

UNDERSTANDING THE VOLATILITY MODEL OF ARCH AND GARCH USING STANDARD MALAYSIAN RUBBER 20 (SMR 20) PRICES

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Abstract: *Natural rubber is one of Malaysia's most important agricultural commodities and contributes significantly to the country's export earnings and economic development. However, fluctuations in rubber prices create uncertainty for producers, traders, investors and policymakers, making volatility analysis an essential area of study. This paper examines the volatility characteristics of Standard Malaysian Rubber Grade 20 (SMR20) prices using the Autoregressive Conditional Heteroscedasticity (ARCH) model and its generalised extension (GARCH). Daily price data covering January 2023 to December 2025 were obtained from the Malaysian Rubber Council (MRC), yielding 726 observations after data cleaning. The price series was transformed into logarithmic returns to satisfy the stationarity requirement prior to model estimation. The ARCH-LM test confirmed the presence of significant ARCH effects in the return series, establishing volatility clustering and conditional heteroskedasticity. Six specifications, namely ARCH(1), ARCH(2), ARCH(3), GARCH(1,1), GARCH(1,2) and GARCH(1,3), were estimated and compared using the Akaike Information Criterion (AIC) and the Schwarz Information Criterion (SIC). The results show that the GARCH(1,1) model records the lowest AIC (3.136771) and SIC (3.162046) values among all six specifications, making it the most appropriate model for capturing the conditional volatility of SMR20 prices. Two major volatility episodes were identified, in the third quarter of 2024 and the first half of 2025, corresponding to the sharp price rally and the subsequent correction. These findings provide useful information for rubber industry stakeholders in relation to price risk management and forecasting.*

Keywords: *Natural Rubber; SMR20; Volatility; ARCH; GARCH; Time Series Analysis*

Introduction

Natural rubber is one of the most important agricultural commodities in Malaysia and has contributed significantly to the country's economic development for many decades (Ali et al., 2021). Among the various grades of natural rubber produced in Malaysia, Standard Malaysian Rubber Grade 20 (SMR 20) is one of the most widely traded and internationally recognised rubber products (Goh et al., 2016). SMR 20 is used extensively in the manufacture of tyres, automotive components and other industrial rubber goods because of its consistent quality and reliability (Virag et al., 2024).

The price of SMR 20 is shaped by a wide range of factors, including global demand and supply conditions, international commodity prices, economic growth, exchange rate movements and weather conditions (Iyer et al., 2014). As a result, rubber prices frequently experience sizeable fluctuations over time. These fluctuations create uncertainty for producers, traders, investors and policymakers alike, which makes price forecasting and volatility analysis increasingly important (Karanasos et al., 2021).

In financial and commodity markets, volatility refers to the degree of variation in prices over a given period. Understanding price volatility matters because it allows market participants to manage risk and to make better investment and production decisions (H & Rishad, 2020). Where volatility is not constant but instead clusters in periods of calm and turbulence, conventional constant-variance models are inadequate and conditional volatility models are required instead.

Although previous studies have examined the volatility of Malaysian natural rubber using ARCH-family models, uncertainty remains regarding the recent volatility behavior of SMR20. There is limited empirical evidence on the behaviour of SMR20 volatility during the post-pandemic period, particularly during 2023–2025. It remains unclear whether volatility shocks in the post-pandemic SMR20 market exhibit a different degree of persistence. Previous studies have also reported mixed findings regarding the most appropriate volatility specification for Malaysian natural rubber, including differences in the performance of standard (Isa & Jamil, 2004), higher-order (Md Ghani & Rahim, 2024), asymmetric (Goh et al., 2016), and regime-switching GARCH models (Abdul Gani et al., 2024). Establishing an appropriate volatility model is important not only for characterizing recent price dynamics but also for supporting the assessment and management of price risk in the Malaysian natural-rubber market.

Against this background, this study has two main objectives. First, it aims to examine the volatility characteristics of Standard Malaysian Rubber Grade 20 (SMR20) prices using ARCH and GARCH models over the period from January 2023 to December 2025. Second, it seeks to identify the most appropriate volatility model for SMR20 prices based on model selection criteria and to analyse the major volatility episodes over the study period. In addressing these objectives, the study investigates whether the SMR20 return series exhibits significant ARCH effects, examines the occurrence and pattern of volatility clustering, and compares six alternative specifications, namely ARCH(1), ARCH(2), ARCH(3), GARCH(1,1), GARCH(1,2), and GARCH(1,3), using appropriate model selection criteria. The study also relates the identified volatility episodes to the observed movements in SMR20 prices to provide a clearer understanding of the dynamics of price uncertainty in the Malaysian natural rubber market. The remainder of the paper reviews the relevant literature, describes the data and methodology, presents and discusses the empirical findings, and concludes with the study's limitations and recommendations.

Literature Review

Conditional Volatility Modelling

The foundation of modern volatility modelling was established by Engle (1982), who introduced the Autoregressive Conditional Heteroscedasticity (ARCH) model. The central insight of the ARCH framework is that the variance of a financial return series need not be constant over time; instead, it can be modelled as a function of past squared error terms, allowing periods of large price movements to be followed by further large movements. Bollerslev (1986) generalised this framework into the GARCH model by adding lagged conditional variance terms to the variance equation, which allows the persistence of volatility to be captured far more parsimoniously than by extending the ARCH lag order alone.

Subsequent extensions have relaxed the assumption that positive and negative shocks affect volatility symmetrically. Nelson (1991) proposed the exponential GARCH (EGARCH) model, while Glosten et al. (1993) developed the threshold specification commonly known as GJR-GARCH. Both allow volatility to respond differently to good and bad news, a feature frequently documented in equity and commodity markets. Model selection across these competing specifications is typically carried out using information criteria, principally the Akaike Information Criterion (Akaike, 1974) and the Schwarz Information Criterion (Schwarz, 1978), both of which penalise the addition of parameters and therefore reward parsimony.

Volatility In Rubber and Commodity Markets

Commodity markets have been shown repeatedly to display volatility clustering, and the rubber market is no exception. Chang et al. (2011) applied a range of multivariate GARCH specifications to rubber spot and futures returns in Thailand, Japan and Singapore, and found evidence of volatility spillovers between markets as well as conditional correlations that vary substantially over time. Ramli et al. (2019) similarly examined rubber price volatility across the ASEAN-3 economies. In the Malaysian context, Goh et al. (2016) analysed the volatility and market risk of rubber prices before and after the global financial crisis, documenting a clear change in the risk profile of the market across the two periods. More broadly, Karanasos et al. (2021) show that commodity and emerging-market volatility is closely tied to macroeconomic fundamentals and to spillovers from global uncertainty.

Previous study suggests that the appropriate volatility specification for SMR20 may differ across market conditions and sample periods. Goh et al. (2016) found evidence of asymmetric volatility in the Malaysian SMR20 market during the post-Global Financial Crisis period, where negative shocks impose greater impact on volatility than positive shocks. That study also demonstrated differences in performance between pre- and post-crisis periods and across horizons. In another study, Isa and Jamil (2004) compared ARCH, GARCH, EGARCH and GJR-GARCH model for Malaysian Ribbed Smoked Sheet Grade 1 (RSS1) and SMR20 price. In contrast to the findings of other studies, they found no general evidence of asymmetric volatility and concluded that the parsimonious GARCH(1,1) model provided a satisfactory fit to the data. They have also reported that the distribution of rubber price changes exhibited heavy tail and sharper peaks than the normal distribution suggesting that a higher likelihood of extreme price movements than would be predicted by the normal distribution.

The presence of structural breaks or changes in volatility regimes is also important considerations in modelling commodity-price volatility. Goh et al. (2016) identified a structural break in SMR20 prices around 2008 Global Financial Crisis using Bai and Perron (1998, 2003) breakpoint test. They reported that the crisis was associated with greater uncertainty in natural

rubber supply and demand higher volatility in the post-crisis period. The findings are consistent with those of Shalini and Prasanna (2016) that reported shifts from low- to high-volatility regimes across commodity markets during the Global Financial Crisis and found internationally traded agricultural commodities such as rubber also experiencing increased volatility. Collectively, these findings suggest that changes in market conditions and volatility regimes may affect both the persistence of volatility and the adequacy of a single-regime GARCH specification.

Recent study suggests that commodity volatility may also be affected following major market disruption such as the COVID-19 pandemic. Pham Thi et al. (2023) documented that natural-resource price volatility remained pronounced during and after pandemic using GARCH (1,1) and TGARCH specifications. Similar study by Iuga et al. (2024) found significant changes in volatility dynamic and market behavior when examining agricultural commodities across pre-COVID, during COVID and post-COVID regimes. These findings indicate that volatility characteristics observed in earlier periods may not necessarily be representative under the post-pandemic market environment. However, the performance of SMR20 from 2023 to 2025 requires further analysis because its price increased sharply before experiencing a significant decline. Given evidence that commodity-price volatility may change across different market conditions and that different GARCH models may perform differently for natural rubber, it is important to re-examine the persistence of SMR20 volatility and assess whether the GARCH(1,1) model remains suitable for the recent market period.

Previous Empirical Studies

The study most directly related to the present paper is Ghani and Rahim (2019), entitled Modeling and Forecasting of Volatility using ARMA-GARCH: Case Study on Malaysia Natural Rubber Prices. That study analysed 1,953 daily observations of SMR 20 prices covering 4 January 2010 to 29 December 2017, with the objective of identifying the most suitable ARMA-GARCH specification for modelling and forecasting rubber price volatility. Several ARMA and GARCH combinations were compared using the Akaike Information Criterion, the corrected Akaike Information Criterion, the Schwarz Bayesian Criterion and the Hannan-Quinn Criterion. The authors documented volatility clustering and significant ARCH effects in the SMR 20 return series, and identified ARMA (1,0)-GARCH (1,2) as the best-performing specification for both estimation and forecasting. Ghani and Rahim (2023) subsequently extended this line of work by introducing a modified weighting function to build a more robust GARCH forecasting model for rubber prices.

The present study follows the same broad methodological approach but differs in two respects. First, it covers a more recent and considerably more turbulent sample period, January 2023 to December 2025, during which SMR 20 prices experienced both a sharp rally and a substantial correction. Second, it focuses on comparing the pure ARCH family directly against the GARCH family across a common set of six specifications, rather than on the joint ARMA-GARCH mean-and-variance structure. This allows a clean assessment of whether the addition of lagged conditional variance terms improves model performance for the current market environment.

Methodology

This study uses daily time series data to examine the volatility of Standard Malaysian Rubber Grade 20 (SMR20) prices in Malaysia over the period January 2023 to December 2025. SMR20 is the benchmark grade for Malaysian natural rubber and is widely traded in both domestic and

international markets, which makes it an appropriate commodity for volatility analysis. All estimation was carried out using EViews software.

Data Collection

Daily price data for SMR20 were obtained from the official website of the Malaysian Rubber Council (MRC). A daily frequency is consistent with the requirements of volatility modelling, since it provides a sufficient number of observations to capture short-term price fluctuations. Table 1 presents the description of the data used.

Table 1: Data Description

Symbol	Variable Name	Measurement	Source
SMR20	Standard Malaysian Rubber Grade 20	Daily price (MYR sen/kg)	Malaysian Rubber Council (MRC)

Source: Malaysian Rubber Council (MRC), www.myrubbercouncil.com

Prior to analysis, the raw data underwent a cleaning process to ensure accuracy and consistency. The dataset was examined for missing values, non-trading days and inconsistencies in price recording. Observations corresponding to public holidays and weekends, where no price was recorded, were removed. A small number of zero return values were observed, reflecting days on which the SMR20 price remained unchanged; these were retained because they represent genuine market conditions. Following cleaning, the final dataset comprises 726 daily observations.

Because ARCH and GARCH models require stationary data, the raw price series was converted into a log return series. The log return is computed as:

$$r_t = \ln(P_t / P_{t-1}) \times 100 \quad (1)$$

where r_t is the log return at time t , and P_t and P_{t-1} denote the SMR20 price at time t and $t-1$ respectively. Multiplying by 100 expresses returns in percentage form, which improves numerical stability during estimation and follows the convention adopted in most empirical work on commodity price volatility.

Before estimating the models, the Lagrange Multiplier (LM) test for ARCH effects is applied to the return series. The null hypothesis states that no ARCH effect is present in the residuals. If the p-value falls below 0.05, the null is rejected, confirming conditional heteroskedasticity and justifying the use of ARCH and GARCH models.

The ARCH Model

The ARCH model of Engle (1982) specifies the conditional variance as a function of past squared error terms. Three ARCH specifications are estimated in this study. The ARCH(1) model uses a single lagged squared residual:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 \quad (2)$$

The ARCH(2) and ARCH(3) models extend this by including two and three lagged squared residuals respectively:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 \quad (3)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \alpha_3 \varepsilon_{t-3}^2 \quad (4)$$

where σ_t^2 is the conditional variance at time t , α_0 is the constant term, and ε^2 denotes the squared residual from the corresponding lagged period. The conditions $\alpha_0 > 0$ and $\alpha_i \geq 0$ must be satisfied for all i in order to guarantee a positive conditional variance.

The GARCH Model

The GARCH model of Bollerslev (1986) extends the ARCH framework by incorporating lagged conditional variances into the variance equation, allowing the persistence of volatility to be captured more parsimoniously. Three GARCH specifications are estimated. The GARCH(1,1) model, the most widely used specification in the volatility literature, includes one lagged squared residual and one lagged conditional variance:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (5)$$

The GARCH(1,2) and GARCH(1,3) models extend the specification by adding second and third lagged conditional variance terms respectively:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \beta_2 \sigma_{t-2}^2 \quad (6)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \beta_2 \sigma_{t-2}^2 + \beta_3 \sigma_{t-3}^2 \quad (7)$$

where α_1 measures the short-term impact of past shocks on current volatility and the β coefficients measure the persistence of volatility over time. The stationarity condition requires that the sum of the α and β coefficients be less than one. Model selection across all six specifications is based on the Akaike Information Criterion (Akaike, 1974) and the Schwarz Information Criterion (Schwarz, 1978), where lower values indicate a better balance between goodness of fit and parsimony.

Findings And Discussions

This section presents the empirical results of the volatility analysis. The analysis proceeds in five stages: a descriptive overview of the SMR20 price series, the pre-estimation diagnostic test for ARCH effects, estimation results for the ARCH models, estimation results for the GARCH models, and model comparison and selection based on information criteria.

Descriptive Overview of The SMR20 Price Series

Figure 1 presents the daily SMR20 price series in Malaysian Ringgit sen per kilogram over the full study period. Visual inspection reveals a distinctly non-stationary path characterised by three broadly identifiable phases.



Figure 1: Malaysia Natural Rubber (SMR20) Daily Price Series, January 2023 – December 2025

Source: Malaysian Rubber Council (MRC). Prices Are Expressed in MYR Sen/Kg.

In the first phase, from January to approximately June 2023, prices were relatively stable, fluctuating narrowly between roughly 550 and 650 sen per kilogram. This subdued level reflected weak global demand for natural rubber following post-pandemic supply chain normalization. The second phase, from July 2023 to September 2024, is characterized by a pronounced and sustained upward trend, with prices reaching a peak of approximately 850 to 950 sen per kilogram by mid-to-late 2024. This rally was driven by a combination of recovering global demand for rubber-based products, production constraints in major producing countries, and currency dynamics. The third phase, from October 2024 to December 2025, witnessed a notable price correction followed by relative stabilisation at approximately 700 to 800 sen per kilogram, likely reflecting demand moderation and inventory adjustment in the global market. The non-stationary nature of the level series is evident from the trending behaviour and the absence of mean reversion. To satisfy the stationarity requirement for ARCH and GARCH estimation, the raw price series was therefore transformed into the log return series specified in Equation (1).

ARCH-LM Test for Heteroskedasticity

Prior to estimating the models, the Lagrange Multiplier test for ARCH effects was applied to the SMR20 log return series. The test examines whether the squared residuals of the mean equation exhibit serial correlation, which would indicate conditional heteroskedasticity. The results are reported in Table 2.

Table 2: ARCH-LM Test Results

Test Statistic	Value
F-statistic	19.2153
Prob. F (1, 722)	0.0000
Obs*R-squared (Chi-Square)	18.9876
Prob. Chi-Square (1)	0.0001
Decision	Reject H_0 — ARCH effects confirmed

Source: Authors' Estimation Using EViews. Test Conducted At Lag Order $q = 1$ On the SMR20 Log Return Series, At The 5% Significance Level.

The test yields a Prob. Chi-Square value of 0.0001, well below the 5 per cent critical threshold, so the null hypothesis of no ARCH effect is rejected. This confirms that the SMR20 log return

series exhibits statistically significant conditional heteroskedasticity: the volatility of returns is not constant over time but clusters into periods of heightened and subdued market activity. The finding is consistent with Ghani and Rahim (2019), who documented ARCH effects in Malaysian SMR20 price data over the earlier 2010 to 2017 period, and it formally justifies the application of ARCH and GARCH models to the series.

Estimation Results for ARCH Models

Three ARCH models were estimated on the SMR20 log return series, each differing in the number of lagged squared residuals used to model conditional variance. Figure 2 plots the estimated conditional variance paths produced by all three specifications.

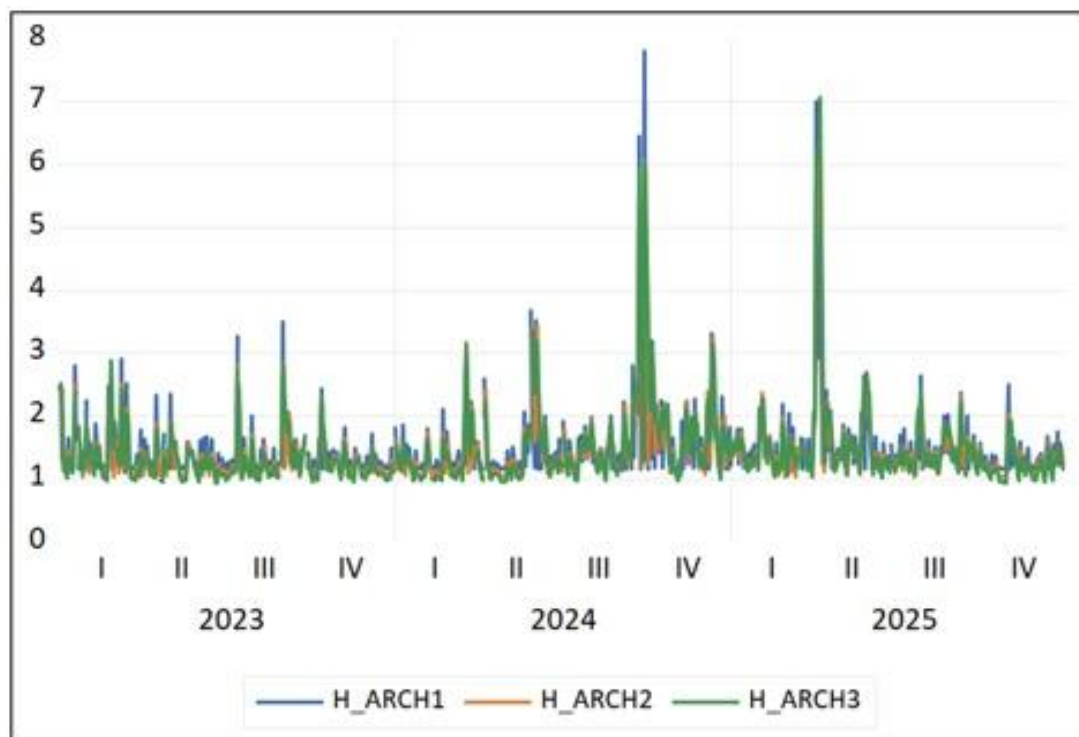


Figure 2: Estimated Conditional Variance — ARCH(1), ARCH(2) And ARCH(3)

Source: Authors' Estimation Using EViews. H_ARCH1, H_ARCH2 And H_ARCH3 Denote The Estimated Conditional Variance From The ARCH(1), ARCH(2) And ARCH(3) Models Respectively using Eviews 12.

Three observations emerge from Figure 2. First, all three specifications identify the same broad volatility pattern across the sample period, indicating that the ARCH family detects the underlying volatility dynamics robustly regardless of lag order. Under normal market conditions, conditional variance estimates for all three models fluctuate within a moderate range of approximately 1.0 to 2.5, consistent with the relatively stable price behaviour observed in the first phase of Figure 1.

Second, two prominent volatility spikes are clearly identifiable across all three models. The first occurred during the third quarter of 2024, where conditional variance surged to peaks of approximately 6 to 8. This episode corresponds directly with the period of rapid price escalation visible in Figure 1, indicating that price movements during this period were unusually large and erratic. A second episode is observed around the first and second quarters of 2025, where

conditional variance again spiked to approximately 7, coinciding with the price correction and adjustment phase.

Third, a visible divergence between the models appears specifically at the peaks. ARCH(1) records a slightly higher conditional variance peak in the third quarter of 2024, reaching approximately 7 to 8, compared with ARCH(2) and ARCH(3) which peak at approximately 6. This suggests that the single-lag specification amplifies immediate past shocks more aggressively, while the multi-lag specifications distribute the shock effect across two or three lagged terms and produce a more moderated response. Outside the spike periods the three models track closely together, indicating that the differences are concentrated during periods of extreme volatility.

Estimation Results for GARCH Models

Three GARCH models were estimated to assess whether incorporating lagged conditional variances provides superior modelling of SMR20 price volatility. Figure 3 presents the estimated conditional variance paths for all three specifications.

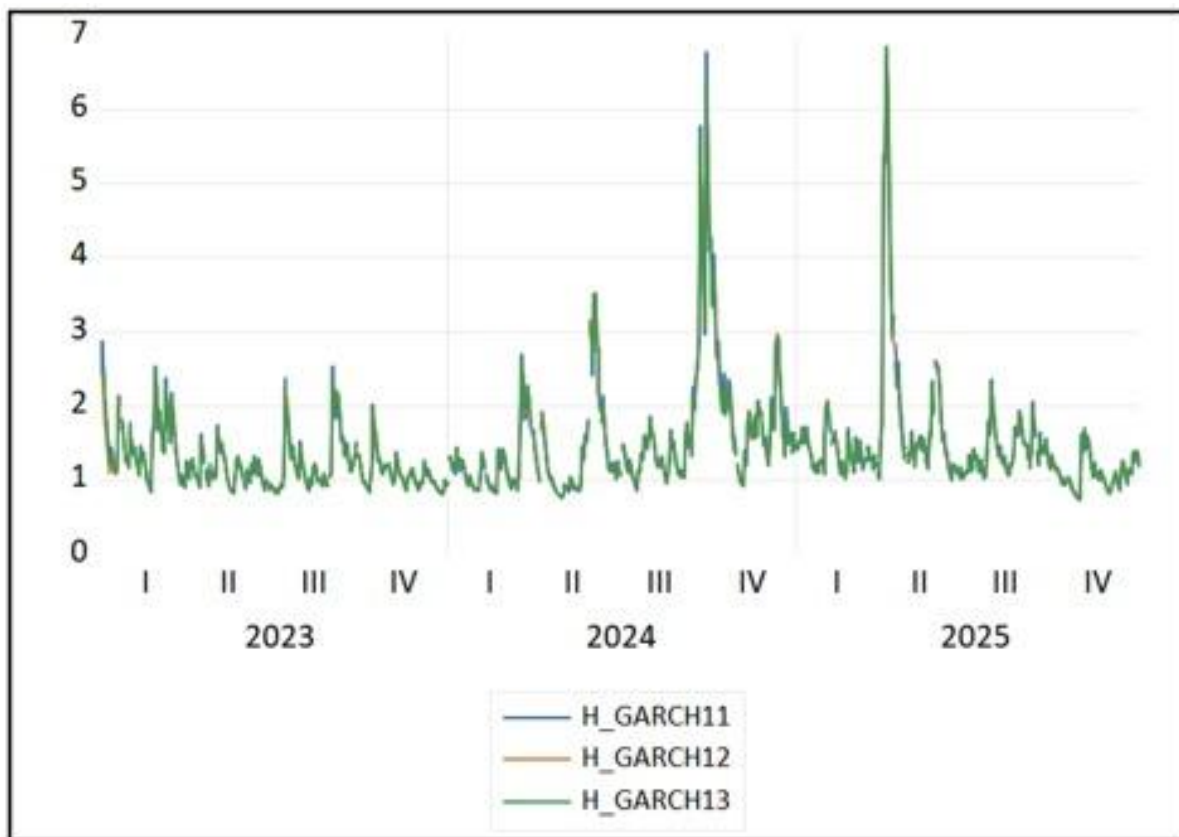


Figure 3: Estimated Conditional Variance — GARCH(1,1), GARCH(1,2) And GARCH(1,3)

Source: Authors' Estimation Using EViews. H_GARCH11, H_GARCH12 And H_GARCH13 Denote The Estimated Conditional Variance From The GARCH(1,1), GARCH(1,2) And GARCH(1,3) Models Respectively, using Eviews 12.

Figure 3 reveals several features that distinguish the GARCH models from their ARCH counterparts. First, GARCH(1,1) and GARCH(1,2) produce virtually identical conditional variance paths throughout the sample period, with their lines largely indistinguishable. This

indicates that adding a second lagged conditional variance term provides no substantive additional information beyond what GARCH(1,1) already captures. GARCH(1,3) exhibits a marginally distinct trajectory at certain peak episodes, particularly in the third quarter of 2024 and the first quarter of 2025, where it records slightly higher conditional variance estimates, although the differences remain small.

Second, compared with the ARCH models, the GARCH specifications produce smoother and more continuous conditional variance series. This smoothing arises from the inclusion of lagged conditional variance terms, which act as a weighted average of past volatility states. GARCH models therefore capture the gradual build-up and decay of volatility more realistically than pure ARCH models, which react abruptly to individual squared residuals.

Third, all three GARCH models identify the same two major volatility episodes as the ARCH models, with peaks of approximately 6 to 7 in the third quarter of 2024 and approximately 6.5 to 7 in the first half of 2025. However, the post-spike mean reversion is more gradual, with conditional variance declining steadily rather than abruptly. This is consistent with the interpretation that SMR20 price volatility is persistent once elevated and takes several periods to return to baseline levels, a stylised fact well documented in commodity markets (Karanasos et al., 2021).

Model Comparison and Selection

To determine the most appropriate specification, all six models are compared using the Akaike Information Criterion and the Schwarz Information Criterion. Both impose a parsimony penalty on model complexity, with lower values indicating a better balance between goodness of fit and simplicity. The log-likelihood value is also reported for completeness. Table 3 presents the full comparison.

Table 3: Model Comparison Based On AIC, SIC And Log-Likelihood

Model	Type	AIC	SIC	Log-Likelihood
ARCH(1)	ARCH	3.179639	3.198596	-1151.209
ARCH(2)	ARCH	3.169028	3.194304	-1146.357
ARCH(3)	ARCH	3.162713	3.194307	-1143.065
GARCH(1,1)	GARCH	3.136771	3.162046	-1134.648
GARCH(1,2)	GARCH	3.138424	3.170018	-1134.248
GARCH(1,3)	GARCH	3.141893	3.179807	-1134.507

Source: Authors' Estimation Using EViews. AIC = Akaike Information Criterion; SIC = Schwarz Information Criterion. Lower AIC And SIC Values Indicate A Better Model. GARCH(1,1) Records The Lowest Values On Both Criteria.

The results in Table 3 provide a clear basis for model selection. Within the ARCH family, model fit improves monotonically as the lag order increases: ARCH(3) achieves the best AIC (3.162713) and the highest log-likelihood (-1143.065) among the ARCH models, outperforming both ARCH(2) and ARCH(1). This confirms that incorporating additional lags of past squared residuals provides meaningful incremental improvements in capturing SMR20 return volatility. Nonetheless, every ARCH model is outperformed by every GARCH specification.

Among the GARCH models, GARCH(1,1) achieves the lowest AIC (3.136771) and the lowest SIC (3.162046) of all six specifications, making it the overall best-performing model. GARCH(1,2) records a marginally higher log-likelihood (-1134.248 against -1134.648), but this negligible improvement in fit is penalised by the additional parameter, resulting in a higher AIC of 3.138424. GARCH(1,3) records the weakest performance within the GARCH family on both criteria, confirming that extending the GARCH order to three lags offers no benefit. On the basis of both information criteria, GARCH(1,1) is selected as the optimal model for the conditional volatility of Malaysian SMR20 prices over the 2023 to 2025 period.

Discussion Of Findings

The empirical results collectively yield four substantive insights. First, the ARCH-LM test confirms the presence of time-varying conditional volatility in SMR20 log returns, establishing that rubber price uncertainty is not constant but evolves systematically in response to market shocks. This is consistent with the evidence reported by Ghani and Rahim (2019) for the earlier 2010 to 2017 sample and aligns with the broader commodity volatility literature, which consistently documents volatility clustering in agricultural markets (Chang et al., 2011; Karanasos et al., 2021).

Second, the identification of two major volatility episodes carries economically meaningful interpretations. The third-quarter 2024 surge corresponds with the period of highest recorded SMR20 prices in the sample, reflecting market uncertainty about the sustainability of the rally amid recovering demand and supply-side constraints. The early-2025 episode captures the correction phase, indicating that downward price adjustments were themselves accompanied by elevated short-term uncertainty. Accurate modelling of such episodes matters for industry stakeholders: producers can use volatility estimates to manage price risk, traders can adjust position sizing, and policymakers can gauge periods of commodity price instability.

Third, the consistent superiority of GARCH over ARCH models across all information criteria confirms the theoretical advantage of GARCH in capturing the persistence of commodity price volatility. Including lagged conditional variance allows the model to represent the long-memory decay of volatility shocks, a feature that ARCH cannot replicate without a very large number of lags. GARCH(1,1) accomplishes this with only two parameters, making it both statistically efficient and practically interpretable. Fourth, the selection of GARCH(1,1) partially diverges from Ghani and Rahim (2019), who identified ARMA(1,0)-GARCH(1,2) as optimal for the 2010 to 2017 sample. This difference may reflect structural change in SMR20 market dynamics between the two periods, particularly the more volatile and trend-driven price behaviour observed during 2023 to 2025 compared with the relatively range-bound conditions of the earlier sample. Nonetheless, both studies converge on the same fundamental conclusion: GARCH-based models are appropriate and effective tools for modelling the conditional volatility of Malaysian natural rubber prices.

Limitations And Recommendations

While this study provides useful insights into the volatility behaviour of Malaysian natural rubber prices, several limitations should be acknowledged. First, the analysis is based on a relatively short sample period of three years. Although the dataset contains a large number of observations, the period may not capture longer-term volatility patterns or structural changes across different economic cycles. External events such as global economic crises, trade disruptions or major policy changes occurring outside the sample window may affect rubber price volatility in ways not reflected in these findings. Second, the study is limited to the

historical price series of SMR20 alone and does not incorporate other macroeconomic or market-related variables. The natural rubber market is influenced by exchange rate fluctuations, crude oil prices, inflation, global automotive demand, weather conditions and supply disruptions. Excluding these variables limits the models' ability to explain the underlying causes of volatility and restricts the analysis to the statistical modelling of price behaviour.

Third, only six volatility specifications are estimated. These are widely used and effective at capturing volatility clustering, but standard ARCH and GARCH models assume that positive and negative shocks affect volatility symmetrically. Commodity markets are known to respond differently to good and bad news, and this asymmetry cannot be captured by the models employed here. Fourth, model selection relies on information criteria without an extensive out-of-sample forecasting evaluation, so although GARCH(1,1) performs best on AIC and SIC, its forecasting performance across different market regimes remains to be established.

Several recommendations follow. Future studies should employ a longer sample period covering multiple market conditions, including expansion, recession and commodity boom phases, in order to produce more robust findings on long-run volatility behaviour. Additional explanatory variables such as exchange rates, oil prices, inflation and global demand indicators should be incorporated to move beyond purely statistical modelling toward economic explanation. Researchers are also encouraged to explore asymmetric specifications such as EGARCH (Nelson, 1991) and GJR-GARCH (Glosten et al., 1993), which can capture leverage effects that the symmetric models used here cannot. Finally, comprehensive out-of-sample forecasting analysis would provide practical evidence on the usefulness of these models for producers, traders, investors and policymakers who require accurate volatility forecasts for risk management purposes.

Conclusion

This paper analysed the volatility dynamics of Standard Malaysian Rubber Grade 20 prices using daily data from January 2023 to December 2025. Because natural rubber is one of Malaysia's principal agricultural commodities, understanding the behaviour of its price volatility is important for producers, traders, investors and policymakers alike. ARCH and GARCH models were employed to model the conditional volatility of SMR20 returns.

The SMR20 price series exhibited substantial movement over the period, with a sustained rally followed by a correction. The series was transformed into log returns to satisfy the stationarity condition, and the ARCH-LM test confirmed the presence of significant ARCH effects, establishing conditional heteroskedasticity and volatility clustering in the return series.

Three ARCH and three GARCH specifications were estimated and compared. All six models successfully identified the two major volatility episodes in the sample. However, the GARCH models consistently outperformed the ARCH models, since they incorporate both past shocks and past volatility in the estimation process. The GARCH(1,1) model recorded the lowest AIC and SIC values among all six specifications, indicating the best balance between goodness of fit and parsimony.

The findings therefore establish that SMR20 price behaviour in Malaysia exhibits volatility clustering and persistent conditional volatility, and that GARCH models, particularly GARCH(1,1), are well suited to modelling and forecasting volatility in this market. These results provide a useful empirical basis for risk management and price stability analysis in the Malaysian natural rubber industry.

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