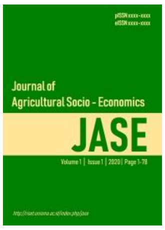

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VOLATILITY ANALYSIS OF BROILER CHICKEN PRICES IN THE RAMADHAN PERIOD: A STRATEGIC FOOD PERSPECTIVE

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Abstract. The price volatility of broiler chicken, a strategic food commodity in Indonesia, becomes a critical issue that escalates significantly during each Ramadan period. This annual phenomenon negatively impacts consumer purchasing power and the sustainability of culinary MSMEs. This study aims to analyse the patterns and measure the persistence level of broiler chicken price volatility to understand the market dynamics during this high-demand period. Using weekly time-series data from the National Strategic Food Price Information Centre (PIHPS) from March 2017 to April 2023, this research applies the Generalised Autoregressive Conditional Heteroscedasticity (GARCH) model. The analysis begins with the ADF stationarity test, the ARMA model identification, and the ARCH effect test to validate the use of the GARCH model. The results show that the price data is stationary at the level and exhibits a significant ARCH effect. The GARCH (1,1) model was selected as the best fit for capturing volatility dynamics. The estimation results indicate the presence of volatility clustering with a high degree of persistence ($\alpha + \beta = 0.743$). The larger GARCH coefficient ($\beta = 0.485$) compared to the ARCH coefficient ($\alpha = 0.258$) shows that past volatility has a stronger effect on current price changes than new events do. A high level of persistence implies that a price shock will not dissipate quickly, suggesting that reactive, short-term stabilisation policies are likely to be less effective.

Keywords: Volatility, GARCH, Broiler Chicken, Food Prices, Ramadhan.

INTRODUCTION

Food security is an essential pillar in maintaining the social, economic, and political stability of a country (Amalia et al., 2022; Guiné et al., 2021). In Indonesia, broiler chickens are a strategically significant commodity in national food consumption (Vanany et al., 2021). As the most widely consumed and most affordable source of animal protein for the majority of people, broiler chickens have become an important barometer of household purchasing power and well-being (Kleyn & Ciacciariello, 2021) The stability of supply and prices not only affects people's nutritional conditions, but also becomes a significant component in the calculation of national inflation, especially from *the volatile food* group (Matthias et al., 2016).

The broiler chicken supply chain is inherently complex and prone to turbulence (Mostaghim et al., 2024; Solano-Blanco et al., 2020). Price dynamics at the upstream level, such as the price of chicken seeds (Day Old Chicken), feed that is highly dependent on imported components, and energy costs, create high potential volatility even under normal conditions (Biçoku & Zeqiri, 2024). However, this vulnerability has escalated drastically during certain seasonal periods, especially during the holy month of Ramadan and ahead of Eid al-Fitr. This period is marked by a massive and predictable surge in demand, driven by changing people's consumption patterns for iftar dishes, suhoor, and holiday celebrations. The surge in demand comes not only from the household sector, but also from thousands of Micro, Small, and Medium Enterprises (MSMEs) in the culinary sector who have significantly increased their production.

The confluence of structurally volatile commodities with extreme seasonal demand shocks creates an unsettling annual phenomenon: sharp and uncontrollable price volatility. Patterns that repeat each year indicate significant price increases, often not followed by improvements in service quality or product availability, and sometimes even accompanied by scarcity at the retail market level. This "expensive and rare" phenomenon creates a chain negative impact. For households, especially low- and middle-income groups, rising prices of broiler chickens directly erode their food spending budgets, forcing substitutions to cheaper protein sources or even reducing portions of consumption (Birhanu et al., 2023);(Queenan et al., 2021). For MSME players, price volatility disrupts business planning, reduces profit margins, and threatens the sustainability of their businesses which are at the peak of the season (Sharma & Rai, 2023).

Although the phenomenon of rising broiler chicken prices during Ramadan is in the spotlight of the media and the public every year, there is an important research gap to fill (Srikasem et al., 2024). Many existing analyses tend to be descriptive in nature only reporting price increases or focusing on reactive short-term solutions, such as market operations (Uçak et al., 2024). Research that rigorously examines the mechanisms of volatility, quantifies the extent of fluctuation, pinpoints the critical supply chain nodes most impacted, and analyses the underlying factors beyond mere demand increases (such as speculative behaviour or information asymmetry) remains scarce.

This research is both vital and innovative. The urgency resides in the necessity to transition from reactive measures to more efficacious preventative strategies. The innovation resides in an analytical framework that prioritises volatility as the central issue, rather than merely price surges, and employs the Ramadan season as a particular context to examine the response of a strategic food supply chain system to significant pressures. This study seeks to thoroughly analyse volatility patterns to establish a robust empirical basis for proactive policy development aimed at stabilising prices, safeguarding consumers, and ensuring the sustainability of stakeholders across the purebred chicken supply chain.

METHODS

2.1 Data Sources and Collection

The research used secondary data in the form of *time series* data. Secondary data is a collection of data that refers to information collected from existing data (Ajayi, 2017; Johhson & Sylvia, 2018; Olabode, et al., 2018). The data in this study is sourced from the National PIHPS (National Strategic Food Price Information Center) through *the https://www.bi.go.id/hargapangan* website. The type of data used is weekly *time series* data on Broiler chicken commodity prices. Quantitative data is used to calculate the volatility of cooking oil commodity prices during Ramadhan in Indonesia. The method used in this study is *ARCH/GARCH* using the Dummy variable and using Eviews 12 as an analysis tool.

2.2 Data Analysis

The study used a research model on the price volatility of cooking oil commodities, which used a forecasting method with a time series that was most widely used as Autoregressive (AR), Moving Average (MA), or a combination of the two (ARIMA) to analyze the volatility of Broiler chicken commodity prices during Ramadhan in Indonesia. Using this method, forecasting results can be obtained with high accuracy as long as the assumption of the homocedasticity of the error is met. A very well-known approach designed for conditional variety-modeling and forecasting, one of which is ARCH (Autoregresive Conditional Heteroscedastic).

This model was first introduced by Engle (1982) at the time of the analysis of inflation volatility in the UK. Bollerslev (1986) developed this method so that it became Generalized Autoregresive Conditional Heteroscedastic (GARCH). This model is used when the state of data volatility is high and low. This situation illustrates the existence of heteroscedasticity, where the magnitude of the error obtained depends on past errors or due to changes in variants in line with changes in the time used (Al-Najjar, 2016; Lestari et al., 2022). The model that will be used in the study is the ARCH/GARCH model, so the modeling and discussion of the results of the analysis will be focused on the context of the model. Data testing in this study will use Eviews 12 software.

The GARCH model is used for its ability to capture the phenomenon of volatility clustering, which is a tendency in which periods of high fluctuations will be followed by periods of high fluctuation, and vice versa. This is especially relevant for food commodity prices that often experience shocks.

The GARCH model consists of two main equations:

a. Mean Equation: Modeling the price return. Often use the ARMA model (p,q).

$$R_t = \sum_{i=1}^{p} \Phi_i R_{t-1} + e_t + \sum_{j=1}^{q} \emptyset_j e_{t-j} \quad (1)$$

Where εt is residual (shock/innovation) at time t.

b. Variance Equation: Modeling volatility (conditional variance). The commonly used GARCH(p,q) model is GARCH (Lama et al., 2015):

$$\sigma_t^2 = w + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (2)$$

Where:

- $\sigma_t^2 =$ Varian kondisional (volatilitas)pada hari ke - t
- ω = Constant (mean of long-term variance)
- ϵ_{t-1}^2 = The square of the residual in the previous period (the ARCH effect), representing information about the shock or *news* from the previous period.
- σ_{t-1}^2 = Conditional variance in the previous period (the GARCH effect), representing the "memory" or persistence of volatility from the past period.
- α_1= ARCH coefficient, measures the response of volatility to market shocks.
- β_1= Ganch coefficient, measures the degree of volatility persistence.

This research will be carried out through several systematic stages:

1. Data Stationarity Test: Perform a stationaryness test on price return (Rt) data using the Augmented Dickey-Fuller (ADF) test. Time series data must be stationary so that the estimation results are valid. The hypothesis is:
   a. H_0: Data has a root unit (not stationary).
   b. H_1: Data does not have a root unit (stationary).
2. Average Model Identification (ARMA): Determine the optimal p and q orders for the ARMA model by analyzing the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots from the return data.
3. ARCH Effect Test (ARCH-LM Test): Performs an ARCH Lagrange Multiplier (LM) test on the residues of the ARMA model to check if there is a conditional heteroscedasticity effect.
   a. H_0: There is no ARCH effect (constant/homoskedastic variance).
   b. H_1: There is an ARCH effect (non-constant/heteroscedastic variance). If H_0 is rejected, then the use of the ARCH/GARCH model is appropriate.
4. GARCH Model Estimation: Estimates the GARCH(1,1) model (or any other corresponding order) using the *Maximum Likelihood Estimation (MLE) method*.
5. Model Diagnostic Test: Checks the feasibility of the estimated GARCH model by ensuring that the standardized residuals no longer contain autocorrelations and ARCH effects.
6. Analysis and Interpretation:
   a. Analyzes the coefficients α_1 and β_1. The sum (α_1+β_1) indicates the degree of volatility persistence. If the value is close to 1, it means that the shock in the price of chicken will have a long-lasting impact (not quickly returning to normal conditions).
   b. Create a conditional variance plot () from the results of the GARCH model estimation.σ_{t-1}^2
   c. Visually and statistically compare the level of volatility in the Ramadhan period with the period outside of Ramadhan for several years. This will be the main empirical evidence to answer the research question.

RESULT AND DISCUSSION

3.1 Broiler Chicken Meat Commodities (Non-Ramadhan and Ramadhan)

The change in the weekly price of Broiler chicken meat commodities in Indonesia for the period March 2017 to April 2023, is presented in Figure 1. The price of Broiler chicken meat fluctuates throughout the year. These data support the findings of (Mir et al., 2017; Wickramarachchi et al., 2017; Chaudhry & Miranda, 2024).

Figure 1 shows that the commodity price of Broiler chicken meat has experienced the development of a trend pattern of price changes. Patterns of decline and price increases are not constant or variable on average. The highest price development occurred in 2022, precisely in the fourth week of April, amounting to Rp. 42,000, and the lowest price occurred in 2020 in the third week of April amounting to Rp. 28,750. The highest price spike in Broiler chicken meat in 2022 occurred due to the high price of chicken feed at that time, resulting in a price spike in Broiler chicken meat production.

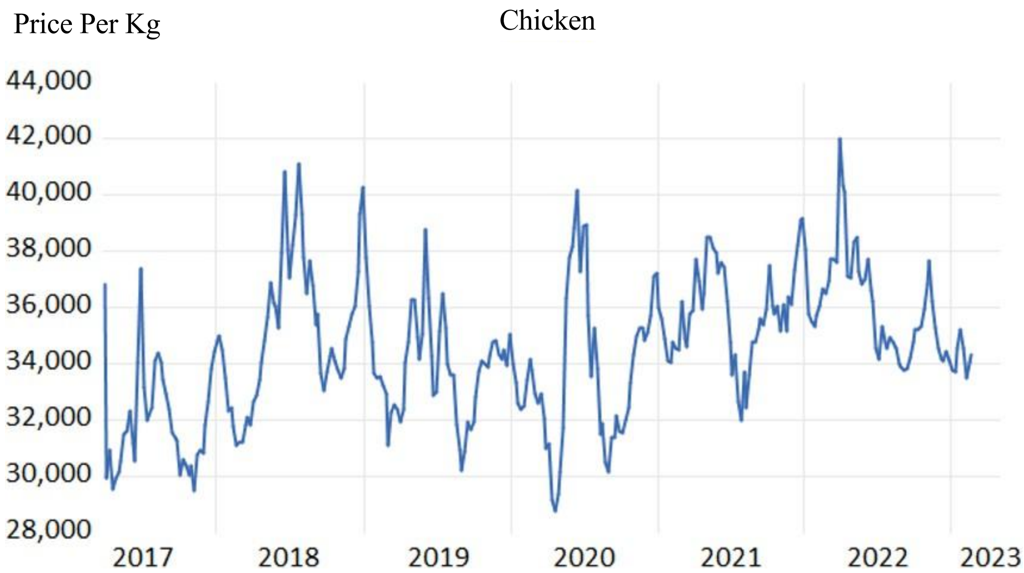

Figure 1. Development of Broiler Chicken Meat Commodity Prices in Indonesia in 2017-2023 Based on Weekly Data

3.2 Stationary Test of Broiler Chicken Meat Price Data

The stationarity test on Broiler chicken meat price data is the first step to ensure that the data has a constant mean and variance. The root test through the ADF (*augmented dickey fuller*) method was carried out to test the data by looking at *the t-Statistic value > test critical value* of 5% or p-value < α (0.05). The results of the data testing can be seen in Table 1.

Table 1. Stationary Test of Commodity Price Data of Broiler Chicken Meat

ADF test				
Level	*Test critical value 5%*	*t-Statistic*	Prob.	Information
Level	-2.870743	-4.892436	0.0000	Stationary

Source : Processed Data, 2023.

Table 1 shows that the stationary testing of Broiler chicken meat price data obtained results are the *test critical value of 5%* of -2.870743, *t- Statistic* of -4.892436, prob. of 0.000 which means the value of *t-Statistic > test critical value of 5%* and prob. < α (0.05). Test results from Table 1. It can be concluded that the commodity price data of Broiler chicken meat has been stationary at the level level.

Based on the two test criteria above, it can be concluded very convincingly that the commodity price data for broiler chicken meat used in this study is stationary at the level. This finding has important implications for the next stage of analysis. Since the data is already stationary at the level, it can be directly used for subsequent econometric modelling, such as the ARMA model for mean equations and the GARCH model for variance equations, without requiring further transformation processes, like first differencing. This simplifies the modelling process and allows the interpretation of the data to remain in its original form, that is, the actual price rather than its changes. Therefore, these results provide a strong and reliable foundation for proceeding to the volatility analysis stage using the ARCH/GARCH model, as one of its main requirements has been met.

3.3 ARMA Model Estimation

ARMA modeling with ACF and PACF Correlogram is an ARMA model estimation that can be used to identify AR (p) and MA (q) values, diagnostic tests, estimate ARMA model parameters, and also identify the volatility value of Broiler chicken meat prices by knowing the ARCH *effect.*

1. Correlogram *Test*

   Corrobogram tests on Broiler chicken meat price data showed that *the Autocorrelation Function* (ACF) and *Partial Autocorrelation Function* (PACF) plots decayed rapidly, indicating data stationarity. On the other hand, the statistical significance of the Q-Stat value (Ljung-Box) confirms that the data is not random (*white noise*) and has a significant autocorrelation structure. These findings are the basis for determining the appropriate ARMA model order at the next stage of analysis.

2. ARMA Model Parameter Estimation

The best ARMA model obtained in the previous calculation can be seen by estimating the selection of the ARMA model. The use of *the Maximum Likehood method* to find the best ARMA model is seen by the magnitude of the R2 value, and the smaller value of the AIC (*Akaike Info Criterion*). The selection of ARMA's best models can be seen in Table 2.

Table 2. Estimated ARMA Model Parameters

Type	R2	AIC	SC	H-QC
ARMS (1 0)	0,007502	17.02892	17.06526	17.04345
ARMS (1 1)	0.018614	17.02424	17.07269	17.04361
ARMS (0 1)	0.010122	17.02630	17.06264	17.04083

Source : Processed Data, 2023.

The test results from Table 2 obtained the best model, namely the ARMA model (1 1). The choice of the ARMA model (1 1) is due to its larger R2 value and smaller AIC (*Akaike Info Criterion*) value than other ARMA models

3. Diagnostic Tests

Residual testing of previously obtained models is carried out with diagnostic tests. Models that have residual random or *white noise* are the best form of models seen from the ACF and PACF *Correlograms*. The value of a model is stated as random or white noise if the p-value is > α (0.05).

The best model obtained during the test was ARMA (1 1), the p-value obtained exceeded the value of α (0.05) which means it was insignificant, and the presence of ACF and PACF values that did not exceed the limit line. This is the main reason why the ARMA model (1 1) is the best model.

4. ARCH *Effect Test*

Testing whether there is a heterokedasticity in Broiler chicken meat price data needs to be carried out, namely by using the ARCH *effect* test. This is done using the ARCH LM test method for the best ARMA model obtained previously, namely ARMA (1 1). The criteria for the test are the f-Statistic probability value and the R2 probability value which can be significant if the value is < α (0.05). If the p-value has a value of > α (0.05), then it can be said that the price data of Broiler chicken meat is not significant because of *heterogeneity* or there is no element of volatility in it.

The f-Statistic *probability value* of the test is (0.0005) < α (0.05), and the probability value of R2 (0.038410) < α (0.05). The results of the test obtained that *the f-Statistic value* and the probability value of R2 from the ARMA model (1 1) had a value of less than the value of α (0.05), so it was stated that the data was significant. This statement proves that there is an element *of heteroscedasticity* or an element of volatility in it, so the data calculation will be continued to the ARCH/GARCH model. Based on the test results, it can be proven that the price of Broiler chicken meat will undergo drastic changes in price over a long period of time.

3.4 ARCH/GARCH Model Estimates

The estimation of the ARCH/GARCH model can be done by simulating several variance models using the best ARIMA model, namely ARIMA (1, 1). Significant probability values are obtained from estimating the best ARIMA model, which means that there is an element of volatility in it. The volatility test is carried out by testing the significance of the model parameters using ARCH in selecting the ARCH/GARCH model that will be used later. The smallest AIC and SC values of the ARCH model (1) and the GARCH model (1) can be used to select the ARCH or Garch model. The results of the analysis are presented in Table 3.

Table 3. ARCH/GARCH Model Parameter Estimation

Type	AIC	SC
GARCH (1.0)	16.81853	16.87923
GARCH (1,1)	16.78400	16.84470

Source : Processed Data, 2023.

Table 3 presents the results of a comparison between two candidate volatility models, namely GARCH(1.0) and GARCH(1.1), to find the *best-fit model* in explaining the volatility dynamics of Broiler chicken meat prices. Selecting the best model is a crucial step before further interpretation of the parameters.

The selection of the best-fitting model in this study is based on the use of two widely recognized information criteria in time series analysis: the Akaike Information Criterion (AIC) and the Schwarz Criterion (SC), also known as the Bayesian Information Criterion (BIC). Both criteria serve to evaluate the trade-off between model fit and complexity. The AIC assesses how well a model fits the data while penalizing the inclusion of additional parameters, aiming to avoid overfitting. Meanwhile, the SC applies a stricter penalty for model complexity, thus favoring more parsimonious models. Despite their differences in penalization, both criteria follow the same decision rule: the model with the lowest AIC and SC values is considered the most optimal and preferred for further analysis.

A comparison of the model selection criteria clearly shows that the GARCH(1,1) model performs better than the GARCH(1,0) or ARCH(1) model. The GARCH(1,1) produces lower values for both the Akaike Information Criterion (AIC = 16.78400) and the Schwarz Criterion (SC = 16.84470), while the GARCH(1,0) records higher scores with an AIC of 16.81853 and SC of 16.87923. Since lower values in both AIC and SC indicate a better balance between model fit and complexity, these results suggest that the GARCH(1,1) model is more suitable for capturing the volatility behavior of broiler chicken prices.Since both information criteria (AIC and SC) conclusively point to the same result, the GARCH(1,1) model was chosen as the best model for analyzing and modeling the price volatility of Broiler chicken meat in this study.

The selection of the GARCH(1,1) model carries important conceptual implications for understanding the dynamics of broiler chicken price volatility. First, it signifies the rejection of the simpler ARCH(1) model, or GARCH(1,0), which assumes that current volatility is influenced solely by past shocks (measured by the squared residuals of previous periods). This model is insufficient to capture the more complex behavior of price fluctuations observed in the data. In contrast, the acceptance of the GARCH(1,1) model highlights the need to consider both components of volatility: the ARCH effect (α), which reflects the impact of recent shocks, and the GARCH effect (β), which accounts for the persistence or "memory" of volatility from previous periods. Together, these elements provide a more comprehensive and realistic representation of the volatility structure in the broiler chicken market.

This indicates that the price volatility of Broiler chickens has a persistence or "memory" nature. This means that periods of high instability (high volatility) are likely to persist and be followed by other periods of instability. In contrast, quiet periods (low volatility) tend to be followed by quiet periods as well. This phenomenon is known as *volatility clustering*, which is well captured by the GARCH model(1,1).

3.5 Volatility Measurement

The best model to be used for the analysis of the volatility value of changes in the commodity price of Broiler chicken meat is the GARCH value (1.1) by taking into account the α and β values of the model. The data on changes in the value of volatility can be seen in the Table 4.

Table 4 presents the results of the final estimate of the GARCH model(1,1), which has previously been identified as the best model for analyzing the price volatility of Broiler chicken meat (DAR) commodities. These results provide in-depth quantitative insights into the characteristics and behavior of price volatility in the market.

Based on the coefficients obtained, the variance equation (volatility) for the price of Broiler chicken meat can be written as follows:

$$\sigma^2DARt = 332516.4 + 0.257679\varepsilon^2DARt\text{-}1 + 0.485069\sigma^2DARt\text{-}1$$

This equation mathematically summarizes the dynamics of the price volatility of Broiler chickens from day to day.

Table 4. Commodity Price Volatility of Broiler Chicken Meat

Variable	Coefficient α & β	Constant (C)	Equation	Volatility (α + β)
DAR	α = 0.257679 β = 0.485069	332516.4	σ2DARt = 332516.4 + 0.257679ε2DARt-1 + 0.485069σ2DAR t-1	0.742748

Information:

α = Resid Coefficient (-1)^2 (ARCH)

ε2DARt-1 = *Squared residual* price in period to t-1

Source : Processed Data, 2023.

Constant (ω = 332516.4): The value of this constant represents the long-term or average volatility level of the Broiler chicken price when there is no market shock. This is the base value or "floor" of price uncertainty. This large value is reasonable because it is a variance from the price data itself, not from the return data in percentages.

ARCH coefficient (α = 0.257679): The α coefficient (alpha) measures the reactivity or sensitivity of volatility to shocks or "news" from the previous period (represented by ε^2_{t-1}). A value of 0.257679 indicates that about 25.8% of the magnitude of yesterday's price shock will contribute to the increase in volatility today. This indicates that the Broiler chicken meat market is quite sensitive to new information or unexpected events (e.g., news of disease outbreaks, feed import policies, or sudden spikes in demand). The greater the value of the α, the more "volatile" or "spiky" the market's response to shocks will be.

GARCH coefficient (β = 0.485069): The β coefficient (beta) measures the degree of persistence or "memory" of the volatility itself. A value of 0.485069 means that about 48.5% of yesterday's volatility level will carry over or affect today's volatility level. The greater β value of this α is a very common and important finding. This confirms the existence of the phenomenon of volatility clustering, where periods of high volatility tend to be followed by other periods of high volatility, and periods of calm will be followed by periods of calm. This means that chicken price instability has "momentum" and does not just disappear.

Volatility Persistence Analysis (α + β) shows the Persistence level (α + β = 0.742748): The sum of the ARCH and GARCH coefficients (α + β) measures how long the effects of a shock will last in the market. A value of 0.742748 indicates a fairly high degree of persistence. Since the value is less than 1, this indicates that the GARCH model is stable and the effects of the shock will eventually subside (not explosive). Volatility will tend to return to its long-term average. However, this value close to 0.75 implies that the shock to the price of Broiler chickens will not disappear quickly. The effects will be felt over the next few periods before the market calms down completely.

The results of the GARCH(1,1) analysis provide several important implications for understanding and managing broiler chicken meat price volatility. First, the analysis confirms the presence of volatility clustering, indicating that the market does not behave randomly; instead, periods of instability tend to group together, aligning with visual patterns seen in the price charts particularly around events like Ramadhan, where price turbulence lasts for extended periods. Second, the market demonstrates a reactive but persistent volatility structure. Although it responds significantly to new information (α = 0.258), the stronger influence comes from past volatility levels (β = 0.485), suggesting that yesterday's instability plays a more critical role in shaping today's volatility than real-time news. This highlights the market's strong "memory" effect. Lastly, from a policy and stakeholder perspective, the high persistence rate (0.74) implies that short-term stabilisation efforts, such as one-day market operations, may be insufficient. Price shocks are likely to linger, highlighting the need for more structural, long-term interventions to control volatility. For breeders and traders, these findings underline the importance of adopting effective risk management strategies to mitigate the impact of sustained periods of market uncertainty.

CONCLUSION

Based on the results of the analysis and discussion of the price volatility of broiler chicken meat in Indonesia for the 2017–2023 period, several key conclusions can be drawn. First, the prices exhibit a high degree of volatility with a distinct and recurring seasonal pattern, particularly marked by significant spikes leading up to and during the Ramadan and Eid al-Fitr periods. This conclusion is visually supported by the price development chart, which consistently shows annual fluctuations. Second, methodologically, the price data is confirmed to be stationary at the level, allowing for valid econometric analysis. The detection of a statistically significant ARCH effect (p-value < 0.05) further indicates the presence of time-varying volatility, justifying the application of the GARCH model.

The GARCH (1,1) model was identified as the best fit for capturing the dynamic behaviour of price volatility in the broiler chicken market. The model results show that price changes are affected by both recent shocks and the lasting effects of past volatility, which confirms that volatility tends to group together. Moreover, the GARCH coefficient ($\beta = 0.485$) being greater than the ARCH coefficient ($\alpha = 0.258$) suggests that the "memory" of past volatility plays a more dominant role than recent market disturbances. With a combined persistence value of 0.743, it is evident that once a shock occurs, its impact on price volatility tends to linger over time.

Given these findings, the primary policy implication is the urgent need to transition from reactive to proactive and systematic risk management strategies. This includes implementing anticipatory buffer stock policies before critical periods like Ramadan and improving public communication to reduce uncertainty and speculation. However, such short-term actions must be complemented by long-term structural solutions, particularly targeting the upstream sector to stabilise feed and DOC prices. To coordinate these efforts effectively, it is recommended that the government adopt the GARCH model as an early warning system, enabling more timely, data driven, and strategic interventions instead of sporadic responses to price fluctuations.

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