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STRUCTURAL BREAKS AND STOCK RETURN VOLATILITY IN MALAYSIA

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Abstract:

This study investigates the effect of structural breaks on volatility modelling in the Malaysia stock market using daily KLCI return data from the year 2001 to 2024. Knowing that the financial market often experiences sudden shifts due to economic crises, political transitions, and various global events, this study explores if such structural breaks can significantly influence the estimation of volatility under the ARCH framework. The Iterative Cumulative Sum of Squares (ICSS) algorithm is employed to detect multiple variance shifts in the KLCI return series before the ARCH-type models are estimated by incorporating the identified breakpoints. Three significant structural break dates are identified which coincide with the recovery period of major economic and political events such as the Asian Financial Crisis in 1997, the stock market plunge in China, Japan and Europe in 2007, and the 2008 Global Financial Crisis. In addition, results of the ARCH model indicate consistent negative and statistically significant coefficients for three break dummies across ARCH specifications. The negative coefficients suggest a decline in conditional volatility following each structural break, implying that these events marked transitions into relatively more stable periods rather than heightened market turbulence. This study emphasises the significance of accounting for structural breaks in volatility modelling. The inclusion of breakpoints improves model predictability, offering better insights for investors, policymakers, and analysts

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concerning the market behaviour under evolving economic conditions in the Malaysian market.

Keywords:

Structural Breaks, ARCH Models, Stock Return Volatility, Malaysia Stock Market

Introduction

Stock market volatility plays a vital role in influencing investors' investment behavior. Investors interpret an increase in stock market volatility as an increase in the risk of equity investment and consequently they shift their funds to less risky assets (Chhimwal & Bapat, 2020). This action will puts a downward pressure on the stock prices making room for higher expected future returns to compensate for the excess risk. Malaysia, as one of Southeast Asia's leading economies, presents a compelling case for understanding stock return volatility, particularly in the wake of significant economic disruptions such as the Asian Financial Crisis (1997–1998), the Global Financial Crisis (2008–2009), and the COVID-19 pandemic (2020–2021). These crises serve as structural breaks, altering market dynamics and challenging traditional volatility models.

Structural breaks present sudden shifts in financial time series data, resulting in changes of the underlying series volatilities and making traditional ARCH and GARCH models to be less reliable. These ARCH/GARCH models assume that volatility evolves smoothly over time, but when sudden regime changes occur, the estimated coefficients of the model can become outdated resulting in biased forecasts for stock returns. Because ARCH and GARCH models depend on historical volatility patterns, failure to include for the existence of structural breaks may lead to persistent over- or underestimation of future volatility. By incorporating the structural break detection before modelling the ARCH/GARCH mode, model predictability power may be improved.

The study of regime shifts or structural breaks behavior in time series has attracted a lot of interest from researchers. This is due to the realization that many economic time series experience moments in which the behavior of the series changes quite significantly because of financial crises or abrupt changes in the government policy (Ling et al., 2013; Tahir Ismail et al., 2011; Tran, 2022; Wen Cheong, 2008). Earlier studies have highlighted the importance of structural breaks in stock market volatility, especially during major financial crises. Research findings have shown that Covid-19 pandemic has caused higher stock market uncertainty in multiple regions (Szczygielski et al., 2021) leading to a presence of volatility clustering and asymmetric effect around the pandemic period (Insaidoo et al., 2021). The structural changes were detected not only after the first reported case of Covid-19, but also earlier in the period (Kusumahadi and Permana, 2021). While past research findings have shown the relationship between stock market volatility to past crises such as Asian Financial Crisis, the 2008 Global Crisis, and regional economic disruptions (He et al., 2023), studies examining the effect of breaks in stock market performance without prior assumptions on break locations remain limited. This leaves a gap in understanding how stock return volatility models adapt to unforeseen economic shocks (Hong et al., 2021). This study aims to bridge the gap by investigating how the structural breaks affect stock return volatility model, in providing insights into forecasting accuracy for Malaysia stock market.

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In addition, this study addresses critical gaps in understanding the unique dynamics of Malaysia's stock market. While many studies have analyzed Malaysia stock market using ARCH and GARCH models (see Tran, 2022; Ibrahim and Azmi, 2022; Wang et al., 2024), these studies did not include structural break in their analysis, except for Ismail et al. (2011). Ismail et al. (2011) studied on the structural breaks in Malaysian stock market by using KLCI index data between year 1977 until 2008. Considering the gap in recent research on Malaysia stock market, this study is directed to examine the impact of structural breaks on ARCH volatility modelling for KLCI returns using more updated data. Using daily data, this research spans the year 2001 to 2024, a period that encompasses significant global and regional events, such as the Asian Financial Crisis and the COVID-19 pandemic, which serve as structural breaks in market behaviour.

The rest of this paper is organized as follows: Section 2 discuss on the general findings on the importance of including structural breaks in stock market volatility study, Section 3 describes our econometric methodology, Section 4 presents and discuss the results of structural break dates and ARCH models for KLCI returns, and Section 5 concludes.

Literature Review

Financial time series data, particularly stock returns are always being subjected to unexpected changes in the market. These changes, known as structural breaks, can arise due to major economic events, changes in monetary and fiscal policy, financial crises or changes in the market structure. The existence of structural breaks poses a challenge to traditional time series models, including ARCH-type models, which usually assume constant parameters over the study period.

A structural break can be defined as a situation where the properties of a time series or of a model exhibit a substantial long-term shift in behavior (Brooks, 2019). In the context of financial markets, common sources of breaks include the 1997 Financial Crisis (de Boyrie, 2009; Habimana et al., 2018), Global Financial Crisis in 2008-2009 (Ewing and Malik, 2016; Luo and Chen, 2018; Kalsie and Arora, 2019), and Covid-19 (Karavias et al., 2023; Ndako et al., 2022). Each of this research examined how crises affect return volatility or risk and highlight the limiations of constant-parameter models like GARCH. All the evidence suggest that future research should employ break-adjusted or time-varying models in order to obtain better empirical fit in forecasting volatility.

Various econometric methods have been developed in detecting structural breaks. For example, Perron (1989) in particular choose the break points based on prior observations of the data which lead to the researcher selection on the 1973 oil price crisis. Next is Bai and Perron (1998, 2003) methodology which is widely used in identifying multiple breaks at unknown points in time. This is done by estimating and testing for breaks in a linear ordinary least square regression. Another method is the Zivot-Andrews (1992), which only allows for one break in the intercept, trend. The null hypothesis of this test is there is a unit root in the series. In this study, Zivot-Andrews(1992) transform Perron (1989) unit root test that is conditional on structural change at a known point int time into an unconditional unit root test to indicate the unknown point of the break. In terms of investigating the effect of structural breaks in volatility, the Iterative Cumulative Sum of Squares (ICSS) algorirhm introduced by Inclan and Tiao (1994), is widely cited method (see Aggarwal et al., 1999; Elshareif et al., 2012; and Ahmed et al., 2020) for detecting multiple variance shifts in financial time series. In line with the

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objective of this research, this study will employ the ICSS algorithm in examining how structural breaks affect ARCH model performance using return data like KLCI.

Empirical research suggests that structural breaks are common in emerging market because of their higher vulnerability to external shocks and policy shifts. In the context of Malaysia, studies such as in Elshareif and Kabir (2017) who studied on various global crises and its impact on Malaysia stock market have found that volatility surrounding the identified crises are not persistent over long time. This could be contributed to the failure to include the sudden changes in the volatility which can give the wrong idea about how persistent volatility is in the stock market. Studies conducted by Ismail and Isa (2008) used a regime-switching model to divide Malaysia stock market into two different states based on historical retun data. They used the smoothed probability plot to determine how likely it is that the market was in a particular state at any point in time. A probability value closer to 1 means the model is very confident that the market was in a recession or bear state, while a value closer to 0 indicates the market was in a bull or recovery state. Findings obtained from this research assume that the behavior of a time series data (in this case KLCI returns) changes across different state of economy. These changes between economic state act like structural breaks because every time the model switches regime, it marks a shift in the market's structure. These past findings on Malaysia market emphasized the importance of segmenting the return data into stable periods (before and after breaks) which will allow researcher to fit ARCH models more accurately to each period.

More recent literature points to the breakpoints around 2008 global financial crisis, the 2015 oil price crash, 2018 general election event, and the Covid-19 pandemic which significantly affecting the volatility of the KLCI index. Some research shows a significant effect of the crises and event towards the volatility of stock market in Malaysia, while other shows insignificant relationship as in Azhari etl al., (2021) who found insignificant effect of oil price shocks on Malaysia stock returns. Studies by Morni and Yazi (2021) used the cumulative average abnormal returns of 656 public listed companies in Bursa Malaysia 28 March 2018 until 17 August 2018 with 97 daily observations. Results shown that there is a significant changes in the value of actively traded stock surrounding the government change announcement which highlight the effect of political regime change effect on stock returns in Malaysia. This study is supported by the findings obtained by Lai et al., (2023) who found a significant effect of Malaysia's general election 12 and 13 events in year 2008 and in year 2013, respectively by using KLCi index returns. In relation to Covid-19 pandemic, Gamal et al., (2021) concured that Covid-19 has significant negative effect on the Malaysian stock market. The study also include the structural break procedures in their stationarity test using the Augmented Dickey and Fuller (ADF) and Zivot-Andrews techniques. All these findings point up the relevance of incorporating structural break analysis into ARCH-type volatility models to enhance the accuracy and reliability of stock market volatility predictions.

While many studies in the past have analyzed Malaysia stock market returns volatility using ARCH and GARCH models (see Tran, 2022; Ibrahim and Azmi, 2022; Wang et al., 2024), few have specifically examined structural using updated data after year 2008. For example, Ismail et al. (2011) used KLCI index data between year 1977 to 2008 to explore structural breaks using traditional methods. However, their study precedes several important events such as the 2013 and 2018 general elections, oil price crash in 2015, and the Covid-19 pandemic. Our study extends their work by incorporating daily data covering year 2001 to 2024 and applying the ICSS algorithm to detect multiple breaks without prior assumption on the break dates. Hence,

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our research contributions lie in improving the time frame and empirical reliability to better reflect the dynamic Malaysia stock market.

Methodology

Data Specifications

The data under investigation are daily KLCI index from Refinitive Workspace database . The estimation period for the daily data is from January 2001 until December 2024 with 5163 observations. The KLCI index series are analysed in returns, which is the first difference of natural algorithms multiplied by 100 to express things in percentage terms, following Ismail et al., (2011). The study uses the daily returns series because the study assumes that regime shifts can be observed more clearly across time if low frequency data is used (Tran, 2022).

Iterative Cumulative Sum of Squares Algorithm

Following Rapach, Strauss, and Wohar (2008), we computed the continuous return for KLCI index using R_t=100 log (P_t/P_{t-1}) from time t-1 to t, where P_t is the value of KLCI index at time t, and let $r_t = R_t - \mu$, where μ is the constant (conditional and unconditional) mean of R_t. We observe r_t for t= 1,…, T. Using Inclan and Tiao (1994) cumulative sum of squares statistic, we test the null hypothesis that the unconditional variance of r_t is constant for k=1,…,T. The alternative hypothesis is there is a break in the unconditional variance at some point in the series. The statistic is given by:

$$IT = \sup_k \left| \left(\frac{T}{2}\right)^{0.5} D_k \right|,$$

Where $D_k = (C_k / C_T) - (k / T)$ and $C_k = \sum_{t=1}^{k} r_t^2$ for k = 1, … , T. When $r_t \sim iid\ \mathrm{N}(0, \sigma_r^2)$, Inclan and Tiao (1994) show that $IT \overset{asy}{\sim} sup_r \, |W*(r)|$ under the null hypothesis, where $W*(r) = W(r) - rW(1)$ is the Brownian bridge and $W(r)$ is the standard Brownian motion. Finite sample critical values for IT generated by simulation methods based on past studies and simulation-based tables (e.g. Inclan and Tiao, 1994; Sanso et al., 2004) for T≥1000 are 1.5486, 1.329, and 1.197 at 1%, 5%, and 10% significance level, respectively. When the null hypothesis is rejected, the value of k that maximizes $\left| \left(\frac{T}{2}\right)^{0.5} D_k \right|$ will be the estimate of the break date. Once the first break is detected, the series will be splitted into before break and after break data, creating two segments. The ICSS test is repeated to each segment until all segments are stable (i.e. no more breaks).

Autoregressive Conditionally Heteroscedastic (ARCH) Model

This study employs the arch model introduced by Engle (1982) in analyzing and forecasting time-varying volatility in KLCI time series data. This model captures the volatility clustering or volatility pooling. In other words, the current volatility level tends to be positively correlated with its level with its level during the immediate preceding periods. The conditional variance of random variable, μ_t may be denoted by σ_t^2 which is written as:

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$$\boldsymbol{\sigma_t^2 = var(\mu_t|\mu_{t-1}, \mu_{t-2}, \dots) = E[(\mu_t - E(\mu_t))^2|\mu_{t-1}, \mu_{t-2}, \dots]} \quad \textbf{(1)}$$

It is normally assumed that the conditional variance of a zero mean normally distributed random variable μ_t is equal to the conditional expected value of the squared μ_t. Mathematically, it can be represented as $E(\mu_t) = 0$, so

$$\sigma_t^2 = var(\mu_t|\mu_{t-1}, \mu_{t-2}, \dots) = E[\mu_t^2|\mu_{t-1}, \mu_{t-2}, \dots] \quad (2)$$

In ARCH(q) model, the autocorrelation in volatility is modelled by allowing the conditional variance of the error term, $\boldsymbol{\sigma_t^2}$ is modelled as a function of past squared error terms (with q lags of squared error) as shown in equation (3):

$$\sigma_t^2 = \alpha_0 + \alpha_1\mu_{t-1}^2 + \dots + \alpha_q\mu_{t-q}^2 \quad (3)$$

In this study, a dummy variable will be included in the ARCH(q) model to analyze the effect of structural break on the conditional variance of the series. The conditional mean equation model is presented in equation (4) while the extended variance model is presented in equation (5) as follow:

$$y_t = \beta_1 + \beta_2 y_{t-1} + \dots + \beta_n y_{t-n} + e_t \qquad e_t \sim N(0, h_t) \quad (4)$$

$$h_t = \alpha_0 + \alpha_1\mu_{t-1}^2 + \alpha_2\mu_{t-2}^2 + \dots + \alpha_q\mu_{t-q}^2 + \gamma_t Dummy \quad (5)$$

Where; h_t is the conditional variance to replace the Greek letters, σ_t^2, γ_t is the coefficient for Dummy variable in the variance model; and the $Dummy$ variable equal to 0 for series before the break date, and 1 for series on and after the break dates.

Results and Discussions

Descriptive Statistics

Daily log returns data on the KLCI index is used in this paper. The sample period is from 1 January 2001 until 31 December 2024 consisting 5163 observations. Table 1 reports summary statistics for the KLCI daily return series. The average daily return is 0.0133% with a standard deviation of 0.71%, showing a modest daily volatility. The negative skewness and excess kurtosis indicate that the return distribution is non-normal. In addition, the presence of extreme values as shown by the minimum and maximum return values suggest that large negative price movements occur more frequently during the observed study period. This is supported by Jarque-Bera test finding that rejects the null hypothesis of normality with p-value of less than 5%, which support the case for using models that account for non-normality and volatility clustering.

The Ljung-Box Q statistic at lag 20 is 71.174 with a p-value of 0.000 indicating significant serial correlation in the daily KLCI return series up to the 20th lag. We also performed the Engle

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(1982) Lagrange Multiplier (LM) test for ARCH effects on the KLCI return series. The ARCH LM test at lag 2 and lag 10 produced a Chi-square statistic of 14.40 (p-value = 0.000), and 5.40 (0.000) indicating the existence of significant ARCH effects. The significant Q-statistics for the squared returns along with the ARCH LM test results highlight the evidence of volatility clustering, supporting the use of ARCH-type models in this study.

Table 1: Descriptive Statistics of Daily KLCI Returns

Variables	Estimates	p-values
Mean	0.000133	
Standard deviation	0.007069	
Skewness	-0.785933	
Kurtosis	16.37805	
Minimum	-0.099785	
Maximum	0.066263	
Jarque-Bera (p-value)	41421.92 (0.000)	
Number of observations	5163	
Ljung-Box (r=20) : Return series	71.174	0.000
Ljung-Box (r=20): Squared Returns series	915.21	0.000
ARCH LM (q=2)	14.40	0.000
ARCH LM (q=10)	5.40	0.000

Break Dates in KLCI Returns Series

We apply the ICSS algorithm to the KLCI returns and Figure 1 plots r_t for the series, along with the $\pm$3-standard deviation bands for each of the regimes defined by the structural break identified by the ICSS algorithm. Figure 1 shows that the volatility is not constant for KLCI returns for the period of 2001 until 2024. There are some periods where the returns are more dispersed with wider bands and periods when they are more stable as shown by narrower bands from the mean. Specifically, there is a noticeable spike in the volatility based on the $\pm$3 standard deviation bands around two periods which are from 2008 to 2009, and around early 2020. These spikes could correspond to two major events which are the Global Financial Crisis and Covid-19, respectively.

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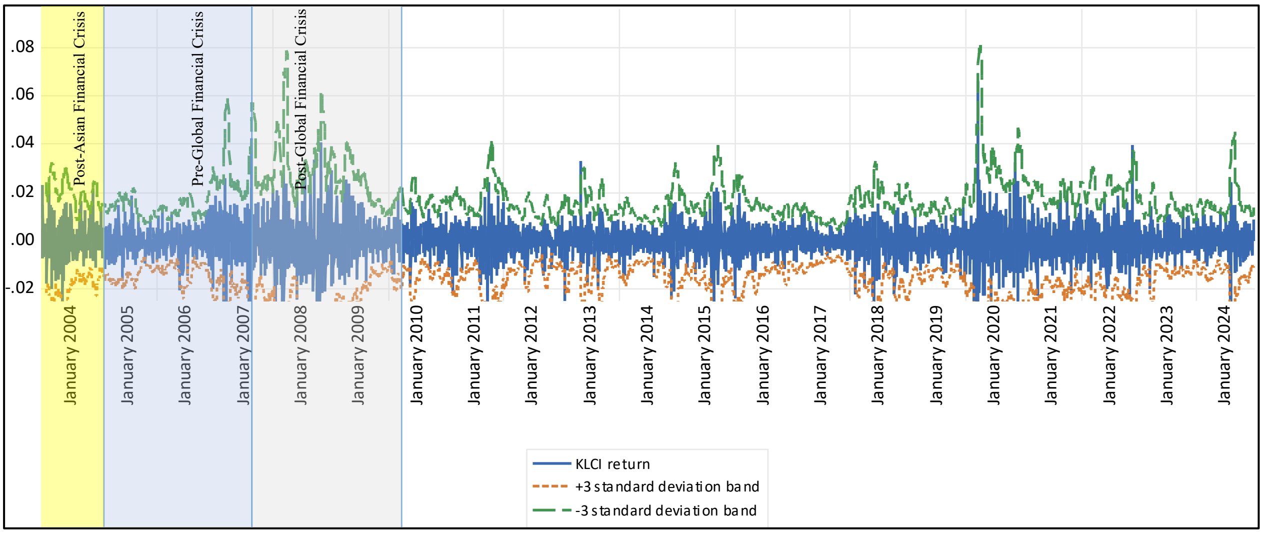

Figure 1: KLCI Returns And ±3-Standard Deviation Bands

Using the Inclan and Tiao (1994) cumulative sum of squares statistic, the IT stat was computed using the KLCI return series. The identified break dates are reported in Table 2. The ICSS algorithm detects at least three structural breaks in the unconditional volatility for the KLCI return series. The break dates are 6 July 2004, 26 Feb 2007, and 31 July 2009, aligning with the Asian Financial Crisis, and pre- and post-period of Global Financial Crisis 2008-2009 periods. Interestingly, for period August 2009 to Dec 2024, no significant break was obtained based on ICSS algorithm. Possible explanations behind this result may include the short-lived nature of volatility in Malaysia stock market.

While stock market returns tend to react negatively to Covid-19 pandemic, the quick recovery as a result of stimulus package offered by government and Bank Negara Malaysia that were expected to stabilize the economy (Song et al., 2021) and allows businesses to reopen after the lockdown period (Aldhamari et al., 2023) may have prevented the ICSS algorithm from flagging Covid-19 as a break date. The ICSS algorithm methodology is designed to detect sudden shifts in unconditional variance, which will pick up abrupt, large and persistent volatility changes. In addition, KLCI index is a proxy of performance of 30 largest stocks in Malaysia that comes from diverse sectors. Studies on Malaysia stock market have shown that during Covid-19, not all sectors were adversely affected. Some sectors such as energy, property, and finance (Mehmood et al., 2021) were underperformed, but not for healthcare, technology, telecommunications and media outperformed or remained stable (Adhamari et al., 2023). The negative effect of Covid-19 on KLCI volatility may have been offset by the positive performance of these defensive sectors.

Table 2: Break Dates and Regime Periods for KLCI returns

Break No.	Break Dates	Max IT stat	Variable Name	Associated Economic Events
1	6 July 2004	3.42324***	DUMMYBREAK1	Post-Asian Financial Crisis
2	26 Feb 2007	8.63074***	DUMMYBREAK2	Pre-Global Financial Crisis
3	31 July 2009	7.98767***	DUMMYBREAK3	Post-Global Financial Crisis

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4	28 April 2004	0.63747	-	
5	30 Dec 2019	0.66028	-	

Note: The Max IT stat value is compared with the Finite sample critical values for IT generated by simulation methods based on past studies and simulation-based tables (e.g. Inclan and Tiao, 1994; Sanso et al., 2004) for T≥1000 is 1.5486, 1.329, and 1.197 at 1%, 5%, and 10% significance level, respectively. *** indicates the significant break dates at 1% level.

ARCH(1) Models Before and After Structural Break

We divide the full sample into before-break and after-break components. The results of ARCH(1) models for each structural break date are presented in Table 3. The mean equation for Model 1(a), Model 2(a) and Model 3(a) indicate that the past returns influence current returns for all break dates. The ARCH (1) model results exhibit clear evidence of structural changes in mean return and volatility over time. In Model 1, before the break 6 July 2004, the autoregressive component AR(1) as proxied by Ri_{t-1} is statistically significant (coef=0.389081, p=0.0000), signalling a strong autocorrelation in index returns, while the moving average, MA(1) coefficient, (ϵ_{t-1}) is not significant. However, after the break, the autoregressive effect weakens and MA coefficient become significant (coef=0.196514, p=0.0049). These results signify a shift from return dependence to shock-driven dynamics. Furthermore, the coefficient of ARCH term (u^2_{t-1}) in the variance equation of Model 1 is higher before the break (coef=0.474170, p=0.0000) than after the break (coef=0.322493, p=0.0000). The lower coefficient value of ARCH term implies reduced volatility clustering and more stable market environment post-July 2004.

Model 2 considers a break on 26 Feb 2007, shows that both AR (1) and MA (1) terms remain significant before and after the break dates. These results suggest that there is strong autocorrelation and responsiveness to past shocks around this date. Moreover, the significant MA (1) coefficient before and after the break reveals the continuous effect of shocks towards returns. In terms of variance, the ARCH term is strongly significant both before and after the break, but with reduced magnitude during post-break which also show a decline in volatility persistence. Similar results were observed in Model 3(b).

In Model 3 (a), the negative coefficient of AR (1) component before the break indicates that the past returns tend to reverse direction around the break date, 31 July 2009. However, this behavior changes after the break. Instead of reversing, prices started to follow the trends. Besides, returns are also influenced by short-term fluctuations and this dependence remain significant even though the magnitude is weakened after the break date. Overall, these findings point to the significance of structural breaks in influencing the persistence of volatility that shows a sign of market stabilization and volatility clustering.

The before the break results mainly indicate that the market had memory. The past return could help investors to predict future return before the break date. For example, if the KLCI index went up by 1% yesterday, then we should expect the market to goes up again today. It behaved in predictable patterns, which also mean less market efficiency. This is because, according to Efficient Market Hypothesis (EMH), in efficient market, prices reflect all available information immediately. Thus, if past returns can predict future returns, that means, prices are not adjusted mainly because of publicly available information.

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For after the break period, it can be concluded that returns became more shock driven (based on the significant MA (1) coefficients). At this stage, the means of past returns are no longer predicting current returns, but shocks or news do. And these new shocks or news being absorbed very quickly by the market. In such condition, market participants become less emotional and reactive and might be more rational and better informed in making buy or sell decisions. At this post break period, market responds directly to new information rather than outdated trends.

Table 3: Findings from ARCH (1) Models Before and After Break Dates

Model 1: ARCH (1) Model with DUMMYBREAK1 variable								
Before break 1: 01/01/2001-5/7/2004					**After break 1: 7/7/2004-31/12/2024**			
Model 1(a): Independent variable-mean equation								
Variable	**Coef.**	**S.E**	**z-Stat**	**p-value**	**Coef.**	**S.E**	**z-Stat**	**p-value**
c	0.000423	0.000377	1.123303	0.2613	0.000304	0.000107	2.842421	0.0045
Ri_{t-1}	0.389081	0.073704	5.278964	0.0000	0.007022	0.061268	0.114612	0.9088
ϵ_{t-1}	-0.091952	0.076462	-1.20258	0.2291	0.104565	0.056645	1.845982	0.0649
Model 1(b): Variance equation								
Variable	**Coef.**	**S.E**	**z-Stat**	**p-value**	**Coef.**	**S.E**	**z-Stat**	**p-value**
c	0.0000511	0.0000331	15.43223	0.0000	0.000365	0.000000565	64.66580	0.0000
u^2_{t-1}	0.474170	0.064303	7.374018	0.0000	0.322493	0.015664	20.58862	0.0000
S.E.R	0.009383				0.007240			
ARCH LM Test	2.433959		R^2	0.1191	0.631506		R^2	0.4268
Model 2: ARCH (1) Model with DUMMYBREAK2 variable								
Before break 2: 01/01/2001-25/02/2007					**After break 2: 27/02/2007-31/12/2024**			
Model 2(a) : Independent variable-mean equation								
Variable	**Coef.**	**S.E**	**z-Stat**	**p-value**	**Coef.**	**S.E**	**z-Stat**	**p-value**
c	0.000769	0.000217	3.550647	0.0004	0.000190	0.000112	1.699672	0.0892
Ri_{t-1}	-0.424876	0.043437	-9.78137	0.0000	0.388079	0.101029	3.841271	0.0001
ϵ_{t-1}	0.692027	0.030073	23.01140	0.0000	-0.32669	0.110849	-2.94717	0.0032
Model 2(b): Variance equation								
Variable	**Coef.**	**S.E**	**z-Stat**	**p-value**	**Coef.**	**S.E**	**z-Stat**	**p-value**
c	0.0000405	0.00000168	24.03136	0.0000	0.0000331	0.00000057	57.41718	0.0000
u^2_{t-1}	0.550610	0.039926	13.79070	0.0000	0.314767	0.016458	19.12528	0.0000
S.E.R	0.008505							

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ARCH LM Test	2.111212		R^2	0.1465	2.084699		R^2	0.1489
Model 3: ARCH (1) Model with DUMMYBREAK3 variable								
Before break 3:01/01/2001-30/7/2009					**After break 3: 1/8/2009-31/12/2024**			
Model 3(a) : Independent variable-mean equation								
Variable	**Coef.**	**S.E**	**z-Stat**	**p-value**	**Coef.**	**S.E**	**z-Stat**	**p-value**
c	0.000550	0.000241	2.280620	0.0226	0.000230	0.00109	2.117439	0.0342
Ri_{t-1}	-0.348434	0.053068	-6.56574	0.0000	0.418437	0.126996	3.294882	0.0010
ϵ_{t-1}	0.592662	0.039911	14.84977	0.0000	-0.359950	0.139872	-2.57343	0.0101
Model 3(b): Variance equation								
Variable	**Coef.**	**S.E**	**z-Stat**	**p-value**	**Coef.**	**S.E**	**z-Stat**	**p-value**
c	0.0000554	0.00000208	26.68203	0.0000	0.0000293	0.000000557	52.64669	0.0000
u^2_{t-1}	0.415596	0.040994	10.13795	0.0000	0.307184	0.017765	17.29129	0.0000
S.E.R	0.009118				0.006496			
ARCH LM Test	1.274066		R^2	0.2592	1.063357		R^2	0.3025

Note:

a. The study employed an ARCH (1) model. Ri_t-1 and ϵ_t-1 are the coefficients of autoregressive term and moving average components of the mean equation model. R^2 and S.E.R denote R-squared and standard error of regression, respectively. The ARCH LM Test is conducted to assess heteroskedasticity in the model.
b. Coef. stands for coefficient value of the regressed variables and S.E. is the standard error value.

ARCH (1) Models with Structural Breaks

Next, we estimate the ARCH (1) model by including the dummy variables (that represents different break dates) as presented in Table 4. Three dummy variables (DUMMYBREAK1, DUMMYBREAK2, and DUMMYBREAK3) are used to test the effects of structural breaks on volatility forecasting using ARCH (1) model. The ARCH (1) Model 4, Model 5 and Model 6 were estimated by incorporating a dummy variable to capture the effect of structural break identified by the ICSS algorithm. Results show that the ARCH effect (lagged squared residuals, u^2_{t-1}) is highly significant in all three models with coefficient value of 0.278 ($p<0.01$), 0.263 ($p<0.01$), and 0.245 ($p<0.01$) as indicated in Model 1(b), Model 2(b), and Model 3(b), respectively.

More importantly, the coefficient of DUMMYBREAK1, DUMMYBREAK2, and DUMMYBREAK3 in the variance equation are all negative and statistically significant at 1% significance level. The results suggest that the identified break periods are associated with lower level of return volatility. In other words, the conditional variance (i.e. volatility) is reduced after the break date. This could possibly happen due to market stabilization, policy interventions, or improved corporate governance standards that were in place following the major events that cause the structural break.

The first break on 6 July 2004 may reflect the Malaysia's post-recovery phase following the Asian Financial Crisis. The development of the Malaysian economy after the crisis with the

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growth of exports (Ping and Yean, 2007) and government active role in providing financial aids to struggling companies and investing in infrastructure projects that created jobs and boosted domestic activity. The second break on 26 February 2007 matches with the Malaysia ability to rebounded quickly despite the global uncertainties that happen due stock market plunge in the China, Japan and Europe in the same period. Malaysia was able to maintain its steady growth due to demand-driven expansion in global high-tech industries, commodities and services, controlled inflation, and stable financial conditions, which also benefited Malaysia (MOF, 2008). The third break on 31 July 2009 occurred shortly after the Global Financial Crisis of 2008-2008. Following the crisis, the government has unleashed two fiscal stimulus programs amounting to RM67 billion (10% of GDP) to sustain the economic growth (Lee, E., 2020).

Table 4: Findings from ARCH (1) Models with Structural Breaks

Model 4: ARCH (1) Model with DUMMYBREAK1 variable				
Model 4(a) : Independent variable-mean equation				
Variable	**Coefficient**	**Std.Error**	**z-Statistic**	**p-value**
c	0.000271	0.000104	2.614169	0.0089
Ri_{t-1}	0.096283	0.051779	1.859507	0.0630
ϵ_{t-1}	0.018716	0.049121	0.381021	0.7032
Model 4(b): Variance equation				
Variable	**Coefficient**	**Std.Error**	**z-Statistic**	**p-value**
c	0.0000587	0.00000772	7.601145	0.0000
u^2_{t-1}	0.277760	0.013485	20.59701	0.0000
DUMMYBREAK1	-0.0000224	0.00000772	-2.905384	0.0037
S.E.R	0.007064			
ARCH LM Test	0.593492		R^2	0.4411
Model 5: ARCH(1) Model with DUMMYBREAK2 variable				
Model 5(a) : Independent variable-mean equation				
Variable	**Coefficient**	**Std.Error**	**z-Statistic**	**p-value**
c	0.000224	0.000102	2.185865	0.0288
Ri_{t-1}	0.275936	0.070153	3.933376	0.0001
ϵ_{t-1}	-0.182723	0.075815	-2.410133	0.0159
Model 5(b): Variance equation				
Variable	**Coefficient**	**Std.Error**	**z-Statistic**	**p-value**
c	0.0000524	0.000000829	63.15011	0.0000
u^2_{t-1}	0.263410	0.0012841	20.51357	0.0000
DUMMYBREAK2	-0.0000193	0.000000943	-20.44370	0.0000
S.E.R	0.007055			
ARCH LM Test	0.817896		R^2	0.3658
Model 6: ARCH(1) Model with DUMMYBREAK3 variable				
Model 6(a) : Independent variable-mean equation				
Variable	**Coefficient**	**Std.Error**	**z-Statistic**	**p-value**
c	0.000224	0.0000983	2.280854	0.0226
Ri_{t-1}	0.297920	0.087824	3.392233	0.0007
ϵ_{t-1}	-0.217532	0.095379	-2.280698	0.0226

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Model 6(b): Variance equation				
Variable	**Coefficient**	**Std.Error**	**z-Statistic**	**p-value**
c	0.0000628	0.000000929	67.63252	0.0000
u^2_{t-1}	0.245328	0.012258	20.01357	0.0000
DUMMYBREAK3	-0.0000336	0.00000101	-33.06845	0.0000
S.E.R	0.007053			
ARCH LM Test	0.612198		R^2	0.4340

Note:

a. The study employed an ARCH (1) model. Ri_{t}-1 and ϵ_{t}-1 are autoregressive term and moving average components of the mean equation model. R^2 and S.E.R denote R-squared and standard error of regression, respectively. The ARCH LM Test is conducted to assess heteroskedasticity in the model.
b. Std. Error represents the standard error values.

Conclusion

In this research, we analyze stock return volatility forecasting in the presence of structural breaks for Malaysia stock market. Understanding this area will assist in decision making process especially in asset pricing strategies, construction of well diversified portfolio in optimizing return and minimizing risk. The present study modelled and estimated volatility in KLCI index prices daily returns and examined the impact of three structural breaks on index price volatility. The study used data ranging from January 2001 to Dec 2024. The data has been pre-tested by confirming the normality with Jarque-Bera, visualizing volatility clustering and assessing heteroscedasticity using ARCH LM test. The identified structural break dates are aligned with three major events which are Asian Financial Crisis 1997, stock market plunge in the China, Japan and Europe in 2007, and 2008 Global Financial Crisis. Interestingly, no structural break was detected during Covid-19 period.

The study also generated before-break and after-break ARCH models and empirical shows Malaysia stock market mean return shifted from return dependence to shock-driven dynamics. Furthermore, the resulting relationship between the dummy break variables are negative and significant indicating that market shocks will have a significant influence on the volatility clustering and its persistence. This could be explained by the potential market resilience and rapid policy response to the global events resulting in temporary volatility spikes. The results of ARCH-LM test confirmed the non-availability of additional ARCH effect within the residuals of the series, which also means that the variance equations have been well specified in all the ARCH (1) models. This study contributes to the literatures by highlighting that not all major economic events necessarily result in structural breaks in stock return series. This emphasizes the importance of robust break identification method in assessing stock market performance. The use of ICSS algorithm in this study may contribute to the overlook of short-term volatility spikes. Future research may benefit from incorporating alternative structural break tests or combining ICSS with GARCH model to better capture the short-term shock effects within the series.

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