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THE EFFECT OF RAINFALL ON CHILI PRICE VOLATILITY IN NORTH SUMATRA: A GARCH-X APPROACH

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Abstract. Red chili is a strategic food commodity whose prices frequently experience high fluctuations, leading to price uncertainty. This study aims to analyze the characteristics of red chili price return volatility in North Sumatra Province and to examine the effect of rainfall on this volatility using the Generalized Autoregressive Conditional Heteroskedasticity model with exogenous variables (GARCH-X). The study uses daily red chili price and rainfall data from 3 May 2022 to 30 June 2025. The estimation results indicate that red chili price volatility is dynamic and predominantly driven by short-run dynamics, while long-run volatility effects are relatively weak. In addition, rainfall does not show a statistically significant effect on red chili price volatility. These findings suggest that red chili price instability is more strongly influenced by internal market dynamics and past price shocks than by exogenous factors such as climatic conditions represented by rainfall.

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INTRODUCTION

Red chili (*Capsicum annuum L.*) is a horticultural commodity with high and strategic economic value in Indonesia, considering its role as a staple ingredient in household consumption as well as a raw material for the processing industry. Highly volatile and difficult-to-predict price fluctuations constitute a vulnerability of this commodity. Sharp price spikes trigger inflation and social unrest, while persistently low prices harm farmers' production incentives (Muflikh et al., 2021). The ARCH-GARCH method has been widely applied to analyze price volatility in various Indonesian agricultural commodities, including shallots and garlic in West Java (Kurnia & Dzikrullah, 2022). In North Sumatra, where this study is conducted, previous research has confirmed that red chili prices exhibit high volatility and are sensitive to various market and climatic factors (Ginting et al., 2023). North Sumatra, as one of the largest red chili production centers on the island of Sumatra, therefore makes the stability of red chili prices in this region have significant implications for regional food security and the welfare of local farmers.

Red chili price volatility arises from interactions among production conditions, distribution systems, and market responses. Because red chili is highly perishable and demand is relatively inelastic in the short run, disruptions in supply can translate rapidly into price movements. Previous research has identified long and complex agricultural value chains, trader responses, and market interactions as important sources of chili price volatility (Muflikh et al., 2021). Weather shocks represent an additional source of supply uncertainty because they can simultaneously affect production volume, harvest timing, and product quality. Kakpo et al. (2022), for example, demonstrate that weather shocks can alter food price seasonality through their effects on agricultural supply. In Indonesia, climate-related disruptions have likewise become an increasing concern for agricultural production (Imelda & Hidayat, 2024). Thus, rainfall is not considered merely as a production variable in this study; it represents an exogenous supply shock that can propagate from agricultural production to market prices and ultimately affect price volatility.

Rainfall is particularly relevant to red chili price volatility because its effect on agricultural production is potentially nonlinear. Insufficient rainfall can constrain plant growth and reproductive processes, whereas excessive rainfall can increase the incidence of disease, fruit damage, and post-harvest losses (Ghosh et al., 2025). Consequently, both rainfall deficits and excesses may reduce effective market supply, although the magnitude and timing of their effects can differ. In North Sumatra, such production shocks may be transmitted to markets through changes in available supply and expectations about future harvests. This mechanism provides a direct theoretical link between rainfall and price volatility: rainfall shocks alter the uncertainty of agricultural supply, which can increase uncertainty in market prices. Accurate rainfall information is therefore important for anticipating agricultural risks and designing early warning systems (Inayah et al., 2024). Although the relationship between rainfall and agricultural production has received considerable attention, empirical evidence linking rainfall directly to the conditional variance of red chili prices remains limited.

Agricultural commodity prices commonly exhibit volatility clustering, in which periods of large price fluctuations tend to be followed by further periods of high volatility (Matondang et al., 2024). This feature motivates the use of conditional volatility models rather than conventional time-series models that assume constant error variance. The ARCH model introduced by Engle (1982) and its generalised form, GARCH (Bollerslev, 1986), provide a framework for modelling time-varying conditional variance. Previous studies have successfully applied ARCH-GARCH models to Indonesian chili prices, including curly chili (Nugrahapsari & Arsanti, 2019; Lestari et al., 2022), as well as to other agricultural commodities (Kurnia & Dzikrullah, 2022). However, standard GARCH models primarily capture the internal dynamics of volatility and do not directly identify whether exogenous shocks contribute to changes in conditional variance.

The GARCH-X framework extends the standard GARCH specification by incorporating observable external variables directly into the conditional variance equation. Previous applications demonstrate its usefulness for identifying the contribution of exogenous factors to commodity price volatility, including exchange rates, international prices, and other external shocks (Yeasin et al., 2020; Chaovanapoonphol et al., 2023). More recent studies have also incorporated climate-related uncertainty into agricultural commodity volatility models, indicating growing interest in the interaction between climate conditions and market risk (Salisu et al., 2025). Vorsah et al. (2025), for instance, show that GARCH-X can improve the modelling of maize price volatility by explicitly accounting for exogenous influences. However, these studies do not establish whether observed rainfall shocks are directly transmitted into the conditional variance of red chili prices in an Indonesian regional market. Existing Indonesian studies have largely examined chili price volatility through ARCH-GARCH models (Nugrahapsari & Arsanti, 2019; Lestari et al., 2022) or examined rainfall in relation to agricultural production rather than market-level price risk. The unresolved issue is therefore not simply whether GARCH-X can be applied to another region, but whether climatic variability constitutes a measurable source of conditional price risk in a geographically specific red chili market. Addressing this issue provides a basis for distinguishing volatility generated by endogenous market dynamics from volatility associated with exogenous weather shocks.

Against this background, this study aims to (1) quantify the effect of rainfall on the conditional volatility of red chili prices using a GARCH-X model and (2) characterise the dynamics and persistence of red chili price returns in North Sumatra Province. The analysis contributes by explicitly modelling rainfall as an exogenous source of conditional price risk rather than treating it only as a determinant of agricultural production. Focusing on North Sumatra also extends the existing literature on regional red chili price volatility by examining how climatic shocks may propagate from production conditions to market-level price instability. The findings are expected to provide empirical evidence relevant to climate-informed early warning systems and red chili market stabilisation policies.

METHOD

This study uses daily time series data with an observation period from May 3, 2022, to June 30, 2025. The collected data consist of two main variables, namely daily red chili prices and daily rainfall data in North Sumatra. The red chili price data were obtained from the Bank Indonesia Food Price Information System (BI), which records daily transactions in traditional markets. Daily rainfall data were obtained from the BMKG Tobing observation station. The station was selected because of its geographical relevance to the study area and its availability of continuous daily observations over the study period. Since the analysis focuses on the relationship between rainfall conditions and market-level price volatility, the rainfall series is interpreted as an indicator of local weather shocks that may affect agricultural supply and subsequently market prices, rather than as a complete measure of rainfall conditions across the entire province. Both datasets were collected consistently only for working days (Monday, Tuesday, Wednesday, Thursday, and Friday) during the observation period, resulting in a total of 832 observations for each variable used in this study.

Before entering volatility modeling, the daily chili price data were transformed into a daily return series using log returns. This transformation is required because volatility analysis using the GARCH-X approach requires data in the form of returns to measure percentage fluctuations in price changes over time. Rainfall was retained in its original daily level and incorporated into the conditional variance equation with a one-observation lag. The lagged specification is intended to reduce simultaneity between rainfall and observed market prices and to allow rainfall occurring in the preceding observation period to precede the observed price volatility. The one-period lag should therefore be interpreted as a short-run weather-shock specification rather than as an assumption that the full agricultural response to rainfall occurs within one day. Given the available daily market-price frequency, the specification provides a parsimonious representation of the immediate transmission of weather conditions into market risk.

This study analyzes chili price volatility using the Generalized Autoregressive Conditional Heteroskedasticity model with an exogenous variable (GARCH-X). The analysis is conducted through several systematic stages. The first stage is data transformation and stationarity testing. Daily chili price data are transformed into a daily return series using log returns: $R_t = ln(P_t) - ln(P_{t-1})$, where$R_t$ is the chili price return at period t, P_t is the chili price at period t, and P_{t-1} is the chili price in the previous period. Meanwhile, rainfall data are used in lag-1 form to capture delayed effects. The stationarity of the return series is then tested using the Augmented Dickey-Fuller (ADF) test. If the series is not stationary, differencing is applied until stationarity is achieved.

The second stage is conditional mean modeling using ARIMA. Conditional mean modeling is carried out using the ARIMA(p,d,q) model. The model order is identified through the patterns of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF), and selected based on the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The selected ARIMA model is then tested using the Ljung-Box test to ensure that the white noise assumption is satisfied, which serves as a valid basis for volatility modeling.

The third stage is testing for ARCH effects. The residuals from the ARIMA model that satisfy the white noise assumption are tested to detect the presence of conditional heteroskedasticity using the ARCH-LM test. If the test result is significant, it indicates the presence of volatility clustering and GARCH modeling can be continued.

The fourth stage is the core of the study, namely volatility modeling using GARCH-X(r,s). This model consists of two main equations. The mean equation is modeled in equation (1). Meanwhile, the conditional variance equation, which is the main focus, is modeled in equation (2).

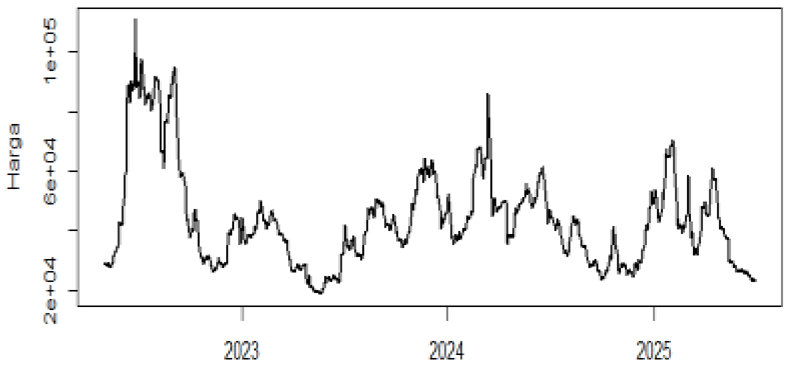
$$R_t = \mu + \sum_{i=1}^{p} \phi_i R_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \tag{1}$$

$$h_t = \omega + \sum_{i=1}^{r} \alpha_i {\varepsilon^2}_{t-i} + \sum_{j=1}^{s} \beta_j h_{t-j} + \gamma X_t, \tag{2}$$

where X_t is the exogenous variable of lag-1 rainfall, and γ measures its effect on volatility. Parameter estimation is performed using Maximum Likelihood Estimation (MLE). The best model is selected based on the smallest AIC and BIC values and the passing of Ljung-Box and ARCH-LM diagnostic tests on standardized residuals and their squares, to ensure that volatility has been fully modeled.

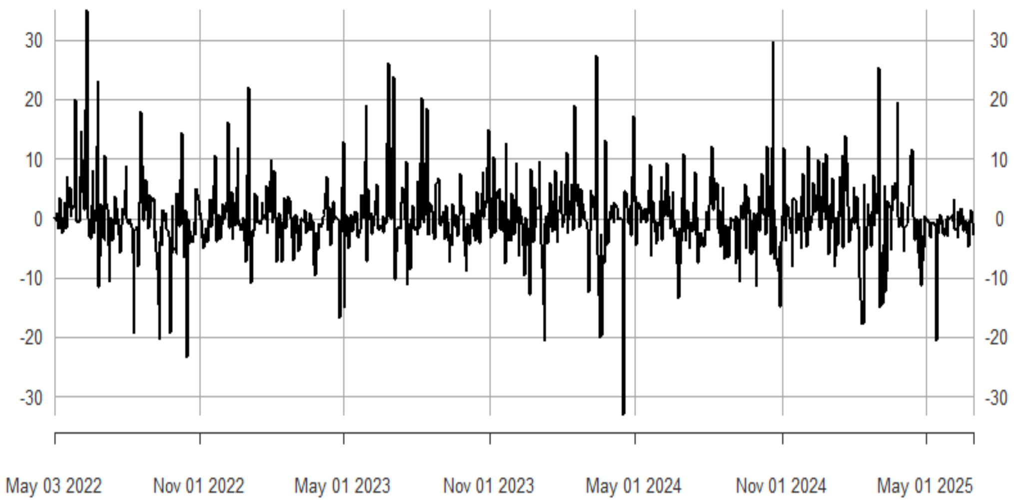
RESULT AND DISCUSSION

This study uses two main variables, namely chili prices and rainfall, which have been transformed into weekly returns for volatility analysis. Figure 1 (Chili Price Chart) shows the time series pattern of chili prices during the study period (May 3, 2022 to June 30, 2025), where very high price fluctuations with extreme movements are observed. Chili price data exhibit highly significant volatility with extreme price ranges from IDR 19,220 to IDR 96,230, indicating price sensitivity to various market and climatic factors. Figure 2 (Chili Price Return Chart) presents the transformation of prices into returns, which clarifies the volatility pattern with alternating clusters of high and low volatility. Figure 3 (Rainfall) illustrates daily/weekly rainfall patterns that also show significant variation, including several periods with no rainfall (zero values) and periods of intense rainfall. Meanwhile, Figure 4 (Lag-1 Rainfall) shows rainfall shifted one period backward (lag-1), where the value at time t represents rainfall at period t–1. These visual patterns provide an initial overview of unstable and highly fluctuating data characteristics, indicating the need for a modeling approach capable of capturing such volatility.

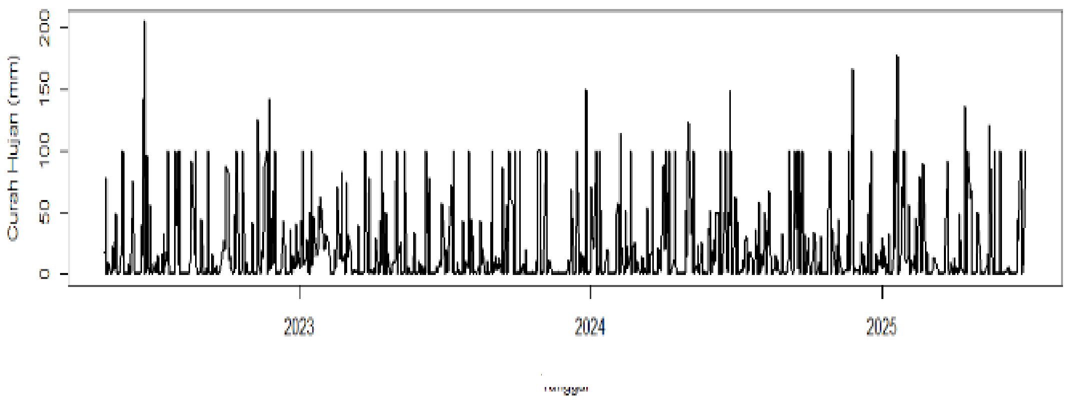


Source: Data processed, 2025

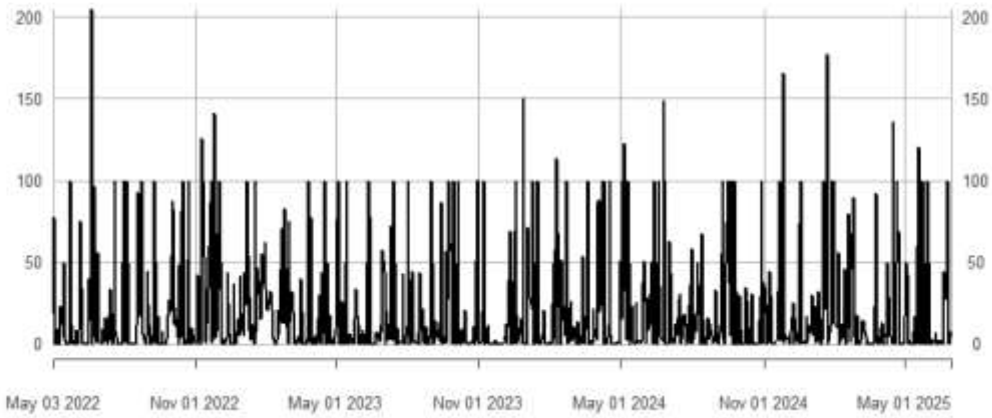
Figure 1. Chili price



Source: Data processed, 2025
Figure 2. Chili price return



Source: Data processed, 2025
Figure 3. Rainfall



Source: Data processed, 2025
Figure 4. Rainfall lag-1

The statistical description of the Chili Price Return and Lag-1 Rainfall variables provides a quantitative overview of their characteristics. Chili price returns have a mean of −0.0274% per week, indicating an overall downward price trend during the study period. However, the lower median (−0.332%) suggests a left-skewed distribution. The volatility of chili price returns is reflected in a standard deviation of 5.9405%, with extreme values ranging from −35.0183% (largest decline) to 32.9455% (largest increase). A positive skewness value (0.6207) indicates a right-tailed distribution, while high kurtosis (6.5306) indicates leptokurtosis, meaning a more peaked distribution with fat tails compared to a normal distribution, which is characteristic of financial data containing extreme outliers. The Jarque–Bera test yields a p-value of 0, confirming that the distribution of chili price returns is statistically non-normal.

Meanwhile, rainfall has an average of 20.3629 mm per week with a much lower median (4.500 mm), indicating the presence of several periods with very high rainfall that pull the mean upward. The standard deviation of 32.5656 mm reflects substantial rainfall variability, ranging from 0 mm (no rainfall) to 204.9000 mm (extreme heavy rainfall). A high skewness value (2.0356) indicates a strongly right-skewed distribution, where most observations are concentrated at low values with several extreme high outliers. The kurtosis value of 3.8481 indicates a flatter (platykurtic) distribution compared to the normal distribution.

The non-normal distribution, high volatility, and significant skewness and kurtosis observed in both variables support the use of the GARCH-X approach in this study. The GARCH model is specifically designed to handle data with volatility clustering and non-normal distributions, while the X (exogenous) component allows external variables such as rainfall to explicitly influence price volatility. These descriptive findings provide a methodological justification for selecting a volatility model that is robust to the observed data characteristics.

As a preliminary step before applying the model, it is important to ensure that the time series data satisfy the stationarity assumption. Therefore, unit root testing is conducted using the Augmented Dickey–Fuller (ADF) method to evaluate whether chili price returns and one-period lagged rainfall are stationary or contain a unit root.

Table 1. Results of the Augmented Dickey–Fuller (ADF) stationarity test

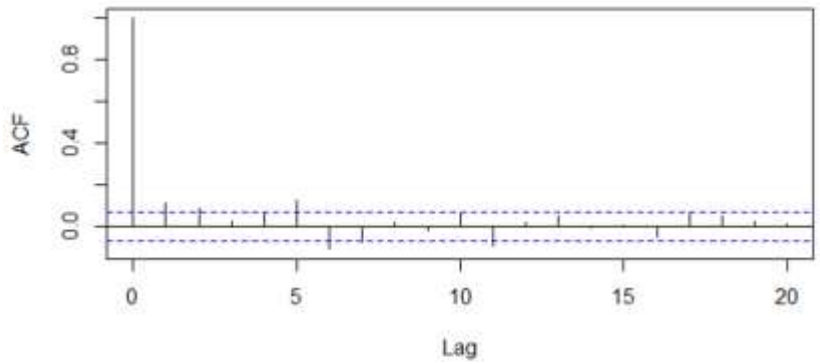
Variable	ADF test statistic	p-value	Conclusion
Chili Price Return	-9.3559	< 0.01	Stationary
Lag-1 Rainfall	-8.4754	< 0.01	Stationary

Source: Data processed, 2025

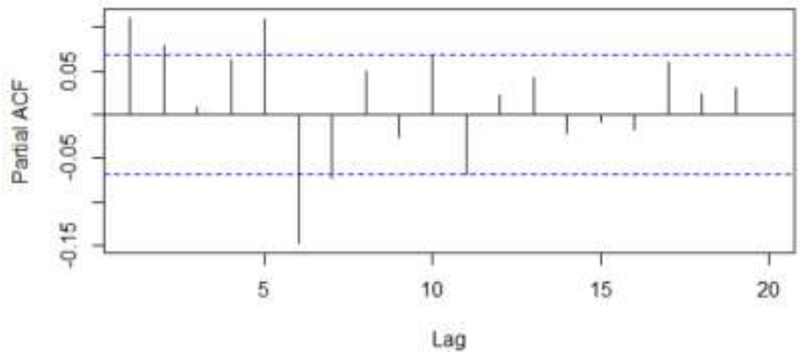
Based on Table 1, the Augmented Dickey–Fuller (ADF) unit root test is applied to assess data stationarity. The null hypothesis (H_0) states that the data are non-stationary, while the alternative hypothesis (H_1) states that the data are stationary. The results indicate that both variables, namely rainfall and chili price returns, are stationary at level (I(0)). The Dickey–Fuller statistics are far more negative than the critical values, and the very small p-values (< 0.01) lead to rejection of H_0, providing strong evidence that both time series are stationary. The complete results are presented in Table 1. With the stationarity assumption satisfied, ARIMA modeling proceeds by identifying autocorrelation patterns in chili price returns using the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) to determine the appropriate AR and MA components.

Figure 5 presents the ACF for chili price returns. Most autocorrelation bars lie within the confidence interval (blue dashed lines), although several lags exceed the boundary, indicating significant autocorrelation in the return data. The gradual decay pattern suggests that the influence of past returns on current returns is persistent but weakens over time. This characteristic is consistent with agricultural commodity return data, which typically exhibit short-term memory effects from previous price shocks.

Figure 6 displays the PACF for chili price returns. The first lag (lag 1) shows a significant value exceeding the confidence interval, while subsequent lags generally fall within the interval. The PACF cut-off after the first lag indicates that autocorrelation in chili price returns mainly originates from the direct influence of returns one period earlier. This pattern suggests a possible AR(2) specification for the autoregressive component.



Source: Data processed, 2025
Figure 5. Autocorrelation Function (ACF) of chili price returns



Source: Data processed, 2025
Figure 6. PartialAutocorrelation Function (PACF) of chili price returns

Based on the ACF's gradual decay and the PACF's cut-off after the first lag, chili price returns exhibit characteristics consistent with an ARMA (Autoregressive Moving Average) model. This combination suggests considering mixed models such as ARMA(2,1) or the simpler AR(2) model. These identification results provide the basis for estimating and selecting the optimal ARIMA model before proceeding to volatility modeling using the GARCH-X approach.

Based on Table 2, the observed volatility pattern is broadly consistent with previous studies of chili markets in Indonesia. Nugrahapsari and Arsanti (2019) documented substantial volatility in curly chili prices using the ARCH-GARCH approach, while Lestari et al. (2022) also found pronounced volatility in red chili prices. Miftahuljanah et al. (2020) further showed that chili price volatility is closely associated with price transmission across market levels. These findings support the presence of substantial short-term price dynamics in chili markets and provide an empirical basis for applying a conditional volatility model in the North Sumatran market. However, unlike studies that primarily focus on the statistical characteristics of chili price volatility, the present analysis further examines whether rainfall contributes to conditional price volatility through a GARCH-X specification.

The selection of the ARIMA model aims to determine the optimal conditional mean specification before conducting volatility modeling using the GARCH-X approach. The selection process was carried out by evaluating sixteen ARMA models with various order combinations, ranging from ARMA(1,1) to ARMA(4,4). The criteria used in model selection include the Akaike Information Criterion (AIC), Bayesian

Information Criterion (BIC), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the Ljung–Box test on residuals to ensure that the residuals approximate white noise conditions.

The evaluation results of the sixteen models are presented in Table 2. Based on the comparison of selection criteria, ARMA(2,4) was chosen as the most appropriate model. This model has an AIC value of 5255.484 and a BIC value of 5293.207, which are among the best in comparison to all tested models. The difference in AIC between ARMA(2,4) and the model with the lowest AIC, namely ARMA(3,4), is only 1.486, which is practically considered insignificant ($\Delta AIC < 2$). This indicates that a model with lower complexity is still able to provide comparable fit quality. In addition, the RMSE value of 5.791 and MAE of 3.643 indicate good and stable predictive accuracy. Although the MAPE value is very high, this condition commonly occurs in return data with values close to zero, therefore accuracy measures such as RMSE and MAE are considered more representative in evaluating model performance.

Table 2. Results of ARIMA model selection for chili price returns

Model	AIC	BIC	RMSE	MAE	LB_res_p
ARMA(3,4)	5253.998	5296.436	5.779053	3.644136	9.80E-02
ARMA(4,2)	5255.399	5293.122	5.791060	3.637819	2.45E-02
ARMA(2,4)	**5255.484**	**5293.207**	**5.791357**	**3.642584**	**6.11E-02**
ARMA(4,4)	5255.833	5302.987	5.778480	3.643920	9.89E-02
ARMA(4,3)	5255.937	5298.375	5.785893	3.639999	4.28E-02
ARMA(3,3)	5266.742	5304.465	5.83136	3.707745	7.06E-04
ARMA(1,4)	5271.470	5304.478	5.855386	3.696525	3.52E-05
ARMA(1,1)	5271.961	5290.822	5.878629	3.69395	3.86E-06
ARMA(2,1)	5273.745	5297.322	5.877855	3.698765	3.41E-06
ARMA(4,1)	5274.089	5307.097	5.864778	3.688601	1.05E-05
ARMA(1,2)	5275.365	5298.942	5.883643	3.702885	2.14E-06
ARMA(2,2)	5275.576	5303.868	5.877252	3.700684	3.02E-06
ARMA(3,1)	5275.716	5304.008	5.877751	3.700178	3.17E-06
ARMA(3,4)	5253.998	5296.436	5.779053	3.644136	9.80E-02
ARMA(4,2)	5255.399	5293.122	5.791060	3.637819	2.45E-02
ARMA(2,4)	5255.484	5293.207	5.791357	3.642584	6.11E-02

Source: Data processed, 2025

From the residual diagnostics perspective, the Ljung–Box test on the residuals of the ARMA(2,4) model produces a p-value of 0.0611, which is greater than the significance level $\alpha = 0.05$. This result indicates the absence of significant autocorrelation in the residuals, so the residuals can be considered to satisfy the white noise assumption. Meeting this assumption is an important prerequisite in the GARCH-X modeling framework, as innovations in the mean equation that are free from autocorrelation are required to validly model conditional volatility.

In addition to meeting statistical and diagnostic criteria, the ARMA(2,4) model is also considered efficient from the model structure perspective. By involving only two autoregressive parameters and four moving average parameters along with one constant, this model is relatively simple yet capable of adequately capturing the dynamics of chili price returns. The application of the parsimony principle in model selection helps to avoid overfitting, improve estimation stability, and maintain the model's generalization ability. Based on overall considerations of statistical criteria, residual diagnostics, model structure efficiency, and economic interpretation, ARMA(2,4) is selected as the optimal conditional mean specification. This model provides a strong and consistent foundation for the subsequent analysis stage, namely testing for ARCH effects and estimating the volatility model using the GARCH-X approach.

After the ARMA(2,4) model was selected as the optimal conditional mean specification, the next step was to test for the presence of ARCH (Autoregressive Conditional Heteroskedasticity) effects in its residuals. This test aims to detect whether residual volatility is time-varying and exhibits volatility clustering patterns, which serve as the empirical basis for further volatility modeling using the GARCH-X approach. The test was conducted using the ARCH-LM (Lagrange Multiplier) test with the null hypothesis (H_0) stating that there is no ARCH effect (residuals are homoskedastic), and the alternative hypothesis (H_1) stating that there is an ARCH effect (residuals are heteroskedastic). The results of the ARCH-LM test are presented in Table 3.

Table 3. Results of model estimation and diagnostics

ARCH LM-test	Value
Chi-Square	34.213
p-value	0.000624

Source: Data processed, 2025

Based on Table 3, the p-value of 0.0006244 is far below the 5% significance level (0.05). This leads to the rejection of H_0, so it can be concluded that there is a significant ARCH effect in the residuals of the ARMA(2,4) model. This finding indicates that residual volatility is not constant, but instead exhibits a pattern of conditional heteroskedasticity in which the magnitude of fluctuations tends to cluster over certain periods. In the context of chili prices, this reflects that market returns experience periods of high uncertainty followed by periods of calm, a characteristic commonly found in agricultural commodities due to seasonal factors, supply shocks, or policy changes.

With the detection of ARCH effects, GARCH-X modeling becomes empirically relevant. The GARCH-X model is not only capable of capturing volatility clustering patterns, but also allows for testing the influence of exogenous variables such as seasonal factors, trading volume, or policy on the volatility of chili price returns. Therefore, the next step is to estimate and select the GARCH-X model to better understand volatility dynamics more comprehensively.

Given the presence of significant ARCH effects in the residuals of the ARMA(2,4) model, the next step is to model the volatility of chili price returns using the GARCH-X approach (GARCH with exogenous variables). This model allows researchers to quantify the extent to which external factors such as climate conditions (in this case rainfall) contribute to fluctuations in the volatility of chili price returns.

The process of determining the best model was conducted by evaluating combinations of p and q orders in the GARCH-X model. The selection of the best model was not only based on statistical information criteria such as the smallest Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), but also required to meet strict diagnostic tests. These diagnostic tests include the Ljung-Box test on residuals to ensure the white noise assumption is satisfied, as well as the Ljung-Box test on squared residuals to ensure that no remaining ARCH effects are present.

Table 4. GARCH-X variance models

Model	AIC	BIC	RMSE	MAE	LB_res_p	LB_res²_p
GARCHX (5,5)	6.22902	6.33761	0.98373	0.63630	0.02465	0.43595
GARCHX (5,1)	**6.32242**	**6.40815**	**0.99696**	**0.62927**	**0.08621**	**0.42613**
GARCHX (5,3)	6.32726	6.42440	0.99704	0.62934	0.08661	0.42655
GARCHX (5,4)	6.32861	6.43149	0.99702	0.62898	0.08561	0.45051
GARCHX (1,1)	6.37682	6.43969	1.01454	0.63848	0.06444	0.00043
GARCHX (3,2)	6.37702	6.45704	0.99727	0.62604	0.04028	0.00061
GARCHX (2,1)	6.37925	6.44783	1.01454	0.63848	0.06444	0.00043
GARCHX (1,2)	6.37925	6.44784	1.01449	0.63841	0.06441	0.00043
GARCHX (4,2)	6.37991	6.46564	0.98630	0.61984	0.04262	0.00060
GARCHX (4,1)	6.38166	6.46168	0.99628	0.62591	0.07838	0.00183
GARCHX (3,1)	6.38167	6.45597	1.01455	0.63848	0.06444	0.00043
GARCHX (2,2)	6.38167	6.45598	1.01450	0.63845	0.06442	0.00043

Source: Data processed, 2025

Based on Table 4, the model selection process was conducted through several elimination stages. In the initial stage, evaluation was based on the Akaike Information Criterion (AIC). At a glance, the GARCH-X(5,5) model shows the lowest AIC value of 6.2290. However, this model cannot be selected as the best model because it does not satisfy the white noise assumption in the residuals. This is indicated by the Ljung-Box test probability value of 0.0246, which is smaller than the significance level $\alpha = 0.05$. Rejection of the null hypothesis indicates that the residuals of the model still contain autocorrelation, so the GARCH-X(5,5) model is considered less valid in representing the data.

Next, elimination was carried out on models that still exhibited ARCH effects. Several other models, such as GARCH-X(1,1) and GARCH-X(3,2), although having simpler parameter structures, were also not suitable for selection. These models failed the Ljung-Box test on squared residuals, indicating that heteroskedasticity or ARCH effects had not been fully eliminated from the data.

After excluding models that did not meet diagnostic assumptions, three candidate models remained that were considered valid because they passed the white noise test and were free from ARCH effects, namely GARCH-X(5,1), GARCH-X(5,3), and GARCH-X(5,4). These three models have diagnostic test probability values greater than 0.05, indicating that the residuals are random and the variance is stable. Among the three candidates, the GARCH-X(5,1) model was selected as the best model. This selection was based on the principle of parsimony, where models with simpler structures are preferred if they have comparable diagnostic performance. Although the AIC value of the GARCH-X(5,1) model of 6.3224 is slightly different from the other valid candidates, this model has a simpler lag structure in the GARCH component ($q = 1$) compared to the GARCH-X(5,3) and GARCH-X(5,4) models. In econometric modeling, more parsimonious models tend to be more efficient and minimize the risk of overfitting.

Thus, the GARCH-X(5,1) model is established as the selected model for analyzing the volatility of chili price returns in North Sumatra Province. However, before further interpretation of volatility parameters in this model, it is necessary to first ensure whether the modeled volatility is symmetric or asymmetric. This is important because the presence of asymmetry effects (leverage effects) can cause volatility responses to positive and negative shocks to differ. If asymmetry effects are detected, the use of a symmetric GARCH model (sGARCH-X) becomes less adequate and asymmetric volatility models such as EGARCH-X or GJR-GARCH-X need to be considered. Therefore, the next stage involves testing volatility asymmetry using the Engle–Ng Sign Bias Test.

Table 5. Results of the Engle–Ng sign bias test (Symmetry Test)

Test	t-value	p-value
Sign Bias	0.2136	0.8308
Negative Sign Bias	0.2550	0.7987
Positive Sign Bias	0.6511	0.5151
Joint Effect	0.5445	0.9090

Source: Data processed, 2025

Based on the results of the Engle–Ng Sign Bias Test presented in Table 5, all test components, namely Sign Bias, Negative Sign Bias, Positive Sign Bias, and Joint Effect, have p-values greater than the 5% significance level ($\alpha = 0.05$). In particular, the p-value of the Joint Effect component of 0.9090 indicates no statistical evidence supporting the presence of asymmetry effects (leverage effects) in the volatility of chili price returns.

This finding indicates that volatility responses to positive and negative shocks are symmetric, so volatility fluctuations are not influenced by the direction of price shocks, but rather by the magnitude of the shocks themselves. Thus, the assumption of volatility symmetry in the symmetric GARCH (sGARCH-X) model is satisfied. Therefore, the use of the GARCH-X(5,1) model is considered adequate, and there is no need to use asymmetric volatility models such as EGARCH-X or GJR-GARCH-X.

With no evidence of volatility asymmetry based on the Engle–Ng Sign Bias Test, it can be concluded that the volatility response of chili price returns to both positive and negative shocks is symmetric. This condition indicates that the direction of price shocks is not a determining factor in volatility formation, so the symmetric volatility modeling approach is deemed appropriate. Therefore, further analysis focuses on evaluating the estimated parameters of the GARCH-X(5,1) model to further examine the sources of chili price volatility.

Specifically, this stage aims to examine the contribution of the ARCH component in representing the influence of past price shocks on short-term volatility, as well as the GARCH component in describing the level of long-term volatility persistence. In addition, parameter estimation is also used to assess the extent to which the exogenous variable of rainfall plays a role in explaining the dynamics of chili price volatility after accounting for the effects of past price shocks.

Based on the estimation results in Table 6, the volatility dynamics of chili price returns in North Sumatra are more dominantly influenced by short-term price shocks (short-term effects), while long-term persistence effects are relatively weak. In addition, the exogenous variable of rainfall is not proven to have a significant effect on chili price volatility in the model used.

Table 6. Results of volatility parameter estimation (variance equation) of the GARCH-X(5,1) model

Parameter	Estimate	Std. Error	t value	Pr(>|t|)
mu	-0.4260	0.2414	-1.7648	0.0776
ar1	0.3013	0.0598	5.0369	0.0000
ar2	-0.8835	0.0623	-14.1735	0.0000
ma1	-0.1833	0.0653	-2.8081	0.0050
ma2	0.9418	0.0707	13.3127	0.0000
ma3	0.0534	0.0395	1.3522	0.1763
ma4	0.1473	0.0361	4.0833	0.0000
omega	25.4629	2.0674	12.3164	0.0000
alpha1	0.0253	0.0212	1.1922	0.2332
alpha2	0.0000	0.0181	0.0000	1.0000
alpha3	0.0000	0.0118	0.0000	1.0000
alpha4	0.0000	0.0183	0.0000	1.0000
alpha5	0.2546	0.0357	7.1277	0.0000
beta1	0.0000	0.0770	0.0000	1.0000
vxreg1	0.0000	0.0632	0.0000	1.0000

Source: Data processed, 2025

Short-term shock effects are represented by the ARCH (α) parameters, which are theoretically designed to capture the immediate impact of new shocks on volatility (news impact) (Engle, 1982). The estimation results show that only the α_5 (alpha5) parameter is statistically significant at the 5% significance level with a p-value of 0.0000 and a coefficient value of 0.2546. This finding indicates that chili price shocks occurring five periods earlier still have a significant influence on price volatility in the current period. In other words, when a large price shock occurs in the past, its impact on increasing volatility does not immediately disappear, but persists in the short term for several subsequent periods. This condition reflects the presence of volatility clustering, which is commonly found in agricultural commodities, especially those sensitive to supply and distribution disruptions. Similar findings were reported in Bengkulu Province, where curly red chili price volatility was found to be high at producer and wholesale levels, with the wholesale market acting as the price leader (Miftahuljanah, Sukiyono, & Asriani, 2020). Meanwhile, the α_1 to α_4

parameters are not statistically significant, indicating that price shocks in closer periods, namely one to four lags earlier, do not have a sufficiently strong effect on conditional volatility.

Furthermore, long-term volatility persistence effects are represented by the GARCH (β) parameters, which measure the extent to which past volatility persists and influences current volatility in the long run (Bollerslev, 1986). In this model, the β_1 (beta1) parameter is not statistically significant with a p-value of 1,0000. This result indicates that chili price volatility does not exhibit strong long-term persistence, so high volatility in one period does not automatically continue into subsequent periods in the long run. Thus, chili price volatility in North Sumatra tends to be transitory and is more triggered by specific shocks rather than long-term volatility memory.

The coefficient of lagged rainfall in the conditional variance equation is statistically insignificant, indicating that one-period-lagged rainfall does not directly explain the conditional volatility of red chili prices in North Sumatra during the observation period. This finding differs from previous evidence that weather conditions can affect agricultural markets through their effects on production and food supply. Kakpo et al. (2022), for example, found that weather shocks contribute to food price seasonality in Niger, while Ghosh et al. (2025) demonstrated the importance of rainfall risk for agricultural production. Similarly, Fajri et al. (2017) and Abdi et al. (2022) identified production and supply-related factors as important determinants of red chili prices. The difference may reflect the indirect and delayed transmission of rainfall shocks. Rainfall may first affect crop production, followed by changes in supply, distribution, and market inventories before eventually influencing prices. Therefore, the absence of a significant one-period-lagged rainfall effect should not be interpreted as evidence that rainfall is irrelevant to the chili market. Rather, it suggests that its direct effect on short-term conditional price volatility is limited at the temporal scale examined in this study. This interpretation is also consistent with Muflikh et al. (2021), who emphasised that chili price volatility results from interactions among multiple components of the agricultural value chain.

Taken together, the findings confirm that red chili prices in North Sumatra exhibit substantial conditional volatility, consistent with previous studies of chili markets in Indonesia (Nugrahapsari & Arsanti, 2019; Lestari et al., 2022; Ginting et al., 2023). However, the results also indicate that the immediate contribution of rainfall to price volatility is limited. This finding adds to the existing literature by distinguishing between the existence of climate-related effects on agricultural production and their direct transmission into short-term market price volatility. The results suggest that rainfall-related shocks may require longer transmission periods or operate through intermediate mechanisms such as production, supply, and distribution before affecting market prices.

CONCLUSION

Based on the results of the analysis using the GARCH-X approach, it can be concluded that the volatility of red chili price returns in North Sumatra Province is dynamic and not constant over time, reflecting the presence of volatility clustering characteristics. The transformation of prices into returns produces a stationary time series that is suitable for volatility analysis. Modeling the mean equation using ARMA successfully captures the dynamics of average returns and produces residuals that satisfy the white noise assumption, while the ARCH-LM test results indicate significant conditional heteroskedasticity. This confirms that chili price volatility cannot be explained solely through the mean model, but requires conditional variance modeling. Estimation of the GARCH-X model shows that the volatility of chili price returns is dominated by short-run dynamics, as reflected by the significance of the ARCH component, indicating that price shocks in the previous period play an important role in determining the current level of volatility. In contrast, the influence of long-run volatility is relatively weak, as indicated by the insignificance of the GARCH component, which suggests that chili price volatility is temporary and does not exhibit strong long-term persistence. In addition, the results show that the exogenous variable of rainfall does not have a significant effect on the volatility of chili price returns, indicating that this climatic factor does not directly play a role in determining short-term price uncertainty at the market level. These findings indicate that chili price volatility is more influenced by internal market dynamics and past price shocks than by external factors in the form of rainfall.

Based on the research results, there are several important suggestions that can serve as a basis for policy recommendations and further research development. As chili price volatility is more influenced by past price shocks than by climatic factors, price stabilization efforts should focus on market control mechanisms. Therefore, it is recommended to implement an early warning system based on monitoring daily fluctuations, optimize market operations through buffer stock interventions when patterns of increasing volatility are detected, and improve distribution and logistics systems to reduce the impact of internal market shocks. Furthermore, from a methodological perspective, the results show that the GARCH-X model with a relatively long lag structure in the ARCH component is able to capture the dynamics of chili price volatility well. However, for further development, future research may consider using nonlinear or asymmetric volatility models, such as EGARCH or GJR-GARCH, to examine whether price increases and decreases have different impacts on volatility.

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