MODELING REGIONAL COMMODITY PRICE VOLATILITY IN EAST JAVA

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Abstract

Commodity markets in major production regions are characterized by price volatility arising from perishability, seasonal production, and distribution constraints. While agricultural price volatility has been widely examined at the national level, evidence on regional differences across commodity groups remains limited. This study investigates the volatility dynamics of food and horticultural commodity prices across eight regions in East Java using daily price data from 2018 to 2024. Price series are transformed into logarithmic returns, and volatility is estimated using symmetric and asymmetric GARCH family models. The results reveal significant differences across both commodity groups and regions. Food commodities are consistently best represented by symmetric GARCH models, indicating that volatility is primarily driven by the magnitude of price shocks. In contrast, horticultural commodities are better explained by asymmetric GARCH models, demonstrating that both the magnitude and direction of shocks influence volatility. Horticultural commodities also exhibit greater sensitivity to new information and stronger volatility persistence than food commodities. Moreover, volatility dynamics differ substantially across regions, reflecting variations in production systems and market conditions. These findings highlight the importance of commodity specific and region-specific price stabilization policies to strengthen regional food market resilience.

Keywords*: Commodity price volatility; Food commodities; Horticultural commodities; GARCH models; Regional heterogeneity*

INTRODUCTION

Commodity price volatility has become a major concern in both regional and national economies (Baffes & Kabundi, 2021). Large price fluctuations not only reflect changes in market supply and demand but also signal the degree of economic uncertainty faced by producers, households, and policymakers. Excessive price volatility can undermine farmers’ and traders' incomes, reduce household purchasing power, and weaken the effectiveness of price stabilization and inflation control policies (Theresia, Ikhsan, Kacaribu, & Sumarto 2025; Yunita, 2025).

Among agricultural commodities, horticultural products generally exhibit greater price volatility than staple food commodities because of their perishable nature (Harshana & Ratnasiri, 2023; Yang & Hamori, 2018). Limited storage capacity, seasonal production patterns, and high sensitivity to weather conditions and distribution disruptions cause horticultural prices to respond rapidly to supply shocks (Alfeus & Nikitopoulos, 2022). Consequently, adverse events such as crop failures, extreme weather, and logistical disruptions often trigger sharp price increases that threaten food market stability (Theresia et al., 2025).

Price volatility is widely recognized as a dynamic process that evolves over time, with market responses varying according to the nature of the underlying shocks. In agricultural markets, uncertainty associated with production systems, storage constraints, and distribution networks tends to amplify price fluctuations and reduce market stability (Lu, Su, & Huang, 2023; Yunita, Idfi, & Hariadi, 2026). Understanding the behavior of price volatility is therefore essential, as persistent and uneven price movements can affect producers' welfare, household access to food, and the effectiveness of market stabilization policies.

Although the literature on commodity price volatility has expanded considerably, most existing studies have focused on national or international markets (Guo & Tanaka, 2019). Such aggregate approaches often overlook spatial heterogeneity arising from differences in production conditions, market structures, market integration, and policy effectiveness across regions (Alfeus & Nikitopoulos, 2022). This limitation is particularly relevant in geographically diverse countries such as Indonesia, where regional price dynamics may differ substantially across locations (Laili, Widyawati, & Prasetyaningrum, 2022).

This issue is especially important in East Java Province, one of Indonesia's largest foods producing regions (Hafied, Mardiyati, & Fattah, 2022). The province encompasses highly diverse agricultural systems, ranging from highland horticultural production areas to major rice-growing regions and other staple food production centers. Moreover, the quality of transportation infrastructure and the degree of market connectivity remain uneven across districts. These disparities suggest that commodity price volatility may exhibit substantial spatial variation across districts and municipalities (Guo & Tanaka, 2019). Given East Java's significant contribution to the national food supply, price shocks originating in the province may also have broader implications for national food markets and inflation dynamics (Yunita et al., 2026).

Despite the growing body of research on commodity price volatility, empirical evidence comparing volatility structures across commodity groups and regional markets remains limited. Most previous studies have examined national or international markets in aggregate, providing little evidence on regional differences in volatility persistence or market responses to price shocks. Comparative studies investigating both staple food and horticultural commodities at the subnational level are particularly scarce, especially in developing countries. Consequently, the role of local market characteristics in shaping volatility behavior across commodity groups and regions remains insufficiently understood.

From a regional economic perspective, understanding subnational heterogeneity in price volatility is essential because differences in market structure, commodity characteristics, and distribution systems can generate distinct patterns of price stability across regions (Laili et al., 2022). Identifying variations in volatility persistence, shock transmission, and exposure to market risk provides a more comprehensive understanding of regional market dynamics and offers valuable insights for designing more targeted and effective price stabilization policies.

Previous studies on commodity price volatility in Indonesia have provided important evidence regarding food price dynamics. Nevertheless, their scope has generally been limited to specific commodities, particular periods, or national-level analyses. For example, Hartono, Rahman, Retnoningsih, and Shaleh (2023) examined the volatility of horticultural commodity prices in East Java during the COVID-19 pandemic, whereas Sari, Achsani, Sartono, and Anggraeni (2023) investigated the asymmetric volatility of food prices at the national level. In contrast, the present study systematically compares symmetric and asymmetric volatility structures for both staple food and horticultural commodities across eight major regions of East Java using daily data spanning 2018–2024. By extending the analysis both spatially and temporally, this study contributes to the literature through a comprehensive assessment of regional heterogeneity in volatility persistence and responses to price shocks. Such an approach provides a deeper understanding of regional price dynamics and offers a stronger empirical basis for developing region-specific commodity price stabilization policies.

Accordingly, this study aims to examine the structure and persistence of commodity price volatility across regions in East Java Province during the period 2018–2024. Specifically, it addresses two research questions. First, do volatility characteristics differ between staple food and horticultural commodities at the regional level? Second, to what extent do price volatilities exhibit heterogeneous responses to market shocks across regions?

Drawing on the agricultural commodity market literature, this study proposes two theoretical expectations. First, horticultural commodities are expected to exhibit higher price volatility, stronger volatility persistence, and more pronounced asymmetric responses to market shocks than staple food commodities. This expectation is grounded in the perishable nature of horticultural products, seasonal production patterns, limited storage capacity, and their high sensitivity to weather conditions and distribution disruptions. Second, volatility characteristics are expected to vary across regions because differences in production systems, market integration, and distribution infrastructure create heterogeneous market conditions throughout East Java. These theoretical expectations provide the conceptual framework for interpreting the empirical findings.

This study makes three main contributions. First, it demonstrates that commodity price volatility differs not only across commodity groups but also systematically across regions within a single province, thereby extending the literature on spatial heterogeneity in commodity markets. Second, it is among the first studies to directly compare the performance of symmetric and asymmetric GARCH models for staple food and horticultural commodities using daily data covering the period 2018–2024. This modeling framework enables the identification of distinct volatility structures across commodity groups. Third, the findings provide empirical evidence that regional characteristics play an important role in shaping both volatility persistence and market responses to price shocks, thereby offering policy relevant insights for designing more effective and region-specific price stabilization strategies.

LITERATURE REVIEW

Characteristics of Agricultural Commodity Price Volatility

Agricultural commodity prices exhibit distinctive volatility characteristics compared with financial assets because they are strongly influenced by natural conditions, climatic variability, production seasons, perishability, and storage limitations (Minot, 2014). Unlike manufactured goods, whose supply can be adjusted relatively quickly, agricultural production requires a biological production cycle that makes short-run supply highly inelastic. Consequently, production disruptions caused by extreme weather, pest infestations, or distribution constraints often lead to substantial price fluctuations (Kalkuhl, Braun, & Torero 2016). Conversely, when production increases simultaneously during harvest seasons, prices frequently decline sharply because limited storage capacity and distribution infrastructure are unable to absorb temporary supply surpluses.

These characteristics imply that agricultural price volatility is determined not only by the magnitude of market shocks but also by the intrinsic characteristics of individual commodities. Staple food commodities, particularly rice, generally exhibit relatively low prices volatility because governments frequently intervene through price stabilization programs, public food reserves, and trade regulations (Theresia et al., 2025). In contrast, horticultural commodities such as chili peppers and shallots experience substantially higher volatility owing to their perishability, seasonal production patterns, and greater exposure to supply uncertainty (Firdaus, 2021). Empirical evidence consistently supports this distinction. Hartono et al. (2023) documented pronounced price fluctuations in horticultural commodities in East Java, while Bhinadi (2023); Bakari (2023) reported similar findings for Indonesian horticultural markets and the shallot market in Gorontalo, respectively. These studies demonstrate that horticultural commodities experience considerably larger price fluctuations than staple food commodities. In addition, regional differences in production systems, market structures, and distribution networks are likely to contribute to spatial variation in price volatility. Collectively, previous studies suggest that volatility dynamics across commodity groups and geographical regions follow heterogeneous stochastic processes, implying that different modeling approaches may be required to adequately capture their behavior.

Modeling Commodity Price Volatility

Commodity price volatility is both measurable and predictable; however, there remains considerable debate regarding the most appropriate methods for quantifying and modeling volatility. Volatility modeling plays an essential role in identifying the fundamental drivers of price fluctuations and improving forecasts of future price movements (Bellemare, Barrett, & Just, 2013). Such information provides valuable guidance for production planning, storage management, and marketing decisions, while also supporting the design of effective policy interventions aimed at mitigating the adverse effects of price instability on farmers and food security (Kalkuhl et al., 2016; Rezitis & Stavropoulos, 2010).

Beyond forecasting, volatility modelling contributes to the identification and management of risks associated with agricultural production, marketing, and consumption (Chevallier & Ielpo, 2014; Brooks & Prokopczuk, 2013; Baur & Dimpfl, 2018). A better understanding of the sources and consequences of price volatility enables farmers, traders, processors, policymakers, and other stakeholders to develop more effective risk-management strategies, including production diversification, hedging practices, and institutional policy instruments. Consequently, accurate volatility modelling has become an important analytical tool for strengthening agricultural resilience and enhancing food security.

Kalkuhl et al., (2016) argued that large and unexpected commodity price shocks often generate disproportionate economic impacts, implying that their effects are inherently nonlinear and asymmetric. While households and governments may adapt relatively well to normal price fluctuations, they are generally less prepared for extreme events, which tend to occur with low perceived probability but potentially severe economic consequences. This observation has motivated the development of increasingly sophisticated econometric models capable of capturing the complex dynamics of commodity price volatility.

One of the most prominent stylized facts of commodity prices is volatility clustering, whereby periods of high volatility tend to be followed by further episodes of high volatility, while tranquil periods are similarly persistent (Sari et al., 2023). This characteristic violates the constant variance assumption underlying conventional time-series models such as ARIMA. To address this limitation, Engle (1982) introduced the Autoregressive Conditional Heteroskedasticity (ARCH) model, which explicitly models time-varying conditional variance. Bollerslev (1986) subsequently generalized this framework through the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model by incorporating lagged conditional variances, thereby providing a more flexible representation of volatility persistence. Since then, the GARCH family has become the dominant framework for modeling commodity price volatility (Yang & Hamori, 2018; Alfeus & Nikitopoulos, 2022).

Within the GARCH framework, the ARCH parameter (α) measures the sensitivity of current volatility to new information, whereas the GARCH parameter (β) captures the persistence of past volatility. The sum of these coefficients ($\alpha + \beta$) reflects the degree of volatility persistence, with values approaching one indicating that the effects of shocks dissipate only gradually over time (Bollerslev, 1986). Consequently, persistence parameters provide not only statistical evidence regarding model stability but also economically meaningful insights into the speed at which commodity markets return to equilibrium following supply or demand disturbances. As noted by Alfeus and Nikitopoulos (2022), high persistence indicates the presence of long-memory behaviour, implying that historical shocks continue to influence price uncertainty over extended periods.

Symmetric and Asymmetric Volatility

The standard GARCH model has become one of the most widely used approaches for modeling volatility in time-series data (Bollerslev, 1986). A fundamental assumption of the symmetric GARCH model is that positive and negative shocks of equal magnitude exert identical effects on conditional volatility. Under this framework, volatility is determined by past innovations and historical conditional variances, making the model particularly suitable for financial and commodity markets characterized by persistent volatility.

However, the assumption of symmetric market responses is often violated in agricultural commodity markets. Positive and negative shocks may generate substantially different effects because supply disruptions are generally more difficult to offset than temporary increases in production. Consequently, adverse events such as droughts, floods, pest outbreaks, crop failures, or logistical disruptions frequently produce stronger and more persistent increases in price volatility than favorable production conditions of comparable magnitude (Baffes & Kabundi, 2021).

To account for this phenomenon, several asymmetric extensions of the GARCH model have been developed. Among the most widely applied are the Exponential GARCH (EGARCH), Threshold GARCH (TGARCH), and Asymmetric Power ARCH (APARCH) models. The EGARCH model, captures asymmetric responses through a logarithmic transformation of the conditional variance, allowing positive and negative shocks to influence volatility differently without imposing non-negativity constraints. The TGARCH model introduced by Zakoian (1994) incorporates threshold effects that explicitly distinguish the impacts of positive and negative innovations on conditional variance. Meanwhile, the APARCH model developed by Ding et al. (1993) extends the

GARCH framework by introducing a power transformation of the conditional standard deviation, providing greater flexibility in modelling various forms of heteroskedasticity. In all three specifications, the asymmetry parameter (γ) quantifies whether volatility responds differently to shocks depending on their direction.

The relevance of asymmetric volatility is particularly evident in agricultural commodity markets, especially for perishable horticultural products. Because production cannot be adjusted immediately and storage capacity is limited, negative supply shocks often generate larger and more persistent price responses than equivalent positive shocks. Harshana and Ratnasiri (2023) demonstrated that price transmission along horticultural supply chains is inherently asymmetric, with price increases resulting from supply shortages occurring more rapidly and to a greater extent than subsequent price declines after supply conditions improve. Similarly, Sari et al. (2023) reported significant asymmetric volatility in Indonesian food prices, suggesting that the direction of market shocks plays a crucial role in determining commodity price dynamics. These findings indicate that asymmetric GARCH models are particularly appropriate for commodities whose prices are highly sensitive to production and distribution disturbances.

Empirical Evidence on Agricultural Commodity Price Volatility

A growing body of empirical research suggests that no single volatility model consistently provides the best representation of price dynamics across all agricultural commodities. Differences in commodity characteristics, market structures, government interventions, and geographical conditions generate heterogeneous volatility patterns across products and regions (Yang & Hamori, 2018; Lu et al., 2023).

Several studies have shown that symmetric GARCH models perform well for commodities characterized by relatively stable prices and substantial government intervention. Yang and Hamori (2018), for example, found that conventional GARCH specifications adequately captured the volatility of agricultural commodities subject to effective market stabilization policies. In contrast, studies focusing on more volatile commodities have generally reported superior performance for asymmetric GARCH models. Hartono et al. (2023), analyzing horticultural commodities in East Java, and Sari et al. (2023), examining Indonesian food prices, both concluded that asymmetric models better capture commodity price dynamics because they explicitly accommodate heterogeneous market responses to different types of shocks.

Empirical studies have also documented considerable variation in volatility persistence across agricultural commodities. Alfeus and Nikitopoulos (2022) found evidence of long-memory behavior in several commodity markets, indicating that price shocks continue to influence volatility over extended periods. Conversely, commodities supported by more efficient distribution systems and stronger market stabilization mechanisms generally exhibit lower persistence, reflecting faster market adjustment following supply or demand disturbances (Guo & Tanaka, 2019). Furthermore, the presence of asymmetric effects is not universal. Lu et al. (2023) and Sari et al. (2023) demonstrated that asymmetric volatility varies across commodities and regions, suggesting that local market structures, institutional arrangements, and supply chain characteristics play important roles in shaping volatility dynamics.

Collectively, these findings indicate that volatility models should not be applied uniformly across agricultural commodities. Instead, model specification should account for commodity-specific characteristics and regional market conditions to ensure an accurate representation of price dynamics (Yang & Hamori, 2018; Alfeus & Nikitopoulos, 2022). This perspective also underscores the importance of comparative studies that evaluate multiple GARCH specifications across different commodity groups and geographical regions.

Research Gap

Despite the rapid expansion of research on agricultural commodity price volatility, several important gaps remain. First, most previous studies have focused on a limited number of commodities, such as shallots (Bakari, 2023), horticultural commodities in general (Hartono et al., 2023), or strategic food commodities (Sari et al., 2023). Consequently, relatively little is known about the differences in volatility behavior between staple food and horticultural commodities within a unified analytical framework.

Second, many empirical studies evaluate only a single GARCH specification without systematically comparing alternative symmetric and asymmetric models. As a result, evidence regarding the most appropriate volatility model for different commodities remains limited (Yang & Hamori, 2018; Alfeus & Nikitopoulos, 2022). Given that agricultural commodities differ substantially in production systems, perishability, and market characteristics, model performance is unlikely to be uniform across commodity groups.

Third, comparative analyses of regional volatility within a single province remain scarce, despite considerable spatial heterogeneity in agroclimatic conditions, production systems, market integration, and distribution infrastructure. These regional differences may substantially influence the persistence and transmission of commodity price volatility (Hartono et al., 2023).

To address these gaps, the present study systematically compares a range of symmetric and asymmetric GARCH models to analyze the price volatility of four staple food commodities (rice, beef, broiler chicken, and chicken eggs) and three horticultural commodities (red chili, shallots, and garlic) across eight major regions of East Java. Beyond identifying the most appropriate volatility model for each commodity and region, the study evaluates volatility persistence and asymmetric responses to market shocks. This comparative approach provides a more comprehensive understanding of the mechanisms underlying commodity price risk and offers empirical evidence to support the development of more effective, commodity-specific, and regionally targeted price stabilization policies.

RESEARCH METHOD

Data and Price Transformation

This study employs secondary daily time-series data on food and horticultural commodity prices in East Java Province, Indonesia. The empirical analysis focuses on eight major districts and municipalities: Surabaya, Probolinggo, Malang, Madiun, Kediri, Jember, Blitar, and Tuban. These regions represent the province's principal economic centers and agricultural production areas, thereby capturing the spatial heterogeneity of regional commodity markets.

Daily retail price data were obtained from the National Strategic Food Price Information Center (PIHPS) managed by Bank Indonesia and the East Java Food Availability and Price Information System (Siskaperbapo). The observation period spans from January 2018 to December 2024. The dataset consists of daily retail prices collected from representative traditional markets in each district and municipality.

Prior to estimation, all price series underwent data quality screening. Missing observations resulting from public holidays or reporting delays were first examined to identify the underlying missing-data pattern. Isolated missing values were subsequently imputed using linear interpolation to preserve the continuity of the time series. Price observations were standardized into Indonesian Rupiah per kilogram (IDR/kg) to ensure comparability across commodities and regions. Outliers were identified through graphical inspection and standardized residual analysis. Observations identified as recording errors were corrected or removed, whereas genuine market driven extreme values were retained to preserve the underlying volatility dynamics.

Rather than using nominal prices directly, the empirical analysis is based on daily logarithmic price returns, which are commonly employed in volatility modeling because they stabilize the variance and reduce non-stationarity (Sari et al., 2023). Daily returns are calculated as Formula 1.

$$r_t = \ln(P_t) - \ln(P_{t-1}) \tag{1}$$

Where r_t denotes the commodity price return at time t; while $P_t$and P_{t-1} represent cpmmodity prices at periods t and t-1, respectively.

Commodity Price Volatility Modeling

The empirical analysis follows a sequential modeling procedure. First, the stationarity of each return series was examined using the Augmented Dickey–Fuller (ADF) unit root test. Only stationary return series were used for subsequent volatility estimation. The statistical hypotheses for the ADF test are defined as follows:

H_0: the series contains a unit root (non-stationary)

H_1: the series does not contain a unit root (stationary)

The null hypothesis is rejected when the absolute value of the ADF test statistic exceeds the corresponding MacKinnon critical value or, equivalently, when the *p*-value is smaller than the selected significance level.

Modeling volatility for conditional volatility forecasting cannot rely solely on the Autoregressive Integrated Moving Average (ARIMA) because financial and commodity price series typically exhibit time varying variance, resulting in heteroskedastic residuals. Since the ARIMA model assumes constant error variance, it is not appropriate for capturing volatility dynamics. Consequently, the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model proposed by Bollerslev (1986) was employed to model conditional variance.

Before estimating the GARCH model, a mean equation was specified to capture the conditional mean dynamics of commodity price. hile the mean equation describes the expected changes in commodity prices over time, the GARCH specification models the conditional variance, allowing price volatility to evolve dynamically over time.

In general, the ARIMA(l, d, k) model is expressed as Formula 2.

$$\Delta^d r_t = \mu + \sum_{i=1}^{l} \phi_i \, \Delta^d r_{t-i} + \sum_{j=1}^{k} \theta_j \, \varepsilon_{t-j} + \varepsilon_t, \tag{2}$$

where r_t denotes the commodity price return at time t, μ is a constant term, ϕ_i represents the coefficients of the autoregressive (AR) component, $\theta_j$denotes the coefficients of the moving average (MA) component, and $\varepsilon_t$is the error term at period t.

Prior to estimating the ARCH/GARCH model, the residuals obtained from the mean equation were tested for the presence of conditional heteroskedasticity using the

Autoregressive Conditional Heteroskedasticity Lagrange Multiplier (ARCH–LM) test developed by Engle (1982). This diagnostic test determines whether the residual variance exhibits autoregressive conditional heteroskedasticity.

The statistical hypotheses are defined as follows:

H_0: the residuals do not exhibit ARCH effects

H_1: the residuals exhibit ARCH effects

Rejection of the null hypothesis at the 5% significance level indicates the presence of ARCH effects, implying that an ARCH/GARCH model is appropriate for modeling price volatility. Conversely, if no ARCH effects are detected, a constant-variance model is considered adequate, and GARCH estimation is unnecessary.

Since this study employs return series rather than price levels, the differencing order is zero, and the mean equation is therefore specified as an ARIMA $(l, 0, k)$model. The identification of the mean equation considered combinations of autoregressive orders $l = 0,1,$and 2, and moving average orders $k = 0,1,$and 2. For the variance equation, ARCH orders $p = 0,1,$and 2and GARCH orders $q = 0,1,$and 2were evaluated. Each candidate ARIMA specification was subsequently combined with alternative ARCH/GARCH specifications to identify the most appropriate volatility model.

The optimal model was selected based on several criteria: (i) the statistical significance of all estimated ARCH/GARCH parameters; (ii) satisfaction of the stationarity and model stability conditions; (iii) the absence of remaining ARCH effects in the standardized residuals; and (iv) the lowest values of the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) among the competing specifications.

Symmetric GARCH model

As the baseline specification, this study estimates the standard symmetric GARCH model proposed by Bollerslev (1986). The conditional variance equation is expressed as Formula 3.

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \, \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \, \sigma_{t-j}^2 \tag{3}$$

$$\omega > 0, \alpha_i \geq 0, \beta_j \geq 0.$$

$$\alpha + \beta < 1.$$

where σ_t^2 denotes the conditional variance, ω is a constant, α_i measures the ARCH effect, and β_j represents the GARCH effect.

Following estimation, diagnostic checking was performed using the Ljung–Box test applied to both standardized residuals and squared standardized residuals to verify the absence of serial correlation and remaining ARCH effects.

Asymmetric GARCH model

Although the standard GARCH model assumes identical volatility responses to positive and negative shocks, agricultural commodity prices frequently exhibit asymmetric behavior due to supply disruptions, seasonal production, and distribution constraints. To account for these characteristics, this study estimates several asymmetric GARCH specifications, including EGARCH, GJR-GARCH, TGARCH (Zakoian, 1994), APARCH (Ding et al., 1993), and Component GARCH (CGARCH).

The standard GARCH model assumes that volatility responds symmetrically to positive and negative price shocks. However, agricultural commodity prices, particularly those of food and horticultural commodities, may exhibit asymmetric volatility, whereby negative shocks generate a larger impact on volatility than positive shocks of the same magnitude. To accommodate this behavior, this study estimates several asymmetric GARCH models that are capable of capturing asymmetric volatility dynamics more accurately (Sari et al., 2023).

The Exponential GARCH (EGARCH) model specified as Formula 4.

$$\log(\sigma_t^2) = \omega + \sum_{i=1}^{p} \beta_i \log(\sigma_{t-i}^2) + \sum_{j=1}^{q} \left[\alpha_j \left(\frac{\varepsilon_{t-j}}{\sigma_{t-j}}\right) + \gamma_j \left(\mid \frac{\varepsilon_{t-j}}{\sigma_{t-j}} \mid - \frac{\varepsilon_{t-j}}{\sigma_{t-j}}\right)\right] \tag{4}$$

The EGARCH specification allows conditional volatility to respond differently to positive and negative price shocks, thereby capturing potential asymmetric effects without imposing non-negativity constraints on the variance parameters.

The GJR-GARCH model developed by incorporates a threshold effect through an indicator function that distinguishes shocks (good and bad news) as Formula 5.

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \beta_i \, \sigma_{t-i}^2 + \sum_{j=1}^{q} (\,\alpha_j + \gamma_j I_{\varepsilon_{t-j}<0})\varepsilon_{t-j}^2 \tag{5}$$

where the indicator function is defined as:

$$I_{\varepsilon_{t-j}<0} = \begin{cases} 1, & \varepsilon_{t-j} < 0 \text{ (bad news)} \\ 0, & \varepsilon_{t-j} \geq 0 \text{ (good news)} \end{cases}$$

Accordingly, negative shocks are permitted to exert a different effect on conditional volatility than positive shocks of equal magnitude

The Threshold GARCH (TGARCH) model introduced by Zakoian (1994) models volatility in terms of the conditional standard deviation rather than the conditional variance, thereby allowing negative shocks to exert an additional effect on volatility as Formula 6.

$$\sigma_t = \omega + \sum_{i=1}^{p} \beta_i \, \sigma_{t-i} + \sum_{j=1}^{q} \alpha_j \mid \varepsilon_{t-j} \mid + \sum_{j=1}^{q} \gamma_j \, I_{\varepsilon_{t-j}<0} \mid \varepsilon_{t-j} \mid \tag{6}$$

$$\sum_{j=1}^{q} \alpha_j = 0$$

The Asymmetric Power ARCH (APARCH) model proposed by Ding et al. (1993) further generalizes previous specifications by introducing a power transformation of volatility, thereby providing greater flexibility in modeling the conditional variance process as Formula 7.

$$\left(\sigma_t)^{\delta} = \omega + \sum_{i=1}^{p} \beta_i \, (\sigma_{t-i})^{\delta} + \sum_{j=1}^{q} \alpha_j \, (\mid \varepsilon_{t-j} \mid - \gamma_j \varepsilon_{t-j} \right)^{\delta} \tag{7}$$

In addition to these asymmetric specifications, this study also estimates the Component GARCH (CGARCH) model to capture the long-run dynamics of volatility by decomposing conditional variance into permanent and transitory components. The CGARCH model is specified as Formula 8.

$$\sigma_t^2 = q_t + \sum_{i=1}^{p} \beta_i \left(\sigma_{t-i}^2 - q_{t-i}\right) + \sum_{j=1}^{q} \alpha_j \left(\varepsilon_{t-j}^2 - q_{t-j}\right) \quad (8)$$

where the permanent component of the conditional variance evolves according to Formula 9

$$q_t = \omega + \rho q_{t-1} + \phi(\varepsilon_{t-1}^2 - v_{t-1}) \quad (9)$$

These asymmetric GARCH models enable the identification of the leverage effect, whereby negative shocks induce a larger increase in volatility than positive shocks of the same magnitude. To identify the most appropriate volatility specification, symmetric and asymmetric GARCH models were systematically compared across commodities and regions. For each commodity region pair, multiple candidate models were estimated.

RESULTS AND DISCUSSION

Descriptive Characteristics of Food and Horticultural Commodity Returns

Commodity price volatility is commonly analyzed using price returns rather than nominal prices because returns capture both price increases and decreases and provide a more appropriate measure of market risk. Compared with nominal prices, return series are more sensitive to supply disruptions, demand shocks, and distribution constraints, making them particularly suitable for volatility modelling (Sari et al., 2023; Barman et al., 2021).

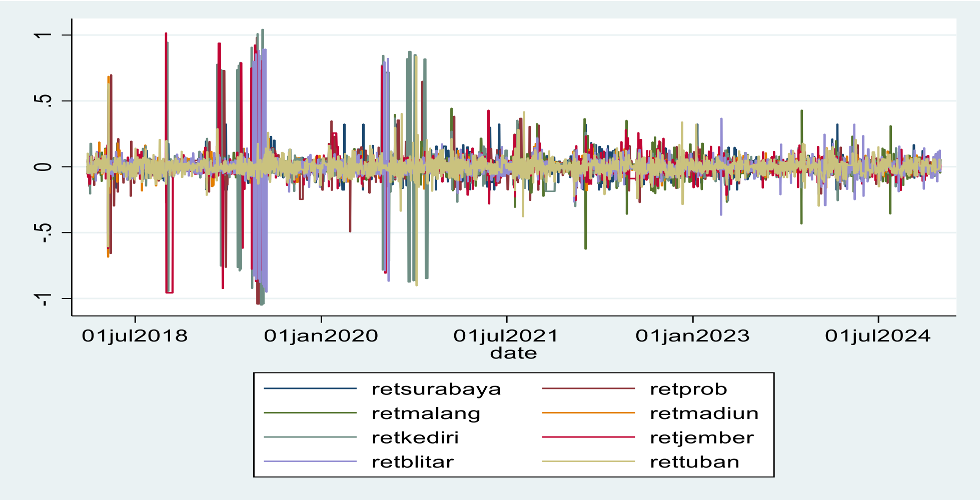

Figure 1. Time Series Plot of Food Commodity Price Returns in East Java

Table 1. Descriptive Statistics of Food Commodity Returns

Region	Food Commodities		
	Mean	Stadev	Min – max
Surabaya	0.0008	0.0138	-1.123 to 0.099
Probolinggo	-0.0003	0.01383	-0.07 to 0.089
Malang	-0.00002	0.01314	-0.092 to 0.062
Madiun	-0.00002	0.0112	-0.058 to 0.061
Kediri	-0.00015	0.0134	-0.112 to 0.085
Jember	0.000074	0.0198	-0.125 to 0.117
Blitar	0.00018	0.0174	-0.099 to 0.107
Tuban	0.00052	0.0144	-0.082 to 0.068

Figure 1 illustrates the daily return series of food commodity prices across the eight study regions in East Java, while the corresponding descriptive statistics are presented in Table 1. Overall, food commodity returns fluctuate around zero throughout the observation period, indicating the absence of persistent upward or downward price trends. This pattern is confirmed by the very small average returns, ranging from −0.0003 to 0.0008, suggesting that food price movements were primarily driven by short-term market shocks rather than long-term structural trends. Similar characteristics have been reported by Minot (2014) and Barman et al. (2021), who found that agricultural commodity returns typically oscillate around zero despite substantial fluctuations in nominal prices.

Although food commodity prices remained relatively stable over the sample period, Figure 1 reveals a simultaneous increase in volatility across nearly all regions during 2019–2020. The synchronized timing of these fluctuations suggests the presence of common regional shocks affecting food markets throughout East Java. This period coincides with the onset of the COVID-19 pandemic, during which mobility restrictions disrupted food distribution networks, altered household consumption patterns, and increased uncertainty regarding food supplies (Bhinadi, 2023; Glauben et al., 2022).

The descriptive statistics further support these observations. The standard deviation of food commodity returns ranges from 0.0112 to 0.0198, indicating relatively low and homogeneous price variability across regions. Although Jember exhibits the highest volatility (0.0198) and Madiun the lowest (0.0112), the overall differences remain modest. This finding suggests that regional disparities in food price risk were limited during the study period, implying that food markets across East Java experienced broadly similar volatility patterns.

A similar conclusion can be drawn from the relatively narrow range of return values, which varies approximately between −0.125 and 0.117 for most regions. The absence of frequent extreme observations indicates that food commodity prices generally experienced moderate fluctuations despite several temporary disturbances. Moreover, volatility visibly declined after 2020, with return series gradually reverting to values close to zero and exhibiting smaller amplitudes. This pattern suggests that food markets progressively returned to normal conditions following improvements in supply chain performance, stronger interregional distribution, and the implementation of government price stabilization measures (Bakari, 2023).

In contrast, Figure 2 reveals markedly different behaviour for horticultural commodities. Compared with staple food commodities, horticultural price returns exhibit substantially larger and more frequent fluctuations, indicating considerably higher market uncertainty. This visual evidence is consistent with the descriptive statistics presented in Table 2, where the standard deviation of horticultural returns ranges from 0.0529 to 0.442, substantially exceeding the corresponding values for food commodities. The large difference in dispersion suggests that horticultural markets are exposed to considerably greater price risk.

The higher volatility of horticultural commodities can largely be explained by their supply-side characteristics. Production of shallots, garlic, and red chili is highly dependent on seasonal cultivation cycles, weather conditions, and pest outbreaks. Because agricultural production cannot be expanded immediately following supply disruptions, short-run supply remains relatively inelastic. Consequently, even modest production shortfalls may generate substantial price increases when consumer demand remains relatively stable. These structural characteristics make horticultural prices considerably more volatile than food prices.

Limited storage capacity further amplifies these fluctuations. Because horticultural commodities are highly perishable, excess supply during harvest periods cannot easily be stored, resulting in rapid price declines. Conversely, production shortages quickly translate into sharp price increases because inventories are insufficient to offset temporary supply deficits. These dynamics became particularly evident during **2018–2020**, when disruptions to transportation and logistics associated with the COVID-19 pandemic intensified market instability.

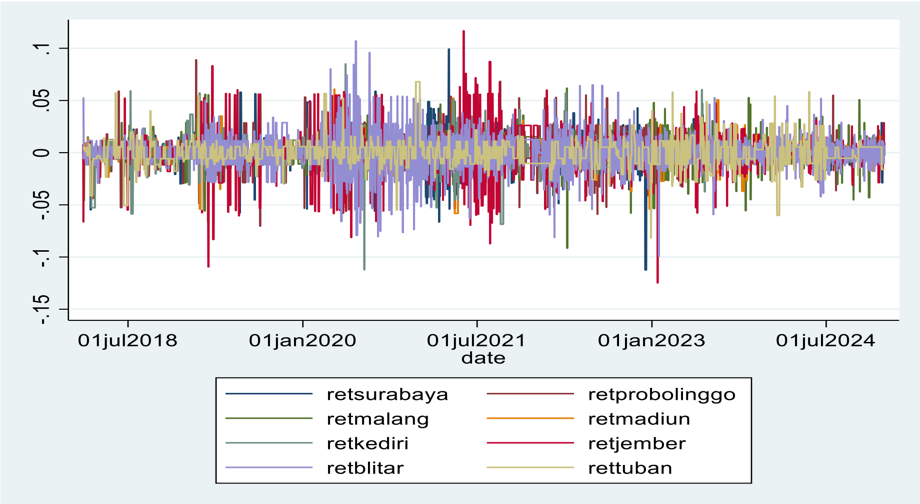

Figure 2. Time Series Plot of Horticultural Commodity Price Returns in East Java

Table 2. Descriptive Statistics of Food and Horticultural Commodity Returns

Region	Food Commodities			Horticultural Commodities		
	Mean	Stadev	Min – max	Mean	Stadev	Min – max
Surabaya	0.0008	0.0138	-1.123 to 0.099	0.001	0.442	-6.94 to 6.93
Probolinggo	-0.0003	0.01383	-0.07 to 0.089	0.0005	0.094	-1.04 to 0.98
Malang	-0.00002	0.01314	-0.092 to 0.062	0.0028	0.064	-0.661 to 0.575
Madiun	-0.00002	0.0112	-0.058 to 0.061	0.0002	0.0529	-0.685 to 0.685
Kediri	-0.00015	0.0134	-0.112 to 0.085	0.0036	0.155	-1.05 to 1.041
Jember	0.000074	0.0198	-0.125 to 0.117	-0.0056	0.137	-0.957 to 1.02
Blitar	0.00018	0.0174	-0.099 to 0.107	-0.00075	0.098	-0.951 to 0.89
Tuban	0.00052	0.0144	-0.082 to 0.068	0.00004	0.065	-0.903 to 0.84

Figure 2 also indicates that volatility tends to increase and decrease simultaneously across several regions, suggesting that horticultural markets are influenced by common regional factors such as seasonal production patterns, climatic conditions, and synchronized supply shocks. This observation is consistent with Firdaus (2021), who documented strong interregional linkages in the price dynamics of horticultural commodities in Indonesia.

Despite these common movements, substantial regional heterogeneity remains evident. Surabaya records by far the highest standard deviation (0.442) and the widest return range (−6.94 to 6.93), indicating the occurrence of several episodes of exceptionally large price adjustments during the sample period. As the principal trading and distribution hub in East Java, commodity prices in Surabaya are highly responsive to supply conditions across multiple production regions. Consequently, regional supply disruptions are rapidly transmitted to retail markets, producing larger price fluctuations than those observed elsewhere (Bakari, 2023; Barman et al., 2021).

Outside Surabaya, Kediri (0.155) and Jember (0.137) also exhibit relatively high volatility, whereas Madiun (0.0529), Malang (0.064), and Tuban (0.065) display considerably lower price variability. These differences indicate that commodity price volatility is influenced not only by commodity-specific characteristics but also by regional differences in production seasonality, dependence on external supply sources, and the efficiency of local distribution systems (Firdaus, 2021).

Overall, the descriptive analysis demonstrates a clear distinction between the two commodity groups. Food commodities exhibit relatively stable price movements characterized by low return variability, whereas horticultural commodities display substantially greater fluctuations and higher market uncertainty. These findings suggest that the underlying price formation mechanisms differ considerably between the two commodity groups. While staple food markets appear to be relatively resilient to short-term shocks, horticultural markets remain considerably more vulnerable because of their perishability, seasonal production cycles, and greater exposure to supply disruptions.

Stationary Test

The stationarity of commodity price returns was examined using the Augmented Dickey–Fuller (ADF) unit root test. The results are presented in Table 3.

Table 3. Stationarity Test of Commodity Price Return

Region	Food Commodities		Horticultural Commodities		Critical Values		
	Statistic ADF	Prob*	Statistic ADF	Prob*	1 %	5 %	10 %
Surabaya	-23.967	0.0000	-26.970	0.0000	-3.430	-2.860	-2.570
Probolinggo	-22.797	0.0000	-22.953	0.0000	-3.430	-2.860	-2.570
Malang	-25.517	0.0000	-33.128	0.0000	-3.430	-2.860	-2.570
Madiun	-19.859	0.0000	-34.142	0.0000	-3.430	-2.860	-2.570
Kediri	-22.034	0.0000	-32.230	0.0000	-3.430	-2.860	-2.570
Jember	-32.958	0.0000	-22.517	0.0000	-3.430	-2.860	-2.570
Blitar	-37.361	0.0000	-41.773	0.0000	-3.430	-2.860	-2.570
Tuban	-18.500	0.0000	-33.198	0.0000	-3.430	-2.860	-2.570

Source: Authors' calculations

Note: * indicates Prob < 5%, implying statistical significance at the 5% significance level

As reported in Table 3, all food and horticultural commodity return series are stationary across the eight study regions. The ADF test statistics range from −18.500 to −37.361 for food commodities and from −22.517 to −41.773 for horticultural commodities. In every case, the test statistics are substantially more negative than the corresponding critical values at the 1%, 5%, and 10% significance levels. Furthermore, all p-values are below 0.01, leading to the rejection of the null hypothesis of a unit root.

From our results indicate that the return series fluctuate around a constant mean without exhibiting stochastic trends, satisfying the stationarity requirement for conditional volatility modeling. The absence of unit roots also implies that subsequent estimates are unlikely to suffer from spurious regression problems, thereby ensuring the reliability of the estimated volatility dynamics.

The finding that all return series are stationary is consistent with the theoretical properties of financial and commodity returns, which typically become stationary after logarithmic differencing (Bollerslev, 1986; Yang & Hamori, 2018). Consequently, all return series are appropriate for estimating the ARCH/GARCH family of models in the subsequent analysis.

Volatility Modeling of Food Commodity Price Returns

Following confirmation that all return series are stationary, the next step involved identifying the appropriate volatility model for each regional food commodity market. The first stage consisted of estimating the conditional mean equation using the ARIMA framework. Because the analysis was conducted on stationary return series, all candidate specifications were restricted to ARIMA(l,0,k) models, with the optimal specification selected according to the best statistical performance.

The residuals obtained from the selected mean equations were subsequently examined using the ARCH–LM test to determine the presence of conditional heteroskedasticity. The selected ARIMA models and ARCH–LM test results are reported in Table 4.

Table 4. Selected Mean Equation and ARCH LM Test Results for Food Commodity Prices

Commodity	Selected Mean Equation	ARCH–LM Test (Lag 3)	Note
Surabaya	ARIMA (2,0,2)	18.74* (0.000)	ARCH effect detected
Probolinggo	ARIMA (1,0,2)	14.62* (0.002)	ARCH effect detected
Malang	ARIMA (1,0,1)	13.88* (0.003)	ARCH effect detected
Madiun	ARIMA (1,0,1)	9.54* (0.023)	ARCH effect detected
Kediri	ARIMA (1,0,2)	17.11* (0.001)	ARCH effect detected
Jember	ARIMA (1,0,1)	15.83* (0.001)	ARCH effect detected
Blitar	ARIMA (1,0,1)	11.47* (0.009)	ARCH effect detected
Tuban	ARIMA (1,0,2)	12.94* (0.005)	ARCH effect detected

* probability of ARCH testing

As shown in Table 4, low-order ARIMA specifications adequately capture the conditional mean dynamics of food commodity returns across all regions. The majority of regions are best represented by either ARIMA(1,0,1) or ARIMA(1,0,2), whereas Surabaya requires a more complex ARIMA(2,0,2) specification. This finding suggests that short-term price movements in food commodities are primarily driven by recent market information, although the largest regional market exhibits slightly more complex temporal dynamics.

The ARCH–LM test provides strong evidence of conditional heteroskedasticity in every return series. All p-values are below the 5% significance level, indicating that the null hypothesis of homoskedastic residuals is rejected. Consequently, the variance of commodity price returns varies systematically over time rather than remaining constant, confirming the presence of volatility clustering. These results justify the application of ARCH/GARCH models to capture the time-varying nature of food commodity price volatility.

After confirming the presence of ARCH effects, several symmetric and asymmetric GARCH specifications were estimated. Model selection was based on two criteria: (i) all estimated parameters had to be statistically significant, and (ii) the preferred model had to exhibit the lowest AIC, reflecting the best balance between model fit and parsimony. The comparison of alternative specifications is presented in Table 5.

Table 5. Comparison of Symmetric and Asymmetric GARCH Model Criteria for Food Commodities

Regional	Model Type		AIC	Selection Best Model
Surabaya	**Simetri**	**GARCH (1,1)**	**-16491**	**GARCH (1,1)**
	Asimetri	EGARCH (1,1)	-16191	
Probolinggo	**Simetri**	**GARCH (1,2)**	**-15949**	**GARCH (1,2)**
	Asimetri	EGARCH (2,1)	-15523	
Malang	**Simetri**	**GARCH (2,1)**	**-15980**	**GARCH (3,1)**
	Asimetri	APARCH (1,2)	-15473	
Madiun	**Simetri**	**GARCH (2,2)**	**-17681**	**GARCH (2,1)**
	Asimetri	TARCH (1,1)	-16734	
Kediri	**Simetri**	**GARCH (1,1)**	**-16394**	**GARCH (1,1)**
	Asimetri	APARCH (1,2)	-16161	
Jember	**Simetri**	**GARCH (1,2)**	**-14030**	**GARCH (1,2)**
	Asimetri	APARCH (1,2)	-13946	
Blitar	**Simetri**	**GARCH (1,2)**	**-14221**	GARCH (1,2)
	Asimetri	APARCH (2,1)	-14159	
Tuban	**Simetri**	**GARCH (2,1)**	**-16384**	GARCH 2,1)
	Asimetri	TARCH (2,1)	-15597	

Source: Author's Computation

The results consistently indicate that symmetric GARCH models outperform their asymmetric counterparts across all eight regions. Based on parameter significance and model selection criteria, conventional GARCH specifications provide the best representation of food commodity price volatility.

This finding suggests that volatility in food commodity prices is primarily determined by the magnitude of market shocks rather than by their direction. In other words, positive and negative price shocks of comparable size generate similar responses in conditional volatility. The absence of statistically meaningful asymmetric effects indicates that the leverage effect is not a dominant characteristic of food commodity markets in East Java. Instead, food price volatility is largely characterized by persistent fluctuations that evolve symmetrically over time.

These findings are consistent with Sari et al. (2023), who likewise reported insignificant asymmetric effects in Indonesian food commodity markets. The absence of asymmetric volatility is likely attributable to the structural characteristics of staple food markets, where prices are strongly influenced by fundamental supply-and-demand conditions rather than speculative behavior. As noted by Bakari (2023), demand for staple food commodities is relatively price inelastic, while price fluctuations are primarily driven by production variability, weather conditions, and distribution efficiency. Under such market conditions, positive and negative shocks of similar magnitude tend to produce comparable adjustments in conditional volatility.

Although symmetric GARCH models are consistently selected across all regions, the estimated model specifications differ with respect to the ARCH and GARCH orders. Surabaya and Kediri are adequately represented by the standard GARCH(1,1) model, whereas other regions require higher-order specifications such as GARCH(1,2) or GARCH (2,1). These differences suggest that regional food markets exhibit heterogeneous volatility dynamics despite sharing a broadly symmetric response to market shocks.

Table 6 reports the estimated ARCH–GARCH parameters for food commodity returns based on the best-fitting symmetric GARCH specification selected for each region. Following model estimation, the Ljung–Box test performed on the squared standardized residuals indicates no remaining serial correlation in any regional model (all p-values > 0.05). This result confirms that the selected models adequately capture the conditional volatility structure of the return series, leaving no significant ARCH effects in the residuals. Consequently, the estimated GARCH models provide an appropriate representation of food commodity price volatility across all study regions.

Table 6. Estimated ARCH–GARCH Parameters for Food Commodities Using the Best Fitting GARCH Model

	Surabaya	Probolinggo	Malang	Madiun	Kediri	Jember	Blitar	Tuban
ARMA (l,d,k)	(2,0,2)	(1,0,2)	(1,0,1)	(1,0,1)	(1,0,2)	(1,0,1)	(1,0,1)	(1,0.2)
GARCH (p,q)	(1,1)	(1,2)	(2,1)	(2,2)	(1,1)	(1,2)	(1,2)	(2,1)
α1	0,440	0.336	0.367	0.344	0.337	0.235	0.293	0.114
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
α2			0.297	0.061				0.051
			(0.000)	(0.003)				(0.025)
β1	0.315	0.455	0.209	0.091	0.586	0.253	0.675	0.747
	(0.000)	(0.000)	(0.000)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)
β2		0.133		0.448		0.487		
		(0.001)		(0.000)		(0.000)		
AIC	-16491	-15949	-15980	-17681	-16394	-14030	-14221	-16384
BIC	-16444	-15902	-15939	-17635	-16359	13989	-14186	-16337
Ljung–Box	2.9844	10.321	2.714	5.531	6.201	7.837	5.989	6.926
test	(0.981)	(0.412)	(0.240)	(0.441)	(0.094)	(0.645)	(0.766)	(0.760)
α + β	0.7552	0,9231	0.873	0.763	0.923	0.957	0.968	0.911

Note: $\alpha_i \geq 0, \beta_j \geq 0, \alpha + \beta < 1$

The estimation results reveal that the optimal ARCH/GARCH structure differs across regions, indicating that food price volatility is characterized by regional heterogeneity rather than a uniform stochastic process. This finding suggests that local market conditions influence the mechanisms through which price shocks are transmitted and absorbed. Similar arguments have been advanced by Baffes and Kabundi (2021), who emphasized that commodity price shocks are mediated by regional market structures rather than being transmitted uniformly across locations.

The ARCH coefficient (α) measures the immediate response of conditional volatility to newly arriving market information, whereas the GARCH coefficient (β) reflects the persistence of past volatility over time (Bollerslev, 1986). Together, these parameters describe how rapidly markets react to new shocks and how long the resulting volatility persists.

Among the eight regions, Surabaya exhibits the largest ARCH coefficient (α_1 = 0.440), indicating that its price volatility is highly responsive to new information. As the principal commercial and distribution hub of East Java, Surabaya is characterized by intensive market transactions and extensive supply networks. Consequently, changes in supply or demand conditions are incorporated into market prices more rapidly than in other regions, causing recent shocks to exert a stronger influence on current volatility. This interpretation is consistent with the findings of Harshana and Ratnasiri (2023); Guo and Tanaka (2019), who argue that highly integrated markets tend to respond more quickly to new information.

In contrast, Probolinggo, Kediri, Jember, Blitar, and Tuban exhibit relatively larger GARCH coefficients, suggesting that current volatility depends more strongly on past volatility than on contemporaneous shocks. These regions are closely associated with agricultural production activities, where supply adjustments are constrained by biological production cycles. As a result, disturbances arising from adverse weather conditions, production shortfalls, or harvesting delays cannot be corrected immediately, allowing volatility to persist for longer periods. Therefore, a relatively large GARCH coefficient should be interpreted primarily as evidence of strong volatility persistence rather than market inefficiency. Similar evidence has been documented by Putri and Wulandari (2022), who reported more persistent food price fluctuations in agricultural production areas of East Java during periods of external shocks such as the COVID-19 pandemic.

All estimated models satisfy the standard stationarity conditions of the GARCH process, with positive ARCH and GARCH coefficients and $\alpha + \beta$ remaining below unity in every region. These results indicate that although volatility shocks dissipate over time, the speed of adjustment differs considerably across regional markets.

The relatively high persistence observed in Probolinggo, Kediri, Jember, Blitar, and Tuban indicates that volatility shocks dissipate slowly, implying prolonged periods of elevated market uncertainty. In these predominantly production-oriented regions, supply disruptions arising from adverse weather conditions, pest and disease outbreaks, or delays in harvesting can affect commodity availability over an extended period. Consequently, market adjustments occur gradually rather than instantaneously, causing the effects of price shocks on volatility to persist across several periods.

Conversely, Surabaya, Malang, and Madiun exhibit comparatively lower persistence, indicating a faster adjustment toward long-run equilibrium following market disturbances. Surabaya benefits from highly developed logistics infrastructure and diversified procurement channels, enabling rapid substitution of supplies from alternative production areas whenever local shortages arise. Likewise, Malang and Madiun maintain relatively strong production bases while remaining well connected to surrounding production centers, allowing regional trade to mitigate temporary supply imbalances. Previous studies have similarly shown that integrated transportation networks and efficient interregional trade accelerate market adjustment following supply disruptions (Barman et al., 2021; Firdaus, 2021; Guo & Tanaka, 2019)

The observed regional differences in volatility persistence suggest that food price dynamics are determined not only by the magnitude of price fluctuations but also by the structural characteristics of regional production and distribution systems. Minot (2014) argued that market structure, storage capacity, and distribution integration are key determinants of the duration of food price volatility following supply disruptions. Regions that serve primarily as agricultural production bases tend to experience more persistent volatility because supply recovery depends on biological production cycles that cannot be accelerated in the short run. By contrast, regions with more integrated distribution networks are better positioned to offset local supply shortages through interregional trade, thereby mitigating the persistence of price shocks. This interpretation is further supported by Theresia et al. (2025), who documented significant interregional food price volatility spillovers in Indonesia, highlighting the importance of efficient regional trade and distribution networks in facilitating faster price stabilization.

Volatility Modeling of Horticultural Commodity Returns

Table 7 reports the selected ARIMA mean equations and the corresponding ARCH–LM test results for horticultural commodity returns across the eight study regions. The selected mean specifications are dominated by ARIMA(2,0,1) and ARIMA(2,0,2) models, while Blitar and Tuban are adequately represented by ARIMA(1,0,2). These relatively low-order ARIMA models indicate that short-run price dynamics in horticultural markets can be captured by recent autoregressive and moving-average components.

The ARCH–LM test confirms the presence of significant conditional heteroskedasticity in all regional return series. The null hypothesis of homoskedastic residuals is rejected at the 5% significance level for every region, indicating that horticultural price volatility varies systematically over time. These results justify the application of the GARCH family of models to characterize the conditional variance of horticultural commodity prices.

Table 7. Selected Mean Equation and ARCH–LM Test Results for Horticultural Commodity Prices

Commodity	Selected Mean Equation	ARCH–LM Test (Lag 3)*	Note
Surabaya	ARIMA (2,0,1)	21.46 (0.000)*	ARCH effect detected
Probolinggo	ARIMA (2,0,2)	19.73 (0.000)*	ARCH effect detected
Malang	ARIMA (2,0,1)	17.82 (0.001)*	ARCH effect detected
Madiun	ARIMA (2,0,2)	18.65 (0.000)*	ARCH effect detected
Kediri	ARIMA (2,0,2)	9.41 (0.024)	ARCH effect detected
Jember	ARIMA (2,0,2)	15.88 (0.001)*	ARCH effect detected
Blitar	ARIMA (1,0,2)	18.12 (0.001)*	ARCH effect detected
Tuban	ARIMA (1,0,2)	16.57 (0.002)*	ARCH effect detected

Note: *probability of ARCH testing

Unlike the results obtained for food commodities, model comparison consistently shows that asymmetric GARCH specifications outperform conventional symmetric GARCH models across all study regions (Table 8). This finding represents one of the principal empirical results of the study, indicating that volatility in horticultural commodity prices cannot be adequately explained solely by the magnitude of market shocks. Instead, the direction and nature of shocks play an equally important role in determining subsequent volatility dynamics.

The best asymmetric models reflects the intrinsic characteristics of horticultural commodities. Products such as chili, shallots, and garlic are highly perishable, strongly dependent on seasonal production, and particularly vulnerable to weather disturbances, pest infestations, and distribution disruptions. Consequently, adverse supply shocks generally generate much larger increases in price uncertainty than favorable production shocks of comparable magnitude. Under these market conditions, volatility responds asymmetrically to new information, making asymmetric GARCH models more appropriate than their symmetric counterparts. Similar conclusions have been reported by Harshana and Ratnasiri (2023); Sari et al. (2023), who demonstrate that agricultural commodity markets frequently exhibit asymmetric volatility arising from supply-side constraints.

Table 8. Presents the Selected Best Fitting Models for Horticultural Commodities

Regional	Model Type		AIC	Selection Model
Surabaya	Simetri	GARCH (1,1)	-6503	EGARCH (1,1)
	Asimetri	**EGARCH (1,1)**	**-6673**	
Probolinggo	Simetri	GARCH (2,2)	-7355	EGARCH (2,2)
	Asimetri	**EGARCH (2,2)**	**-7430**	
Malang	Simetri	GARCH (1,1)	-7502	TGARCH (1,1)
	Asimetri	**TGARCH (1,1)**	**-7601**	
Madiun	Simetri	GARCH (2,1)	-8604	EGARCH (2,1)
	Asimetri	**EGARCH (2,1)**	**-8719**	
Kediri	Simetri	GARCH (1,2)	-5470	EGARCH (1,2)
	Asimetri	**EGARCH (1,2)**	**-5519**	
Jember	Simetri	GARCH (2,1)	-6531	APARCH (2,1)
	Asimetri	**APARCH (2,1)**	**-6566**	
Blitar	Simetri	GARCH (1,2)	-7054	EGARCH (2,1)
	Asimetri	**EGARCH (1,2)**	**-7261**	
Tuban	Simetri	GARCH (1,1)	-7269	APARCH (1,1)
	Asimetri	**APARCH (1,1)**	**-7397**	

Source: Author’s Computation

Among the asymmetric specifications, EGARCH is selected as the optimal model for Surabaya, Probolinggo, Madiun, Kediri, and Blitar. The dominance of EGARCH indicates the presence of leverage effects, whereby negative shocks exert a larger influence on future volatility than positive shocks of similar magnitude. In horticultural markets, this phenomenon is economically plausible because supply disruptions, such as crop failures, extreme weather events, or transportation bottlenecks, typically trigger immediate and substantial price increases, whereas favorable production conditions generally lead to more gradual price adjustments.

In Malang, the TGARCH specification provides the best fit, suggesting the existence of a threshold effect in volatility. This result implies that market uncertainty rises disproportionately once price shocks exceed a critical magnitude, indicating that the response of volatility is nonlinear. Such behavior is consistent with regional markets where temporary supply disturbances remain manageable until they surpass the market's adjustment capacity, after which volatility escalates rapidly.

Meanwhile, Jember and Tuban are best characterized by the APARCH model, indicating that both the size and the direction of shocks jointly determine conditional volatility. Unlike standard GARCH models, APARCH allows volatility responses to vary according to the magnitude of market disturbances, implying that large shocks amplify not only current volatility but also the market's sensitivity to subsequent shocks. This behavior is particularly relevant in production-oriented regions, where climatic disturbances or harvest failures may generate persistent uncertainty throughout successive production cycles.

Overall, the consistent dominance of asymmetric GARCH models across all regions demonstrates that horticultural commodity markets exhibit substantially more complex volatility dynamics than staple food markets. While food commodity volatility is largely explained by persistent fluctuations of similar intensity regardless of shock direction, horticultural markets display clear evidence that negative supply shocks generate disproportionately larger increases in volatility. This finding highlights the importance of accounting for asymmetric risk when modeling horticultural commodity prices and suggests that volatility management policies should focus not only on reducing the frequency of market disturbances but also on mitigating the consequences of adverse supply shocks

Table 9. Estimated ARCH–GARCH Parameters for Horticultural Commodities Using the Best Fitting GARCH Model

	Surabaya	**Probolinggo**	**Malang**	**Madiun**	**Kediri**	**Jember**	**Blitar**	**Tuban**
ARIMA (l,0,k) GARCH (p,q)	(2,0,1) EGARCH (1,1)	(2,0,2) EGARCH (2,2)	(2,0,1) TGARCH (1,1)	(2,0,2) EGARCH (2,1)	(2,0,2) EGARCH (1,2)	(2,0,2) APARCH (2,1)	(1,0,2) EGARCH (2,1)	(1,0,2) APARCH (1,1)
ARCH-LM	0.590 (0.000)	0.439 (0.000)	0.451 (0.000)	0.471 (0.000)	0.652 (0.015)	0.483 (0.000)	0.471 (0.000)	0.504 (0.000)
ω (konstanta)	0.0815 (0.000)	0.0646 (0.006)	0.012 (0.000)	0.0013 (0.000)	0.025 (0.000)	0.027 (0.000)	0.389 (0.000)	0.112 (0.000)
α1 (ARCH)	0.396 (0.000)	0.493 (0.000)	0.404 (0.000)	0.396 (0.000)	0.127 (0.000)	0.277 (0.000)	0.205 (0.000)	0.472 (0.000)
α2 (ARCH)		0.013 (0.004)		0.289 (0.000)		0.380 (0.000)		
β1 (GARCH)	0.423 (0.000)	0.027 (0.011)	0.356 (0.000)	0.838 (0.000)	0.295 (0.000)	0.362 (0.000)	0.771 (0.000)	0.327 (0.000)
β2 (GARCH)		0.494 (0.000)			0.562 (0.000)			
γ1 (Leverage Effect)	-0.670 (0.000)	-0.231 (0.000)	0.421 (0.003)	0.579 (0.000)	0.479 (0.000)	-0.285 (0.000)	0.533 (0.000)	-0.178 (0.000)
AIC	-6673	-7430	-7601	-8719	-5519	-6566	-7261	-7397
BIC	-6351	-7371	-7560	-8667	-5478	-6520	-7220	-7356
Ljung–Box test	12.575 (0.648)	6.393 (0.320)	8.189 (0.519)	8.923 (0.530)	13.812 (0.635)	3.665 (0.123)	9.273 (0.369)	2.389 (0.271)

Source: Author's Computation

Table 9 presents the estimated parameters of the best-fitting GARCH models for horticultural commodities across the eight regions. All key parameters are statistically significant at the 5% level, indicating that the selected specifications adequately capture the volatility dynamics of horticultural commodity prices. Furthermore, the Ljung–Box test applied to the squared residuals produces p-values greater than 0.05 for all regions, suggesting the absence of remaining autocorrelation in the squared residuals. These results confirm that the estimated models have successfully captured the conditional heteroskedasticity in the data, leaving white-noise residuals and providing a reliable basis for interpreting the volatility behavior of horticultural commodity prices.

The positive and statistically significant ARCH coefficients (α) across all regions indicate that current price volatility responds strongly to new information and recent price shocks. According to Bollerslev (1986), the ARCH parameter measures the immediate impact of unexpected shocks on current conditional volatility. In horticultural markets, this behavior reflects the high sensitivity of prices to short-term disruptions in production, weather conditions, and distribution networks. Unlike staple food commodities, most horticultural products are highly perishable, implying that supply disturbances are rapidly transmitted into market prices. As emphasized by Alfeus and Nikitopoulos (2022), the perishable nature of horticultural commodities causes information regarding production, harvesting, and transportation conditions to be incorporated into prices almost immediately, thereby amplifying short-run volatility. Nevertheless, the magnitude of this sensitivity differs across regions. Probolinggo (α_1 = 0.493), Tuban (α_1 = 0.472), Malang (α_1 = 0.404), Surabaya (α_1 = 0.396), and Madiun (α_1 = 0.396) exhibit relatively stronger responses to short-run shocks, whereas Kediri records the lowest ARCH coefficient (α_1 = 0.127), suggesting that volatility in this region is less influenced by newly arriving information. These regional differences imply that the speed at which markets react to supply disruptions varies according to local production systems, distribution efficiency, and market structure.

The positive GARCH coefficients (β) indicate that horticultural price volatility is highly persistent over time. As explained by Bollerslev (1986), the GARCH parameter measures the extent to which past volatility is transmitted into future volatility, with larger coefficients indicating a slower return to the long-run equilibrium. Madiun (β_1 = 0.838), Blitar (β_1 = 0.771), Kediri ($\beta_1 + \beta_2$ = 0.857), and Probolinggo ($\beta_1 + \beta_2$ = 0.521) exhibit relatively stronger persistence, implying that the effects of price shocks remain in the market for a longer period. In contrast, Surabaya (β_1 = 0.423), Malang (β_1 = 0.356), Jember (β_1 = 0.362), and Tuban (β_1 = 0.327) display lower persistence, indicating a faster adjustment of volatility following market disturbances. Such regional heterogeneity is likely associated with differences in production capacity, marketing systems, transportation infrastructure, and the flexibility of regional supply chains, all of which influence how quickly markets absorb shocks and restore equilibrium.

Compared with staple food commodities, the estimated ARCH and GARCH coefficients for horticultural commodities are generally larger, suggesting that horticultural price volatility is both more sensitive to new shocks and more persistent over time. This finding is consistent with the structural characteristics of horticultural products, whose production is highly seasonal, weather-dependent, and constrained by short storage life. Consequently, even relatively small supply disruptions caused by adverse weather, pest infestations, delayed harvesting, or transportation bottlenecks can rapidly translate into substantial price fluctuations. Similar evidence has been documented by Harshana and Ratnasiri (2023); Hartono et al. (2023); Sari et al. (2023), who report that volatility in Indonesian horticultural markets is primarily driven by seasonal production patterns, perishability, and distribution uncertainty. These characteristics also explain why asymmetric GARCH specifications consistently outperform symmetric GARCH models in representing horticultural price dynamics.

The volatility behavior of horticultural commodities in East Java also exhibits strong asymmetric characteristics, as reflected by the statistically significant asymmetry parameter (γ) in every region. This result indicates that price volatility depends not only on the magnitude of market shocks but also on their direction. Consequently, positive and negative price changes generate different volatility responses, making symmetric GARCH models inadequate for accurately representing horticultural price dynamics. This finding is consistent with the theoretical developments of Ding et al. (1993), and Zakoian (1994), who proposed asymmetric GARCH models specifically to capture differential volatility responses to positive and negative innovations. Likewise, Sari et al. (2023) found that Indonesian agricultural commodity prices exhibit asymmetric volatility, indicating that asymmetric GARCH models provide a superior representation of market behavior compared with conventional symmetric GARCH models.

It should be noted that the economic interpretation of both the magnitude and the sign of the asymmetry coefficient depend on the underlying model specification. Since the best-performing models in this study include EGARCH, TGARCH, and APARCH, whose asymmetry parameters are formulated differently, the estimated γ coefficients cannot be directly compared across regions. Therefore, the principal finding is not the sign of γ itself but rather its statistical significance across all regional markets. The consistently significant asymmetry parameters provide robust evidence that price direction constitutes an essential determinant of volatility formation in East Java's horticultural markets and should therefore be incorporated into both volatility modeling and price forecasting.

Overall, the results reveal fundamental differences in the volatility formation mechanisms of staple food and horticultural commodities. While staple food prices are adequately characterized by symmetric GARCH models, indicating that volatility depends primarily on the magnitude of price shocks, horticultural commodities are consistently better represented by asymmetric GARCH models, implying that both the magnitude and direction of shocks influence volatility dynamics. These differences reflect the contrasting structural characteristics of the two commodity groups. Staple food markets generally benefit from more established distribution systems, stronger government price stabilization policies, and greater storage capacity, resulting in relatively stable price movements. In contrast, horticultural commodities are constrained by perishability, strong dependence on weather and seasonal production, and limited short-run supply flexibility, making their prices considerably more volatile and inherently asymmetric. Similar conclusions have been reached by Alfeus and Nikitopoulos (2022) and Lu et al. (2023), who emphasize that agricultural commodity volatility is fundamentally shaped by local market structures and supply chain characteristics.

CONCLUSION AND SUGGESTION

This study investigates regional commodity price volatility in East Java by jointly examining differences across commodity groups and regional markets. Using daily price returns and GARCH family models, the analysis demonstrates that commodity price volatility varies systematically not only between food and horticultural commodities but also across regions.

The results reveal clear differences in volatility behavior between the two commodity groups. Food commodities exhibit relatively moderate volatility and are consistently best represented by symmetric GARCH models, indicating that price volatility is primarily driven by the magnitude of shocks. In contrast, horticultural commodities display substantially higher volatility and are consistently characterized by asymmetric GARCH models, suggesting that both the magnitude and the direction of price shocks play important roles in determining volatility dynamics. The larger ARCH and GARCH coefficients estimated for horticultural commodities further indicate that these markets are generally more responsive to new information and exhibit stronger volatility persistence than food commodities. These contrasting patterns reflect the distinct structural characteristics of the two commodity groups. While food commodities generally benefit from more established distribution systems, larger storage capacity, and government stabilization programs, horticultural commodities are more vulnerable to seasonal production, weather uncertainty, perishability, and short-run supply constraints.

Beyond commodity differences, the analysis also identifies substantial regional heterogeneity in volatility dynamics. Although all regions experience significant conditional heteroskedasticity, the magnitude of volatility responses, persistence, and the most appropriate GARCH specifications differ across regions. These findings suggest that regional production structures, market integration, distribution efficiency, and supply chain characteristics influence how price shocks are transmitted and absorbed. Consequently, commodity price volatility cannot be viewed as a homogeneous phenomenon, even within a single province.

The findings provide important policy implications. A uniform price stabilization strategy is unlikely to be equally effective across commodities and regions. For food commodities, strengthening interregional distribution systems, maintaining strategic food reserves, and improving market coordination remain appropriate measures to reduce overall price variability. In contrast, managing horticultural price volatility requires more comprehensive interventions that address production and supply-side risks, including improvements in production information systems, cold-chain infrastructure, post-harvest handling, and responsive regional distribution networks. Moreover, regional differences in volatility behavior imply that stabilization policies should be adapted to local market conditions rather than implemented uniformly across East Java.

Overall, this study highlights that both commodity characteristics and regional market structures jointly determine price volatility. Incorporating these two dimensions into volatility modeling provides a more comprehensive understanding of regional agricultural markets and offers a stronger empirical foundation for designing more targeted and effective commodity price stabilization policies.

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