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Article

Seasonal Price Volatility of Cayenne Pepper: A Case Study in East Java, Indonesia

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ABSTRACT

Cayenne pepper is one of the essential food commodities for Indonesian society that frequently experiences price fluctuations. Volatility in cayenne pepper prices can be influenced by seasonal changes, shifts in consumer preferences, and variations in cultivated area. This study aims to analyze seasonal price volatility of cayenne pepper in five major production regencies in East Java during January 2020 to December 2023. The five regencies examined in this study are Malang, Kediri, Blitar, Banyuwangi, and Probolinggo. This study serves as an attempt to map uncertainty in price between seasons, because studies on price volatility rarely break down the level of price volatility between dry and rainy seasons. Analysis employs the ARCH/GARCH model. The study found that Malang, Kediri, and Banyuwangi experience high volatility during the rainy season, with value of ARCH/GARCH Malang (1,150), Kediri (1,164), and Banyuwangi (1,062). Meanwhile, during the dry season the entire research area tends to show low volatility, with ARCH/GARCH values less than 1. These findings confirm that seasonal factors are an important determinant of cayenne pepper volatility and need to be considered in formulating price stabilization policies as well as risk mitigation strategies for producers and supply chain actors.

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INTRODUCTION

Food is one of the crucial elements for poor and developing countries. Impoverished households in these countries often spend up to 60-80% of their total income on food alone (compared to less than 10% in high-income countries) (Headey & Ruel, 2023). Consequently, increases in food prices disproportionately affect household welfare, and contribute to a country's inflation and deflation rates (Baladina et al., 2021). This condition occurs in regions where consumption patterns are dominated by food groups that heavily rely on supplies from other regions (Pradana, 2019). Dependence on external supply sources is one of the factors contributing to supply shocks in a given area. If a shock occurs in the supply and consumption of a commodity, it will be transmitted into price variations. Price variations resulting from such shocks are categorized into predictable and unpredictable variability (Gilbert & Morgan, 2010). Unpredictable variability in food commodity prices leads to price volatility (Ojogho & Egware, 2015).

Public awareness of the dynamics and price volatility of food commodities has been relatively low (Dahl et al., 2020). Volatility reflects the degree of price fluctuation and the temporal equilibrium condition of a commodity (Anindita, 2017). Food price fluctuations can lead to food insecurity and disrupt public access (Sujarwo et al., 2023). Moreover, this condition creates concerns for both producers and consumers (Nugrahapsari & Arsanti, 2019). In the long run, food price volatility affects producers' incomes and disrupts commodity trade activities. This condition hinders producers from planning production effectively due to unpredictable price movements (Sujarwo & Laili, 2023). Among Indonesia's strategic food commodities, cayenne pepper has become a volatile food and contributes significantly to inflation (Muflikh et al, 2021). The price volatility of cayenne pepper is very high than other chili commodities because it is very sensitive to supply disruptions and climate change (Lestari et al., 2022).

Agricultural commodities, including cayenne pepper, have seasonal production cycles, resulting in an unstable supply throughout the year. Production shocks occur due to variations in planting locations and production volumes influenced by natural factors. Meanwhile, consumption shocks are driven by changes in income, fluctuations in substitute commodity prices, and shifts in consumer preferences (Siami-Namini, 2019). Differences in production and consumption levels throughout the year lead to price fluctuations in this commodity (Rachmawati et al., 2020). East Java Province ranks as the top producer of cayenne pepper in Indonesia, contributing an average of 30.38% to national demand (Kementan, 2020). There are five cayenne pepper production centers in East Java Province: Malang, Kediri, Blitar, Banyuwangi, and Probolinggo (BPS, 2022). The contribution of each cayenne pepper-producing region is presented in Figure 1.

Price fluctuations in cayenne pepper play a crucial role in determining its price volatility. The market cannot automatically respond to stabilize price shocks (Huchet-bourdon, 2011). Therefore, this study aims to analyze seasonal price volatility of cayenne pepper in major production centers of East Jawa. The five major production centers are Malang, Kediri, Blitar, Banyuwangi, and Probolinggo regencies. Understanding price volatility in major production centers is praticularly important because these regions constitute primary sources of supply and are highly vulnerable to climate change and production shocks. Previous studies show that climate variability, including excessive rainfall and extreme temperatures, can disrupt agricultural production and increase commodity price volatility by generating supply uncertainty (Steen & Bergland, 2023). As a strategic commodity with high perishability and seasonal production, cayenne pepper is especially susceptible to such weather-induced market fluctuations. Price stability provides price certainty for both consumers and producers while minimizing volatility of strategic commodities, which ultimately affects consumer and producer welfare (Sujarwo & Laili, 2023).

Several studies have extensively examined cayenne pepper price volatility in consumption center and at broader regional scales. For example, hig price volatility has been reported in major Indonesian cities such as Jakarta, Bandung, Semarang, Yogyakarta, and Surabaya, where the distance form production areas increases marketing cost and amplifies price fluctuations (Rachmawati et al., 2020). Other studies Jawal Anwarudin et al. (2013) and Mardiyati & Natsir (2024) have analyzed price volatility at pronvicial and national levels using fluctuations coefficients and descriptive indicators. However empirical evidence on price volatility in cayenne pepper production centers remains limited, especially regarding the level of price volatility between dry and rainy seasons. Existing studies generally focus on agrregate market behaviour and do not explicitly compare volatility patterns between dry and rainy seassons in major production center.

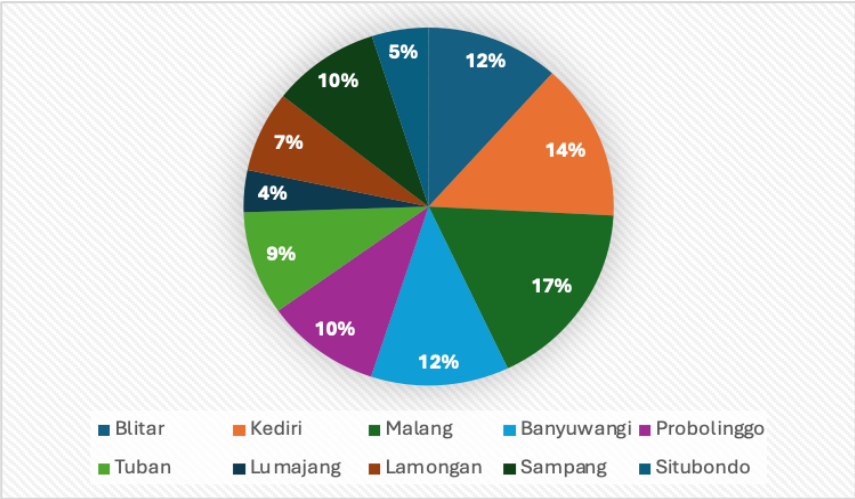


Figure 1
Contribution of Cayenne Pepper Producing Regions in East Java Province
Source: BPS, 2022

This studies is important because production centers are origin of supply shocks, and climate induced disruptions may propagate through marketing chanels and significantly affect consumer price (Aurélien & Emmanuel, 2024). Futhermore, climate change is expected increase the frequency of weather extremes, there by intensifying agriculture price volatility in production center area (Mustafa et al., 2024; Nguyen & Randall, 2024). Therefore, this research contributes to a better understanding of the dynamics and price volatility of cayenne pepper, which is essential for adressing market uncertainties. Market uncertainty in cayenne pepper sector can lead inefficiencies in providing price and quantity information across markets (Hartono et al., 2023). Efficienct market information tranmission is essential for making optimal commodity allocation decisions (Serrano-Arcos et al., 2021).

RESEARCH METHOD

Research Data

This study uses daily time-series data on cayenne pepper prices from January 2020 to December 2023. It uses daily data because red cayenne pepper is a perishable horticultural commodity with relatively high price change in the short term. Daily variations in cayenne pepper prices provide a more accurate snapshot of volatility. Cayenne pepper price used at the consumer level to reflect the cumulative impact of production changes, supply disruptions, cost of distribution, and demand conditions in each regency. Seasonal classification was based on the seasonal calendar issued by the Indonesian Agency for Meteorology, Climatology, and Geophysics (BKMG). The rainy season generally occurs from November to April and the dry season from May to October.

Data were obtained from the official website of East Java Food Availability and Price Monitoring Information System (SISKAPERBAPO). The data was processed using Microsoft Excel, including data cleaning, consistency checks, and data entry in a daily time series form. Furthermore, the data were analyzed in the Eviews software, which consists of data stationarity testing, ARIMA model, heteroscedasticity testing, ARCH-effect, and ARCH-GARCH model.

Data Analysis Method

This study employs the Autoregressive Conditional Heteroscedasticity (ARCH) model and the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model for analysis. Overall, several steps are involved in analyzing volatility using the ARCH-GARCH method.

Stationarity Test

According to Brooks (2007), stationarity is a crucial aspect of research involving time-series data. The stationarity test is conducted to ensure that time-series data are not influenced by time-related trends. In this study, a stationarity test is performed using a unit root test. The Augmented Dickey-Fuller (ADF) test is employed to examine stationarity. The formulation used is as follows:

$$\Delta P_t = \alpha_o + \gamma P_{t-1} + \beta_i \sum^{m} \Delta P_{t-1} + \varepsilon_i \quad (1)$$

Where is ΔP_t denotes change in price at time period t (first difference, equal to $P_t - P_{t-1}$), Y_t denotesprice of red cayenne pepper at period t (Rp/Kg), P_{t-1} denotes price of red cayenne pepper in previous period (Rp/Kg), α_0 is constant or intercept term, βi is coefficient, ΔP_{t-1} is lagged firs differences of price, and ε_t is error term.

The decision rule based on this equation is to compare the ADF t-statistic. When the absolute value of the ADF t-statistic is less than the critical value, the null hypothesis cannot be rejected. This indicates that the series contains a unit root and is non-stationary. Meanwhile, if the absolute value of the ADF t-statistic exceeds the critical value, the null hypothesis is rejected, indicating that the series does not contain a unit root and is stationary (Osuagwu, 2020). First, the stationarity test is conducted at the level stage. If the data are already stationary, further testing can proceed. However, if the data are not stationary at the level stage, a different non-stationary process must be performed by conducting a stationary test on first-differenced and second-differenced data.

ARIMA Model

After conducting the stationarity test, if the red cayenne pepper price data are found to be stationary, the analysis proceeds to estimation using the Autoregressive Integrated Moving Average (ARIMA) method. The estimation is performed through a trial-and-error approach. The Box-Jenkins approach builds an ARIMA model, which has fundamental importance in the area of time series analysis (Shumway & Stoffer, 2017).
The general model of ARIMA is as follows:

$$Y_t = \mu + \Sigma pi = 0^{\varphi} Y_{t-1} + \Sigma qj = \theta j \varepsilon t-j + \varepsilon_t \quad (2)$$

Where μ is the mean, q is lagged of error terms, p is lagged of dependent variables, φ is coefficient for AR and θ for MA, ε is random residual with constant variance (white noise), and t-j is lag for a certain period. Optimal ARIMA model was selected based on minimum values of Akaike Information Criterion(AIC) and Schwarz Criterion (SC). Furthermore, estimated model was evaluated by examining statistical significance of AR and MA parameters and by conducting residual diagnostic test. A model is considered adequate when its residuals exhibit white-noise characteristics, indicating that no significant autocorrelation remains in the residual series (Shumway & Stoffer, 2017).

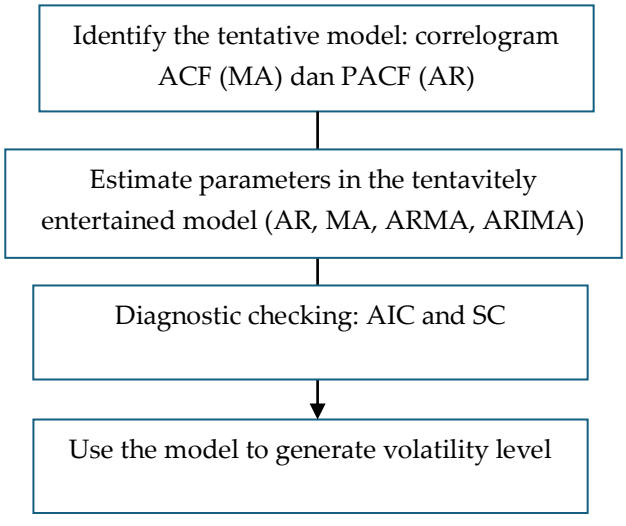


Figure 2
Diagram Processed Determinant ARIMA Model
Source: Shumway & Stoffer, 2017

Heteroscedasticity Tes and ARCH-Effect

A heteroscedasticity test is conducted to determine whether the residuals of the selected mean model exhibit constant variance. According to Engle (1982), when the variance of residuals changes over time (heteroscedasticity), the Autoregressive Conditional Heteroskedasticity (ARCH) model can be employed to capture the volatility pattern. ARCH effect test is performed on residuals obtained from the best model of ARIMA. The use of ARIMA as the mean equation is consistent with the Box-Jenkins method, where the appropriate ARIMA model is first identified based on stationary and diagnostic tests before volatility modelling is conducted (Box et al., 2016). The mean equation ARCH-LM test is specified as:

$$\epsilon_t^2=\alpha_0+\Sigma^p{}_{i=1}+\alpha_i\epsilon^2{}_{t-i}+\nu_t \quad (3)$$

Where ϵ_t^2 is residuals squared at period, representing current volatility or variance, α_0 is intercept, ϵ_{t-i}^2 is residuals squared at past (lags-i), α_i is coefficient of residuals squared, p is number of lags, and v_t is error term. The decision is based on the probability values of the LM statistic. If the p-value of ARCH-LM test is < 0,05, then reject the null hypothesis. This means that the price of red cayenne pepper has an ARCH effect, and ARIMA models can be continued to the ARCH/GARCH analysis (Sujarwo et al., 2023).

ARCH/GARCH Model

The ARCH/GARCH model has been widely used to describe the volatility behavior of a time series. Volatility (fluctuations) in the ARCH/GARCH model is reflected in the variance of residuals, which do not satisfy the assumption of homoscedasticity or constant variance over time (Wang et al., 2025). The equation for ARCH/GARCH is:

$$\sigma^2P_t=\alpha_0+\alpha_1\varepsilon^2P_{t-1}+\beta\sigma^2P_{t-1}+\varepsilon_t \quad (4)$$

Where σ^2 is the residual variance at time t, α_0 is an intercept, ε_{t-1}^2 is the volatility of the previous period or ARCH term, $\alpha_1\beta_1$ are the estimated parameters, σ_{t-1}^2 is the residual variance of previous period or the GARCH term, ε_t is a stochastic factor, and P is the price of red cayenne pepper. The sum of the estimated coefficients $\alpha_1 + \beta_1$ in each model indicates the level of volatility. Thus, volatility can be determined by examining the value of $\alpha_1+ \beta_1$. In this case, α represents the ARCH term, while β represents the GARCH term. If $\alpha_1 + \beta_1 < 1$, it indicates low volatility, which indicates a stationary volatility process; if $\alpha_1 + \beta_1 =$ it signifies high volatility that indicates persistent volatility; and if $\alpha_1 + \beta_1 > 1$, it suggests extremely high volatility that indicates explosive/non-stationary volatility (Bakari, 2023).

The ARCH model is used when the average residual model indicates a conditional heteroscedasticity characteristic by the ARCH effect. Meanwhile, if volatility shows high persistence, requiring many ARCH lags to describe the dynamics of variance, the GARCH model is more recommended to include the previous variance component in the conditional variance equation. ARCH/GARCH model selection is based on the Akaike Information Criterion (AIC) to measure the difference between the true model and estimated model with high probability (Matsuda, 2021). Following model estimation, several diagnostic tests were conducted to evaluate the ARCH/GARCH using the ARCH-LM. The ARCH-LM test was conducted on the standard residuals to confirm that no residual ARCH effect remained. If the probability value is greater than 0,05, then GARCH models succesfully captures the conditional variance dynamics and provide reliable volatility estimates (Priyambodoi & Dyanasari, 2022).

RESULT AND DISCUSSION

Price Changes of Cayenne Pepper in East Java

The movement of consumer prices for cayenne pepper from January 2020 to December 2023 exhibited monthly fluctuations. Distruptions in supply and demand caused changes in cayenne pepper prices. In certain periods, cayenne pepper production was unable to meet relatively constant daily consumption needs of consumers, with demand only increasing during specific seasons or periods. An increasing demand trend during major religious events and the wedding season (Wasita & Hidayat, 2025). At the same time, production really depends on weather and seasonal factors. As a result, any reduction in supply relative to

demand causes higher prices of cayenne pepper, while an oversupply results in lower prices (Ambali & Barchenger, 2025).

The most significant changes in the consumer price of cayenne pepper often occur during the rainy season, from December to March each year. Excessive rainfall may reduce cayenne pepper productivity through an increase in pests and diseases, lower harvest quality, and disruptions in harvesting and distribution activities (Mardiyati & Natsir, 2024; Mir et al., 2020). Weather-related production shocks have been identified as one of the main drivers of cayenne pepper price volatility in Indonesia (Viana et al., 2017; Lestari et al., 2022).

From January 2020 to December, the price of cayenne pepper showed an upward trend (Figure 2). The most substantial price increases generally occurred during the rainy season (November-March), particularly between December and February when rainfall intensity in East Java reaches its peak. Beside wether-related supply disruptions price increase also frequently occured during major religious events especially Ramadhan, Eid al-Fitr, Eid al-Adha, Christmas, and New Years. The average annual price increase in the five main production regencies of East Java was 10.94%, from Rp 33.000,- to Rp 37.000,-. A significant price surge occurred in 2021, reaching 20.76%, from Rp 37.000,- to Rp 45.000,-. The spread of the COVID-19 pandemic across Indonesia was one of the factors contributing to the sharp in cayenne pepper prices in 2021 (Hartono et al., 2023). Restrictions on mobility and economics activities disruptions distribution of agriculture product and supply chain, which can quickly lead to supply shortages and price increases. Besides that, above-normal rainfall due to La Niña in 2020-2021 affected the production of cayenne pepper, which impacted the supply of this commodity. A combination of production constraints and distribution disruptions contributed to the significant increases in price.

Efforts to mitigate price surges of cayenne pepper include ensuring a stable supply in the market by cultivating the crop throughout the seasons, including during the rainy season (Kementan, 2023). High annual variation in price changes can disrupt farmers' production planning, increase income uncertainty, and reduce consumers' access to affordable food. Furthermore, unstable prices complicate the implementation of price stabilization policies and can contribute to broader food inflation. It is necessary to develop effective supply management strategies and market interventions to maintain the availability and affordability of cayenne pepper as a strategic commodity throughout the year (Nugrahapsari & Arsanti, 2019).

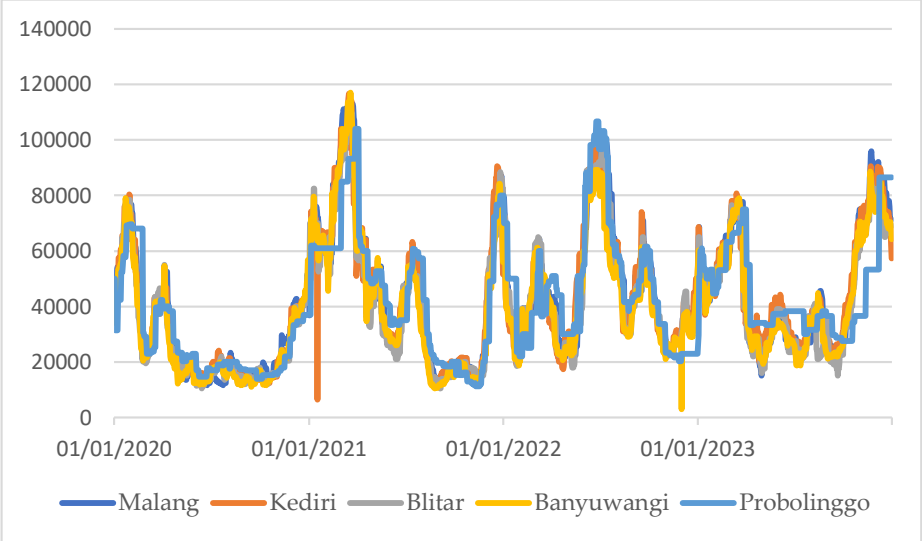


Figure 3
Price Changes of Cayenne Pepper in East Java Production Centers
Source: BPS, 2022

Table 1
Stationarity Test of Consumer-Level Red Cayenne Pepper Price Data

Regencies	T statistic	Critical Value	Probability	Notes
Malang	-3,689965	-3,412902	0,0232	Level
Kediri	-41,48318	-3,412893	0,0000	First difference
Blitar	-4,253065	-3,412906	0,0038	Level
Banyuwangi	-4.028584	-3,412904	0,0081	Level
Probolinggo	-38,05345	-3,412893	0,0000	First difference

Source: Processed Secondary Data, 2024

Table 2
The Best ARIMA Model of Cayenne Pepper at Consumer Level

Regencies	Model	AIC	SC	Significant Parameters
Malang	ARMA (1,1)	18,59466	18,60913	Significant
Kediri	ARIMA (1,1,4)	19,37180	19,38628	Significant
Blitar	ARMA (1,0)	18,92462	18,93547	Significant
Banyuwangi	ARMA (1,1)	18,66704	18,68151	Significant
Probolinggo	ARMA (1,1,1)	19,14352	19,15800	Significant

Source: Processed Secondary Data, 2024

Analysis of Cayenne Pepper Price Volatility

Stationarity Test

The consumer-level cayenne pepper price data, which be used to estimate volatility, must first undergo a stationarity test. Stationarity testing can be conducted using unit root test. One of the common methods for unit root tesing is the Augmented Dickey-Fuller (ADF). The data is considered stationarity if $t_{statistik} <$ test critical value or if the probability is below 5%.

The ADF test results of cayenne pepper in Malang, Blitar, and Banyuwangi were stationary at level, as their ADF t-statistics were greater than the critical value, and the probability values were below 0.05. Meanwhile, the price of cayenne pepper in Kediri and Probolinggo became stationary at the first difference level, with a t-statistic value of Kediri -41,48318 < critical value -3,412893, and a t-statistic value of Probolinggo -38,05345 < critical value -3,412893. The result indicates rejection of the null hypothesis of a unit root and confirm stationary of the difference. Stationarity at first differencing in Kediri suggests that the original price series exhibited non-stationary behaviour due to the presence of a unit root. Non-stationary data at the level indicates significant changes in the data, characterized by fluctuations around its mean and variance (Landjo & Presno, 2021). Therefore, the appropriate time series models for this data are the Autoregressive Conditional Heteroskedasticity (ARCH) model and its extended version, the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model.

Autoregressive Integrated Moving Average (ARIMA) Model

After determining the stationarity of the data for the consumer price of cayenne pepper in the five main production regencies, the selection of the most appropriate ARIMA model is conducted based on tentative models. The best model is chosen by considering statistical significance, the highest coefficient of the Akaike Information Criterion (AIC), and the lowest values of the Schwartz Criterion (SC) (Bambang, 2012). According to the AIC and SC criteria, the optimal model is the one with the smallest residual variance. In selecting the best time series model, it is essential to consider both information criteria and forecasting accuracy (Vogelvang, 2005).

The selection of the ARIMA model using AIC and SC criteria is also recommended by (Brooks, 2007). AIC and SC criteria are recommended for choosing the best ARIMA model because they balance model goodness-of-fit and parsimony to reduce the risk of overfitting (Hyndman & Athanasopoulos, 2018). In this study, the selection of the best ARIMA model for each regency was determined by identifying significant values and eliminating non-significant values. After selecting the significant values, the best model was chosen based on the R-square, AIC, and SC values. The best model for each regency is presented in Table 2.

The best model for Malang Regency is ARMA (1,1), for Kediri is ARIMA (1,1,4), for Blitar is ARMA (1,0), for Banyuwangi is ARMA (1,1), and for Probolinggo is ARIMA (1,1,1). These ARMA and ARIMA models were selected because they have the lowest AIC and SC values compared to other tentative models. The selected best model must also meet the stationarity and invertibility requirements (Diebold, 2007). The chosen best model will then be used for heteroskedasticity analysis and the ARCH-Effect test.

Heteroscedasticity Test and ARCH-Effect

In time series data, it is necessary to conduct heteroskedasticity and ARCH Effect tests to determine whether the price data of cayenne pepper in production center areas exhibit varying or non-constant variance. The data are considered heteroskedastic and to have an ARCH Effect if the probability value is < 0.05. The models used for the heteroskedasticity test are the best ARMA and ARIMA models. The results of the heteroskedasticity and ARCH Effect tests are presented in Table 3.

The results of conditional heteroskedasticity in the residuals was examined using the ARCH-LM test proposed by (Engle, 1982). The null hypothesis states that no ARCH effect exists in the residual series, while the alternative hypothesis indicates the presence of ARCH effects. The probability value of the F-statistic is lower than the 5% significance level, with a value of 0.00 across all regions. Similarly, the results of the ARCH Effect test show the same pattern, with probability values ranging from 0.00 to 0.04, which are also below the 5% significance level. Therefore, the variance in consumer prices of cayenne pepper in each region is not constant (heteroskedastic). Consequently, the analysis proceeds to the next stage, which is the ARCH/GARCH modeling.

Table 3
Heteroscedasticity Test and ARCH Effect of Cayenne Pepper Prices at Consumer Level

Regencies	Statistics Test	Prob
Malang	ARCH-LM	0,0310
Kediri	ARCH-LM	0,0027
Blitar	ARCH-LM	0,0043
Banyuwangi	ARCH-LM	0,0186
Probolinggo	ARCH-LM	0,0475

Source: Processed Secondary Data, 2024

Table 4
Volatility Test of Cayenne Pepper

Regencies	α and β values	Prob	Volatility ($\alpha + \beta$)	ARCH-LM	Volatility level
Malang	α:0,092685	0,000	1,01926	0,7260	Extremely High Volatility
	β:0,926575	0,000			
Kediri	α: 0,115840	0,000	1,014551	0,9333	Extremely High Volatility
	β:0,898711	0,000			
Blitar	α:0,085228	0,000	1,008736	0,5029	Extremely High Volatility
	β:0,923508	0,000			
Banyuwangi	α:0,214375	0,000	0,983606	0,3246	Low Volatility
	β:0,769231	0,000			
Probolinggo	α:-0,008461	0,000	0,5706678	0,5050	Low Volatility
	β:0,579139	0,000			

Source: Processed Secondary Data, 2024

Table 5
Stationarity Test of Cayenne Pepper Prices in the Dry and Rainy Seasons

Regencies	T statistic	Critical Value	Probability	Notes
Malang	-13,27581*	-3,431163	0,0000	First difference
	-11,09054**	-3,431368	0,0000	First difference
Kediri	-13,65997*	-3,431265	0,0000	First difference
	-12,11468**	-3,431471	0,0000	First difference
Blitar	-18,53977*	-3,421212	0,0000	First difference
	-13,25665**	-3,428581	0,0000	First difference
Banyuwangi	-13,37717*	-3,431163	0,0000	First difference
	-15,97986**	-3,431368	0,0000	First difference
Probolinggo	-13,37717*	-3,431163	0,0000	First difference
	-13,77052**	-3,431368	0,0000	First difference

Source: Processed Secondary Data, 2024
Notes: * Dry Season
** Rainy Season

ARCH/GARCH Model

The results of the heteroskedasticity and ARCH Effect tests on the daily price data of cayenne pepper in production center areas indicate price volatility in this commodity. Subsequently, price volatility analysis is conducted using the ARCH/GARCH model. This test aims to assess the magnitude of price shocks occurring in each production center region of East Java Province. The measurement of price volatility is based on the values of α and β obtained from the ARCH/GARCH model estimation. The following are the results of the price volatility analysis at the consumer level.

The price volatility of cayenne pepper is assessed using the ARCH-GARCH approach by summing the coefficients of ARCH (α) and GARCH (β). In this study, the best ARCH/GARCH model for the price of red cayenne pepper in Malang, Kediri, Blitar, Banyuwangi, and Probolinggo was GARCH (1,1). The volatility of red cayenne pepper prices in Banyuwangi and Probolinggo was also low, as indicated by the sums of the ARCH and GARCH coefficients of 0,983606 and 0,5706678. This shows that price volatility was not influenced by the previous price variance or residual variance at the 95% significance level. GARCH models show price volatility that depends on the previous residual and previous volatility (Berger et al., 2019). It means that the current price increase was not influenced by the variation in the price at the last time. The last study shows that areas with relatively consistent harvest patterns, planting schedules, and efficient distribution networks tend to experience lower volatility of cayenne pepper because supply disruptions can be mitigated (Hartono et al., 2023)

Meanwhile, the volatility of cayenne pepper prices in Malang, Kediri, and Blitar was classified as extremely high volatility. This indicated by the sum of the ARCH and GARCH coefficients of 1,01926, 1,014511, and 1,008736, the value > 1. This shows that price volatility is influenced by the previous price variance and the previous residual variance within the 95% significance level. This condition illustrates that traders of cayenne pepper in this regencies experience the risk of loss because price shock higher than in other markets. Price volatility in this classification arises over a more extended period, and that is called permanent volatility (Ligot et al., 2024). Access to market information plays an important role in reducing the potential for marketing failures, minimizing price fluctuations, and minimizing losses for traders and producers (Mariyono et al., 2018).

The diagnostic check after GARCH was conducted using the ARCH-LM test on the standardized residuals. The result on ARCH-LM test show that probability value > 0,05 for Malang (0,7260), Kediri (0,9333), Blitar (0,5029), Banyuwangi (0,3246), this show that no ARCH effects after GARCH estimation models. These findings confirm that the GARCH (1,1) specification successfullly captures the conditional heteroscedasticity in the price series and provides reliable volatility estimates (Bukenya, 2017).

Analysis of Cayenne Pepper Volatility in Dry and Rainy Seasons

Stationarity Test

The stationarity test for red cayenne pepper prices in each production center regency is categorized based on the dry and rainy seasons. Seasonal classification was based on the seasonal calendar issued by the Indonesian Agency for Meteorology, Climatology, and Geophysics (BMKG). The rainy season generally occurs from November to April and the dry season from May to October. Stationarity testing is conducted using a unit root test, with one of the commonly used methods being the Augmented Dickey-Fuller Test (ADF). The data is considered stationary if the t-statistic value is less than the test critical value or if the probability (p-value) is less than 5%.

The stationarity test for consumer-level red cayenne pepper prices, conducted for both the dry and rainy seasons across the five main production regencies, indicates that the data is non-stationary at the level. Therefore, an additional test was performed at the first difference level. The results of this test confirm that cayenne pepper prices in each season and regency have become stationary at the first difference level. ADF t-statistics in all regencies are lower than the critical value, and the probability value < 0,05 significance level.

ARIMA Models

The Box-Jenkins model was determined after the stationary test on red cayenne pepper prices in all regencies was carried out. Some Box-Jenkins models are Auto Regressive (AR), Moving Average (MA), Auto Regressive Moving Average (ARMA), and Auto Regressive Integrated Moving Average (ARIMA) (Setiawati et al, 2021). In this study, the data are stationary at first difference, then the estimation model uses ARIMA. The next step involves ARIMA modeling by selecting the best model based on tentative models. The best model is chosen by considering significance values of the AIC and SC criteria. The selection of the best model is based on the probability values of each tentative model. If the F-statistic probability value is lower than the 5% significance level, the model is considered a good and appropriate estimator. Conversely, if the F-statistic probability value exceeds the 5% significance level, the model cannot be accepted as a good estimator and is deemed unsuitable for use.

In determining the best ARIMA model for the five production center regencies, the first step is to select significant probability values and eliminate insignificant probability values. After obtaining models with significant probability values, the next step is to identify models with AIC and SC values. The best ARIMA models for the dry season in each regency are Malang (3,1,0); Kediri (2,1,6); Blitar (0,1,4); Banyuwangi (17,1,0); and Probolinggo (0,1,8). Meanwhile, the best ARIMA models for the rainy season in each regency are Malang (5,1,5); Kediri (6,1,4); Blitar (4,1,1); Banyuwangi (4,1,1); dan Probolinggo (2,1,7).

Table 6
Best ARIMA Model of Cayenne Pepper Prices in Dry and Rainy Seasons

Kabupaten	Model	AIC	SC	Prob
Malang	ARIMA (3,1,0)*	18,06497	18,11231	Signifikan
	ARIMA (5,1,5)**	18,58826	18,65181	Signifikan
Kediri	ARIMA (2,1,6)*	18,41837	18,48149	Signifikan
	ARIMA (6,1,4)**	19,29542	19,35896	Signifikan
Blitar	ARIMA (0,1,4)*	18,89658	18,92659	Signifikan
	ARIMA (4,1,1)**	19,05799	19,11566	Signifikan
Banyuwangi	ARIMA (17,1,0)*	18,01451	18,06149	Signifikan
	ARIMA (4,1,1)**	19,29654	19,36088	Signifikan
Probolinggo	ARIMA (0,1,8)*	19,01730	19,04373	Signifikan
	ARIMA (2,1,7)**	18,92626	18,98980	Signifikan

Source: Processed Secondary Data, 2024

Notes: * Dry Season

** Rainy Season

Table 7
Heteroscedasticity Test and ARCH Effect of Cayenne Pepper Prices in the Dry and Rainy Seasons

Regencies	Season	ARCH -LM Test
Malang	Dry Season	0,0461
	Rainy Season	0,0032
Kediri	Dry Season	0,0247
	Rainy Season	0,0064
Blitar	Dry Season	0,0042
	Rainy Season	0,0092
Banyuwangi	Dry Season	0,0367
	Rainy Season	0,0062
Probolinggo	Dry Season	0,0071
	Rainy Season	0,0138

Source: Processed Secondary Data, 2024

Heteroscedasticity Test and ARCH-Effect

The next step after obtaining the best ARIMA model for each regency, both for the dry and rainy seasons, is to conduct the ARCH-LM test. Data are considered heteroskedastic; variance was non-constant, and has an ARCH effect if its probability value is less than 5%. If the data of red cayenne pepper price is heteroscedastic, it can produce weak models with a larger variation of measurement error (Bissoondoyal-Bheenick et al., 2020). Furthermore, identifying ARCH effects is crucial for volatility models, as it confirms the existence of time-varying conditional variance that can be a good model estimation for ARCH/GARCH (Engle, 1982).

Based on the ARCH-LM test results in Table 7, the F-statistic probability values for each regency in both seasons were below the 5% significance level. It can be concluded that the price of red cayenne pepper exhibits heteroskedasticity, meaning it has a varying (non-constant) variance. This indicates that cayenne pepper prices during both the dry and rainy seasons exhibit an ARCH-Effect, meaning the prices fluctuate. For data exhibiting an ARCH-Effect, it is necessary to conduct an ARCH-GARCH test to determine the level of price volatility. Furthermore, the analysis enters the next stage, namely ARCH/GARCH modeling.

ARCH-GARCH Model

The red cayenne pepper price data in the five regencies exhibit an ARCH effect, necessitating an analysis of price volatility using the ARCH-GARCH model. The measurement of price volatility is based on the coefficients α and β derived from the ARCH/GARCH model estimation. This analysis aims to assess price fluctuations across the five regencies and compare volatility levels between the dry and rainy seasons. The following presents the results of the volatility analysis for consumer-level cayenne pepper prices.

Price volatility of cayenne pepper based on the ARCH-GARCH approach is determined by summing the ARCH (α) and GARCH (β) coefficients. The daily price of cayenne pepper in three regencies exhibits extremely high volatility during the rainy season namely Malang (1,150762), Kediri (1,164178), and Banyuwangi (1,062532). The volatility in these three regencies falls into the category of extremely high volatility since the sum of the α and β coefficients exceeds 1. This indicates a high level of risk and price variation in each production center. Meanwhile, the other two regencies show volatility values of Blitar (0,797125) and Probolinggo (0,883293), which fall into the low volatility category. During the dry season, the volatility values for the five key production regencies are as follows: Malang (0,932034), Kediri (0,583363), Blitar (0,397248), Banyuwangi (0,85689), and Probolinggo (0,576799). These values fall into the low volatility category since the sum of the α and β coefficients is less than 1.

Table 8
Cayenne pepper price volatility test in dry and rainy seasons

Regencies	α and β coefficients	Probability	Volatility ($\alpha + \beta$)	ARCH-LM	Volatility Level
Malang	α 0,240103	0,0031	0,932034*	0,4721	Low Volatility
	β 0,692317	0,0001			
	α 0,605193	0,0072	1,150762**	0,8352	Extremly High Volatility
	β 0,545569	0,0361			
Kediri	α 0,168654	0,0121	0,583363*	0,5016	Low Volatility
	β 0,414709	0,0043			
	α 0,372048	0,0135	1,164178**	0,7905	Extremly High Volatility
	β 0,792130	0,0026			
Blitar	α 0,178995	0,0043	0,397248*	0,5938	Low Volatility
	β 0,218253	0,0055			
	α 0,773542	0,0427	0,7971251**	0,3641	Low Volatility
	β 0,023655	0,0036			
Banyuwangi	α 0,652721	0,0000	0,856589*	0,4937	Low Volatility
	β 0,230868	0,0197			
	α 0,189627	0,0352	1,062532**	0,6295	Extremly High Volatility
	β 0,872905	0,0259			
Probolinggo	α 0,536217	0,0371	0,576799*	0,4058	Low Volatility
	β 0,040582	0,0567			
	α 0,196752	0,0000	0,883293**	0,3026	Low Volatility
	β 0,686541	0,0001			

Source: Processed Secondary Data, 2024
Notes : * Dry season
** Rainy season

Price fluctuations of cayenne pepper are not solely caused by supply shocks but are also influenced by the inherent characteristics of the commodity. Cayenne pepper is a perishable agricultural product with a limited shelf life. At room temperature, its shelf life typically ranges between 2 and 3 days (Bilang & Laga, 2017). As the freshness of the red cayenne pepper declines, its market price tends to decrease accordingly. Additionally, red cayenne pepper has a seasonal production cycle, whereas consumer demand remains consistent throughout the year. During its cultivation, the cayenne pepper plant is highly dependent on the agroclimatic conditions specific to each production area (Ridho & Nur, 2020). There are two main planting seasons for cayenne pepper: the major planting season occurs from December to January with harvesting in April–May, while the minor planting season takes place in July–August with harvesting in November–December. The planting cycle contributes to the tendency for chili prices to increase toward the end of the year and decline around mid-year, including cayenne pepper (Padapi et al., 2022). The planting cycle of cayenne pepper becomes one of the important things in the development of horticultural crop cultivation. It needs attention from the stakeholders involved, because it is hoped that this vegetable can meet the demand of the local community and reduce imported agricultural products (Harinta et al., 2018)

At the end of the year, during the transition to the rainy season, the price of cayenne pepper begins to fluctuate due to production shocks. One of the main causes of production shocks during the rainy season is the reduction in cultivated area. Farmers tend to switch to rice cultivation because water availability increases during the rainy season (Farid et al., 2012). This condition contributes to price fluctuations of the commodity (Jawal Anwarudin et al., 2013). A high degree of price fluctuation tends to lead to extremely high price volatility. During the rainy season, the price volatility of red cayenne pepper is particularly high in several key production regencies, namely Malang, Kediri, and Banyuwangi. In contrast, during the dry season, the price volatility cayenne pepper remains low across all key production regencies.

CONCLUSION

The price volatility test for cayenne pepper indicates that the average daily price volatility in each key production regency is considerably high. When assessed by season, the results show that the average price volatility during the dry season is low across all key production regencies. In contrast, during the rainy season, several regencies experience extremely high levels of price volatility. Specifically, such high volatility during the rainy season in Malang, Kediri, and Banyuwangi Regencies. This indicates that seasonal factors can affect the volatility of cayenne pepper price. High volatility indicates a high level of variability in cayenne pepper. A high level of price fluctuation variability reflects market instability and implies greater difficulty and risk in forecasting prices. The significant price fluctuations are attributed to the perishable nature of red cayenne pepper, its seasonal production dependency, and the long distribution channels involved in its marketing. Limited production during November and December contributes to price fluctuations toward the end of the year. The seasonal nature of production presents a major challenge in maintaining cayenne pepper price stability, making production shocks a key driver of price fluctuations. On the other hand, demand-side shocks are usually triggered by social events and major religious holidays. In light of these conditions, several policy measures should be implemented. First, adjusting the planting schedules coordinated among production centers can prevent simultaneous harvest and daily shortages. In addition, price stabilization policies, including government market operations and strengthening buffer stock mechanism, are needed to reduce extreme price fluctuations. Lastly, improving supply chain management through better logistics infrastructure and distribution efficiency is very important, so that the supply of cayenne peppers is more stable throughout the year and seasonal price volatility is reduced.

AI DISCLOSURE STATEMENT

During the preparation of this manuscript, the authors used Grammarly to assist with grammar checking, language editing, translation, and improving academic English writing. All outputs generated by these tools were carefully reviewed, verified, and revised by the authors to ensure the accuracy, clarity, and appropriateness of the content. The authors take full responsibility for the integrity, originality, and final content of this manuscript.

DATA AVAILABILITY

The datasets generated and/or analyzed during the current study are available from the corresponding author upon reasonable request.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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