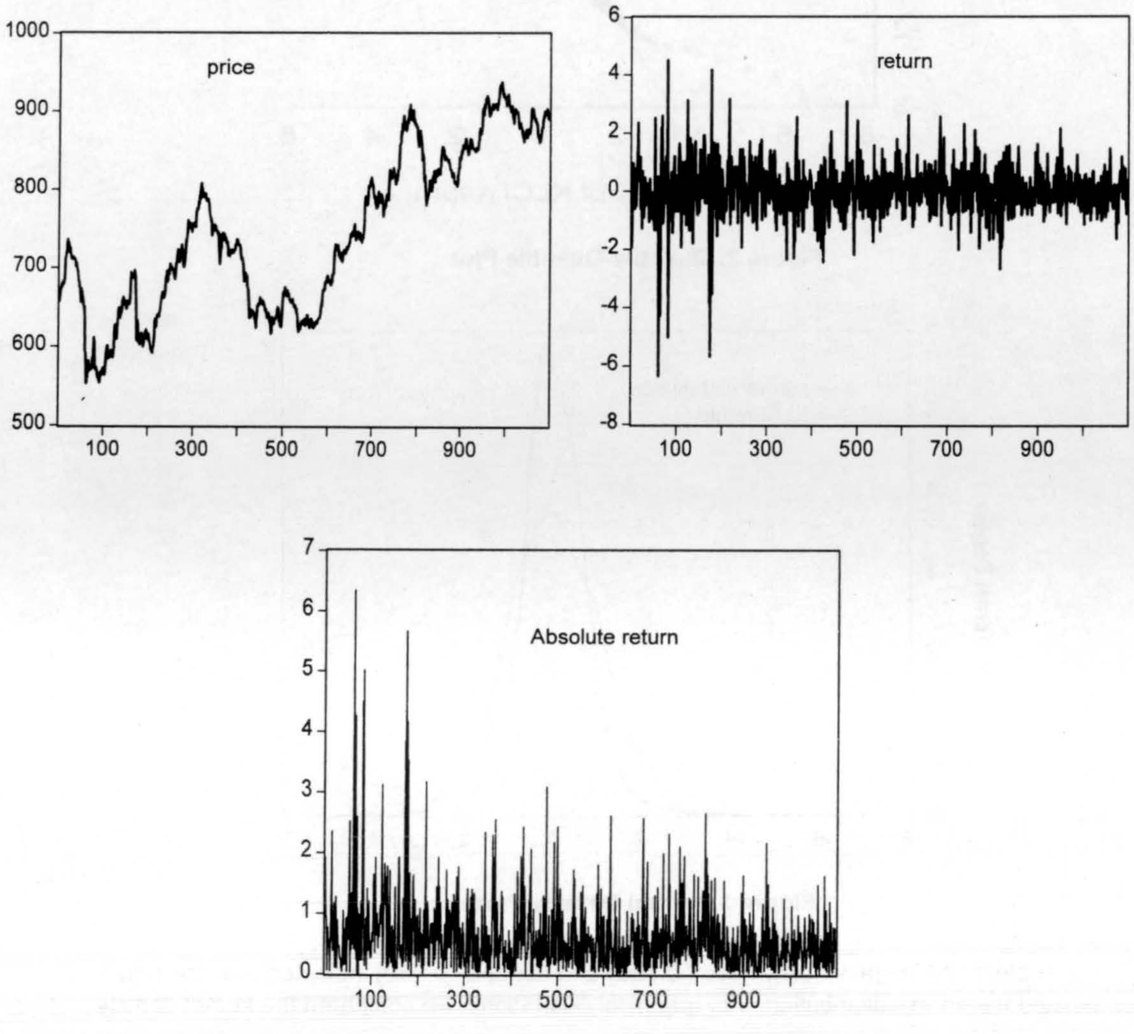

Figure 1. The KLSE Price Index, Daily Return and Absolute Daily Return

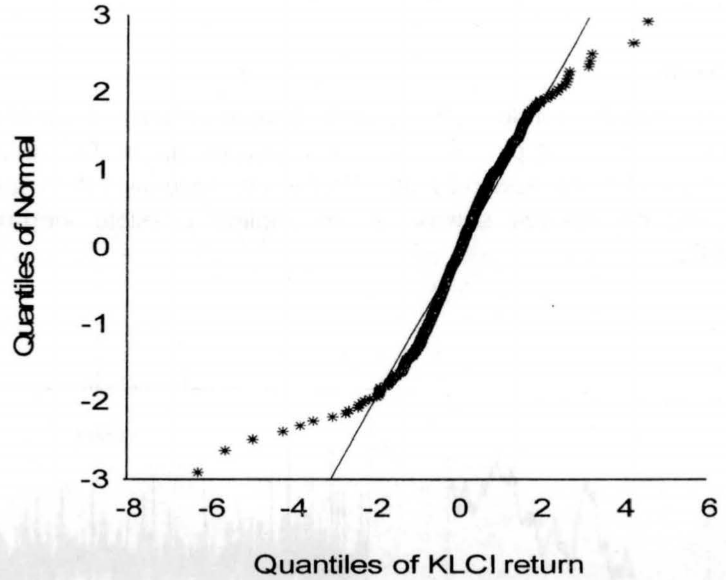

Figure 2. Quantile-Quantile Plot

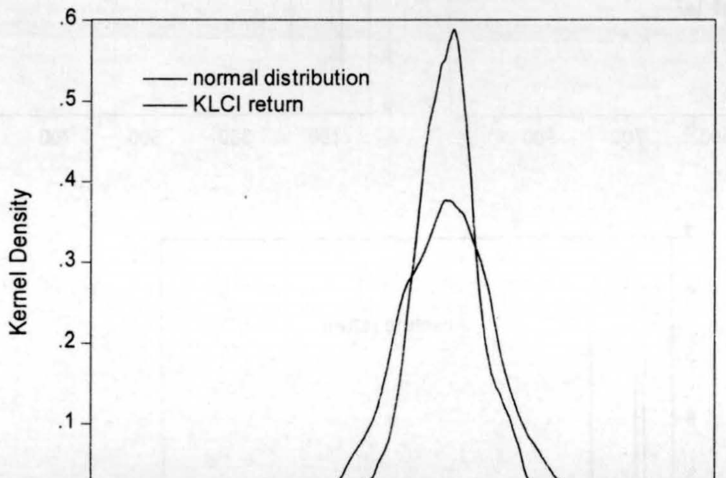

Figure 3. Kernel Density Plots

In Table 1, the negative skewness (-0.598) and kurtosis (9.950) indicated that the return series violated the normal distribution. For graphical illustrations, we compared the kernel density estimates (adjusted histogram) of the probability distribution and the QQ plot for KLCI return with a simulated normal distribution. Figure 2 and Figure 3 evidenced the high peak, heavy tail and slightly asymmetric behaviour compared to a standardized normal distribution. This is further proven by the Jarque-Bera normality test with the rejection of normality at 1% significant level.

Table 1. Descriptive Statistics for Return Series

Statistic	*Estimation*
Mean	0.0245
Maximum	4.5027
Minimum	-6.3422
Std. Dev.	0.8807
Skewness	-0.5984
Kurtosis	9.9504
Jarque-Bera	2277 ^{c} (0.000)
LM ARCH test	141.22 ^{c} (0.000)

LM ARCH test: $r_t^2 = b_0 + \sum_{i=1}^{3} b_i r_{t-1}^2$, TR^2. The value in parenthesis represents the p-value.

Table 2. Autocorrelation and Long-Persistence

Autocorrelation	r_t	r_t^2	$\lvert r_t \rvert$
Lag 1	0.211	0.141	0.182
Lag 2	0.024	0.338	0.238
Lag 3	0.035	0.147	0.120
Lag 4	-0.003	0.154	0.141
Lag 5	-0.026	0.046	0.071
Ljung-Box test	62.53 ^{c} (0.000)	205.96 ^{c} (0.000)	162.99 ^{c} (0.000)
Hurst's estimation			
*Variance-time plot		0.722 (0.975)	0.756 (0.964)
**Range-rescaled plot		0.653 (0.995)	0.631 (0.993)

Notes: ^{c} 1% level of significance. The values in the parentheses represent the p-value and coefficient of determination for Ljung-Box test and Hurst's estimation respectively.

Ljung-Box statistic: $T(T+2)\sum_{i=1}^{12} \frac{ACF_i(proxy)}{(T-i)} \sim \chi_{12}^2$ where ACF denotes the autocorrelation;

Hurst's estimation:

* For the aggregated time series r(n) of a self-similar process, the variance obeys the following large sample property:

$V[r^{(n)}] \sim \frac{V[r]}{n^{\beta}}$, where $r_k^{(n)} = \frac{1}{n}\sum_{i=kn-(n-1)}^{kn} r_i$ and the self-similarity parameter H = 1- (β/2).

** The ratio of R/S is defined as:

$$\frac{R}{S} = \frac{\max\limits_{1\le j\le N}\left[\sum_{k=1}^{j}(r_k - M(L))\right] - \min\limits_{1\le j\le N}\left[\sum_{k=1}^{j}(r_k - M(L))\right]}{\sqrt{\frac{1}{N}\left[\sum_{k=1}^{N}(r_k - M(L))^2\right]}}$$

where M(L) is the sample mean over the time period L. The Hurst's parameter is determined by: $R/S \sim (L/2)^H$.

In Table 2, the return's autocorrelations for the first five lags show that only the first lag is significantly different from zero. The highly significant value for the first-order serial correlation can be caused by the infrequent trading of emerging market. The infrequent trading phenomenon [26,27] occurred in emerging market can be adjusted by a first order autoregressive model. For LM ARCH effect test, the return series rejected the null hypothesis of no relation with its lags.

In Table 2, the squared and absolute returns (proxy volatility) are tested for possible autocorrelation among their lags. Both the volatility proxies have shown higher correlation to their higher lags as compared to the return series. The Ljung-Box tests rejected the null hypotheses of no correlation among their lagged values respectively. Finally, the long-persistence of the proxy volatilities is examined using two time-domain Hurst's parameter estimations. Both the proxies indicated the presence of long-range dependence property with the values of 0.653 and 0.631 for the squared and absolute returns respectively. This preliminary test ensured the relevance of using long-persistence volatility modelling in the model specification.

4.2 Estimation and diagnostic

In Table 3, the results show the maximum likelihood estimation of threshold GARCH(1,1), threshold two components GARCH(1,1) and threshold GARCH(1,1) with breaks. All the models indicated leverage effect with statistically significant asymmetric coefficients (ϕ_c) and implied that downward movements (shock) in the stock market are followed by a greater volatilities than upward movements of the same magnitude. The degrees of freedom of student's t distribution are in the range of 6 to 7 among the models and suggested the presence of non-normal distributed innovations.

Next, the estimated decay rate for permanent component TCGARCH(1,1) is 0.9956 (γ_{1q}) and indicated the remaining shock effects after a month (20 trading days) and a year are approximately 92 and 35 percents respectively.

We also related the log-likelihood ratio test to examine the appropriateness of standard GARCH as compared to CGARCH. The result (15.132)[6] evidenced the presence of components with the rejection of null hypothesis (H_0: no component) at 1% and 5% significant levels respectively. Next, we studied the relevance of structural break inclusion in the TCARCH. Similarly, the log likelihood ratio statistic with the value of 24.54[7] rejected the null hypothesis of no structural break at 5% and 1% significant level respectively. Individually, the permanent component and structural break are two important features in the standard threshold GARCH model specifications. However, it is also interesting to study how the permanent and transitory component volatilities are influenced by the structural breaks.

6 The ratio statistic is based on $-2(L_{garch} - L_{cgarch})$ where L_{garch} and L_{cgarch} can be considered as the log likelihood functions for unrestricted and restricted regression respectively under an asymptotic χ^2 with degree of freedom equal to the additional parameters in CGARCH. The χ^2 critical values are 5.99 and 9.21 for 5% and 1% respectively.

7 Only five out of six additional variables are significant under the estimations. Therefore the χ^2 critical values are 11.07 and 15.09 for 5% and 1% respectively.

Table 3: Maximum Likelihood Estimation and Diagnostic

Without structural break				*With structural break*					
GARCH		*TCGARCH*		*GARCH*		*TCGARCH-transitory*		*TCGARCH- Permanent*	
θ_0	0.0100 (0.694)	θ_0	0.0135 (0.594)	θ_0	0.0097 (0.653)	θ_0	0.0188 (0.370)	θ_0	0.0134 (0.524)
θ_1	0.1501^c (0.000)	θ_1	0.1659^c (0.000)	μ_1	0.1084^b (0.012)	μ_1	0.1099 (0.104)	μ_1	0.1010^b (0.013)
				μ_2	0.3489 (0.198)	μ_2	0.3672 (0.1732)	μ_2	0.3367 (0.183)
α_0	0.1205^b (0.026)	ω	0.5156^c (0.001)	μ_3	0.1544^c (0.003)	μ_3	0.1458^c (0.005)	μ_3	0.1540^c (0.002)
α_1	0.1257^c (0.004)	γ_{1q}	0.9956^c (0.000)						
β_1	0.6522^c (0.000)	γ_{2q}	0.0082 (0.189)	α_0	0.1943^c (0.000)	ω	0.9082^c (0.000)	ω	1.0380^c (0.000)
				α_1	0.1032^b (0.015)	γ_{1q}	0.8005^c (0.000)	γ_{1q}	0.3860 (0.222)
				β_1	0.6492^c (0.000)	γ_{2q}	-0.5233 (0.120)	γ_{2q}	-0.1293 (0.199)
		γ_{1s}	0.0595^a (0.061)	λ_1	-0.1318^b (0.018)			λ_1	-0.3848 (0.122)
		γ_{2s}	0.5944^c (0.000)	λ_2	-0.1437^b (0.015)	γ_{1s}	0.6081^a (0.085)	λ_2	-0.4932^a (0.092)
				λ_3	-0.2761^c (0.003)	γ_{2s}	0.1215 (0.734)	λ_3	-0.9623^a (0.060)
						λ_1	-0.0938^a (0.067)		
						λ_2	-0.1246^b (0.036)	γ_{1s}	0.1697 (0.068)
						λ_3	-0.2744^c (0.005)	γ_{2s}	0.4942^c (0.000)
ϕ_c	0.1054^a (0.095)	ϕ_c	0.1711^b (0.012)	ϕ_c	0.1289^b (0.044)	ϕ_c	0.1269^c (0.009)	ϕ_c	0.2163^c (0.002)
υ	6.1414^c (0.000)	υ	6.8169^c (0.000)	υ	6.3523^c (0.000)	υ	7.2535^c (0.000)	υ	6.8817^c (0.000)
L	-1269.207		-1261.434		-1260.534		-1256.733		-1255.850
AIC	2.324		2.314		2.320		2.316		2.315
(1)*Q-(12) on* $\tilde{a}_t$	14.857 (0.189)		10.929 (0.449)		16.380 (0.174)		15.316 (0.225)		16.093 (0.187)
(2)*Q-(12) on* $\tilde{a}_t^2$	10.470 (0.489)		13.882 (0.240)		12.336 (0.419)		11.748 (0.466)		10.171 (0.601)
(3)*LM(12) test*	0.8502 (0.598)		1.1381 (0.324)		1.0047 (0.442)		0.9443 (0.501)		0.8255 (0.624)
(4)*news impact*									
Sign	0.0054 (0.974)		0.1433 (0.370)		-0.0419 (0.787)		0.1817 (0.536)		0.2303 (0.145)
Negative	-0.1095 (0.538)		-0.0926 (0.605)		-0.0889 (0.596)		-0.0830 (0.374)		-0.0206 (0.899)
Positive	0.0727 (0.494)		0.1074 (0.300)		0.0506 (0.630)		0.0538 (0.699)		0.1413 (0.173)

Notes: a, b and c denote 10%, 5% and 1% level of significance. The values in the parentheses represent the p-value.

$\tilde{a}_t$ represents the standardized residual.

(1), (2): Ljung Box Serial Correlation Test(Q-statistics) on $\tilde{a}_t$ and $\tilde{a}_t^2$: Null hypothesis – No serial correlation;

(3): LM ARCH test: Null hypothesis - No ARCH effect;

(4): Engle and Ng(1993) news impact test based on the regression $\tilde{a}_t^2 = a_1 + a_2 S_t^- + a_3 S_t^- a_{t-1} + a_4 S_t^- a_{t-1}^2 + \varepsilon_t$

We included the structural break elements as the exogenous variables in either the permanent or transitory components respectively. As indicated in **Table 3**, two interesting results have been indicated in the transitory component equation with breaks. Firstly, the degree of freedom of student's t distribution has increased from 6.6523 to 7.2535 which suggested that the innovation is slightly closer to a normal distribution. Secondly, the permanent component (γ_{1q}) decay rate indicated a substantial reduction from 0.996 to 0.801. This implied that there might not be a permanent component in the volatility. We ran the log likelihood ratio test (7.67) and found that we are able to accept the no component hypothesis at 1% level. Although the log likelihood of component-GARCH-break (L=-1256) is greater than the GARCH-break (L= -1260), nevertheless the AICs have shown almost similar results with 2.317 and 2.320 respectively. The CGARCH-break has contributed more penalties in AIC due to the additional variables.

For exogenous variables in permanent component equation, the permanent component (γ_{1q}) has become insignificant at 1% level. This implied that the component feature has been eliminated due to the existence of structural break effect. Due to this, we concluded that the spurious long-persistence volatility is most probably caused by the structural break effects of the volatility.

For diagnostic analyses, our results have shown that the conditional mean equations using the first-order autoregressive are able to overcome the infrequent trading behavior of the KLSE. **Table 3** confirms that all the conditional returns in the Ljung-Box on standardized residuals(Q10) are non-significant at 1% significant level. In addition, all the models indicated no significant serial correlations and ARCH effect in the variance equations at the 1% level respectively. We further analyzed the news impact test to ensure the possible neglected asymmetries in the standardized residuals. As indicated in **Table 3**, the size and leverage effect are not statistically significant at level 1% in all the GARCH models which implied no evidence of unexplained non-linearity, sign or size bias in the positive and negative effects.

5. Conclusion

In this paper, we investigated the news impact, non-normality, time-varying volatility and components feature in the Malaysian stock market under the structural break condition. We also analyzed the influence of structural break on the permanent and transitory components volatilities. The decay rate of permanent components in both equations demonstrated substantial reduction or total elimination ((γ_{1q} becomes insignificant at 5% level) after the inclusion of exogenous structural break factors in either the transitory or permanent components equations. This implied that the structural break has triggered the spurious long-persistence volatility in this specific study. We would like to leave these findings for further theoretical modelling, volatility forecasting and portfolio analysis.

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