Applied Big Data Driven Study on Shock Absorption and Tolerance Bands of Staple Food Commodities Price Volatility in East Java

***Firman Sihol Parningotan*[1]*, Aviliani*[1]*, Jonathan Ersten Herawa*[2] *and Matthew Kartawinata*[3]**
[1]*Fakultas Ekonomi dan Bisnis, Perbanas Institute, Indonesia*
[2]*Magister Ekonomi Terapan, Unika Atmajaya Jakarta, Indonesia*
[3]*Fakultas Bisnis dan Ekonomika, Universitas Atma Jaya Yogyakarta, Indonesia*
Corresponding author: erstenjonathan@gmail.com

Abstract

This study investigates the day-to-day volatility dynamics of five staple food commodities in East Java which are Red Bird's Eye Chili Pepper, Medium Rice, Bendera Powdered Milk, Free-Range Chicken Meat, and Commercial Chicken Eggs. By utilizing daily price data from January 1, 2021, to February 2, 2025, collected via big-data scraping of a government price monitoring website. A GARCH model with Student-t innovations is fitted to each return series, from which one-day 95% Value-at-Risk (VaR) thresholds are derived to establish an evidence-based "tolerance band" for policy intervention. The results show that Red Bird's Eye Chili Pepper has the widest band, with an allowable daily drop of 2.5% and a rise of 10.14%, whereas Bendera Powdered Milk exhibits the narrowest range. All five series display extreme volatility persistence coefficients are near or above 1, but a critical finding is that the markets for Medium Rice and Free-Range Chicken Meat are not shock absorbent, with persistence values exceeding 1. This indicates that any market disruption has a permanent effect on their future volatility, pointing to deep structural inefficiencies. These empirically derived VaR-based guardrails provide a quantitative framework for timely market stabilization, while the persistence analysis highlights the need for long-term structural reforms, particularly for the rice and chicken sectors.

Keywords*: food price volatility, GARCH, value-at-risk, big data*
JEL*:* ***C54, Q11, Q1***

A. INTRODUCTION

The contemporary global economic landscape is marked by significant instability, driven by factors such as geopolitical uncertainty, trade conflicts, and climate crises that threaten the stability of international food supply chains. In this environment, many nations have adopted increasingly protectionist economic policies, including export restrictions and domestic stockpiling of food reserves. This trend towards "agri-nationalism" has amplified global commodity price volatility, heightening the risk of imported inflation in nations like Indonesia. Consequently, the Indonesian government has designated food security as a primary national development priority, focusing on strengthening domestic production and reinforcing distribution systems and food reserves. Although international trade principles advocate for special treatment of food commodities, the erosion of multilateralism has shifted the global trade order from a rules-based system to one dominated by unilateral actions. This shift has rendered multilateral cooperation, the traditional bedrock of international food trade management, less effective and has compelled developing nations like Indonesia to bolster their own food sovereignty to reduce dependency on a volatile global market (Swinnen & McDermott, 2020).

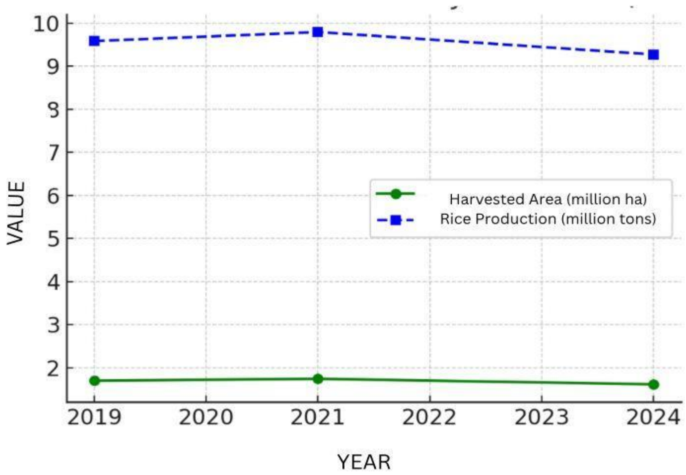

Figure 1. Harvested Area and Rice Production in East Java Province, 2019–2024
Source: Statistics Indonesia

Within Indonesia's economic structure, East Java plays a pivotal role in the food agriculture industry, making it a critical province for national economic stability. The province is a major supplier of agricultural products such as rice, corn, and horticultural crops, and thus serves as a key barometer for national food stability. With a population estimated at 41.5 million in mid-2023, East Java faces significant challenges not only as a primary food producer but also as a major consumption center. As a result, developments in East Java's food sector directly impact public welfare at both regional and national levels.

In addition to rice, East Java is the nation's leading producer of corn, with an estimated output of 4.49 million tons in 2024, representing nearly 30% of the national total. Its horticultural production is similarly dominant, with chili pepper production reaching 562,816 tons (37.9% of national output). These figures establish East Java as a national horticultural hub and underscore its importance in the price dynamics of strategic food items. However, high production volumes do not automatically guarantee supply availability or price stability. Inflation in East Java continues to be driven by the volatile foods component, particularly chili, fish, chicken meat, and rice. In January 2025, volatile food inflation was recorded at 2.95% month-on-month and 3.07% year-on-year. Price increases in this commodity group are particularly detrimental to public purchasing power, especially for low-income households who spend a large portion of their income on food (Mukhlis et al., 2022).

This trend indicates a direct correlation between production fluctuations and inflationary pressures. When production declines due to natural and structural factors, supply tightens and prices tend to rise, forcing households to allocate more funds to meet basic needs. This problem is compounded by an inefficient distribution system and insufficient strategic food reserves for government intervention. Recent studies also show that food price shocks directly impact the welfare of farmers and poor households. While commodity price increases may offer farmers a temporary improvement in their terms of trade, price instability generally erodes welfare, as it is often not accompanied by income protection or access to agricultural input subsidies (Setiadi et.al, 2024).

To stabilize food inflation, the provincial government, together with the Regional (TPID) and Central (TPIP) Inflation Control Teams, has undertaken several initiatives, including optimizing cropping indices, increasing productivity, and developing agricultural technology and data collection. However, these efforts still face significant structural challenges, particularly in financing, technology adoption, and managing risks from agricultural disasters like droughts. While East Java has consistently recorded a rice surplus over the past five years, 1.49 million tons in 2020, declining to 1.13 million tons in 2022, this downward trend signals long-term pressure on food security, especially if the impacts of climate change and land conversion are not promptly addressed. This research, therefore, provides a critical analysis of food price dynamics in East Java, offering a basis for developing more inclusive and resilient regional development strategies to face future food crises.

East Java, one of Indonesia's most populous and economically vital provinces, grapples with significant challenges in upholding household welfare and food security. A critical issue for the region is its pronounced vulnerability to food-price inflation, a problem exacerbated by the diminishing role of agriculture in its economy. Globally, the volatility of food prices has become a primary driver of food insecurity in the 21st century. Although the 2008 global food crisis spurred investments in monitoring domestic food prices, this measure alone is insufficient for gauging changes in diet affordability.

To achieve that, one must also track changes in income or a suitable proxy. In this regard, Headey et al. (2023) demonstrate that the real wages of unskilled workers serve as a timely and cost-effective proxy for monitoring food affordability, especially for non-farm poor households. Their analysis shows that food wages, wages deflated by food price indices, decline rapidly during crises, often by 20–30% within a few months, reflecting sharp reductions in purchasing power as food prices rise faster than wages.

This dynamic highlights how daily fluctuations in essential food prices can quickly erode the real incomes of low-income households. As the authors further argue, understanding household responses to changing prices requires incorporating food-price elasticities into policy design so that interventions can stabilize markets and safeguard access to essential commodities.

B. LITERATURE REVIEW

The Challenge of Food Price Volatility in Developing Economies

Food price volatility, marked by sharp and often unpredictable fluctuations in the cost of essential food items, poses a persistent and critical challenge for developing economies. This is especially evident in East and Southeast Asia, where recent surges in food inflation have heightened concerns about food insecurity and systemic risks (Zhou et al., 2023). Empirical evidence shows that volatility is driven not only by domestic factors but also by broader global forces: international determinants such as oil and fertilizer prices, global economic activity, and geopolitical risk significantly influence food price volatility across market conditions, with geopolitical risk emerging as one of the most consistently important drivers (Zmami & Ben-Salha, 2023).

These vulnerabilities are amplified by structural features of agricultural markets. Food commodities typically exhibit inelastic short-run supply and demand, meaning that even modest disruptions can translate into large price swings. Cross-country evidence shows that volatility is shaped by production variability, limited stock levels, weak governance, and high transaction costs, all of which restrict the ability of markets to stabilize prices during shocks (Kornher & Kalkuhl, 2013). Climate-related shocks have become an increasingly prominent source of instability, as meteorological fluctuations, such as temperature anomalies and rainfall variability, exert statistically significant effects on crop price volatility, particularly for climate-sensitive commodities in developing agrarian economies (Kumar et al., 2025).

For regions like East Java, these global and structural pressures intersect with ongoing structural transformation. As the agricultural share in the provincial economy declines and the region becomes more reliant on food sourced externally, exposure to national and international market dynamics increases. East Java's domestic price-stabilization measures can thus be undermined by policy decisions and shocks originating elsewhere, underscoring that food price volatility is not merely a local supply issue but a systemic challenge embedded in wider economic and geopolitical networks.

Determinants of Staple Food Price Volatility

Food price volatility arises from a complex interaction of structural, climatic, macroeconomic, and market forces. Foundational work shows that volatility is shaped by both supply-side shocks, such as weather disruptions, yield variability, and technological constraints and demand-side fluctuations, market expectations, and policy dynamics (Chavas et al., 2014). Importantly, food price movements contain both long-term trends and high-frequency components, implying that volatility reflects persistent structural factors as well as short-run shocks that can trigger sudden spikes or declines. Empirical evidence indicates that global drivers such as energy prices, international demand conditions, and market uncertainty significantly contribute to fluctuations in food price volatility across countries (Wang et al., 2018).

On the supply side, climate-related shocks, including extreme temperatures, erratic rainfall, droughts, and other weather anomalies, are shown to exert significant upward pressure on crop prices and destabilise market conditions. A systematic meta-analysis demonstrates that climate variability consistently contributes to fluctuations in food prices across different global regions (Birgani et al., 2022), while recent modelling evidence finds that climate-induced shocks significantly intensify price volatility through production disruptions and technological constraints (Kazeem, 2024). The global agricultural futures market is also highly responsive to uncertainty in energy and climate systems: energy-market volatility and climate-risk uncertainty spill over into agricultural commodity prices, reinforcing volatility through cost channels and expectation-driven mechanisms (Anupam Dutta et al., 2024).

Beyond climatic pressures, global macro-financial conditions play a central role in transmitting and amplifying food-price instability. Swings in oil and fertiliser prices, geopolitical disruptions, and volatility in global demand collectively shape the volatility of international food-price indices and contribute to persistent price uncertainty, particularly in developing economies (Zmami, 2025). For many developing countries, volatility in global commodity prices, international demand fluctuations, or exchange-rate changes seeps through imperfect supply-chain integration and trade linkages. Studies demonstrate that when international price volatility rises, domestic food prices also tend to experience increased volatility, especially where domestic production is low or markets are highly reliant on imports (Ceballos et al., 2016).

Market structure and efficiency further determine how these shocks are transmitted through food supply chains. Integration between local, regional, and global markets shapes whether international or wholesale price shocks translate into domestic retail prices; weak integration or poor infrastructure can block or distort this transmission, increasing the likelihood of localised price spikes and inefficiencies. Empirical evidence shows that retail prices respond more strongly to upstream price increases than to decreases, indicating asymmetric price transmission that disadvantages consumers when wholesale costs rise but cushions intermediaries when they fall (Rezitis et al., 2018). Infrastructure and logistics are also critical: access to dense, well-connected road networks reduces food price volatility by smoothing transport costs, facilitating distribution across regions, and improving market access, while regions suffering from poor connectivity or logistical bottlenecks are more vulnerable to supply disruptions or regional price shocks that cannot be arbitraged away (Lambert et al., 2025).

Taken together, structural, market-integration, and infrastructural dynamics illustrate how vulnerabilities can accumulate and reinforce one another. For a region such as East Java, whose structural transformation involves a declining agricultural base and growing dependence on external food sources, these dynamics heighten exposure to global and national market shocks and limit the stabilising power of local policy tools.

Socio-Economic Consequences of Food Price Volatility

Food price volatility has profound socio-economic consequences, disproportionately affecting vulnerable populations, particularly low-income and food-insecure households in developing countries. These impacts extend beyond short-term affordability to shape long-term nutritional outcomes, poverty dynamics, and overall household welfare. Volatility undermines food security by reducing access to essential items: when prices surge, the purchasing power of low-income urban consumers and rural net food buyers declines sharply, forcing them to reduce not only the quantity but also the quality of food consumed. Evidence from developing countries demonstrates that food-price shocks significantly contract household food consumption, especially in contexts where fiscal space to cushion the shock is limited (Meyimdjui & Combes, 2021). Such shifts toward cheaper, less nutritious foods heighten the risks of micronutrient deficiencies and child malnutrition, with consequences that can persist across generations.

A useful way to capture this erosion of affordability is through the concept of food wages, nominal wages deflated by a relevant food-price index, which provides a timely and sensitive indicator of real food access for poor households. During price surges, if wages fail to keep pace, real food wages can decline sharply, reflecting an immediate loss of purchasing power. Research shows that rising food prices substantially increase poverty risks in developing economies, particularly among net food purchasers who bear the brunt of inflationary pressure (Headey, 2018). As affordability deteriorates, households often resort to harmful coping strategies such as reducing essential non-food expenditures, taking on high-cost debt, or selling productive assets, all of which weaken long-term resilience.

Producers are also affected by volatile prices. Persistent volatility generates uncertainty that discourages investment in productivity-enhancing inputs, constraining potential yield improvements and perpetuating structural stagnation. Recent evidence highlights that higher food-price volatility reduces household food security by limiting access to adequate diets and constraining the ability of households to smooth consumption during shocks (Amolegbe et al., 2021). These dynamics underscore why food-price volatility poses a significant challenge for both consumers and producers, especially in regions experiencing rapid urbanisation and a declining agricultural share, where a growing proportion of the population is becoming net food consumers.

Research Gaps and Niche

Despite extensive work on food prices and volatility, several important gaps remain in the literature, particularly with respect to data frequency, spatial resolution, and methodological approaches. Existing research consistently highlights the importance of understanding the relationship between agricultural output and price stability, as disruptions in either dimension can threaten household welfare. However, a key limitation in much of the existing literature lies in the frequency of the data employed. Studies relying on monthly or annual observations risk overlooking the rapid, often daily, adjustments households make when prices shift. High-frequency data provide a sharper lens: they capture short-term fluctuations and allow researchers to observe consumption responses and market dynamics with far greater precision. Recent evidence demonstrates that high-frequency indicators can track economic conditions more accurately and in a timelier manner than traditional, lower-frequency datasets (Gascon & Schmitz, 2020). This granularity is crucial for improving elasticity estimates and supporting policy interventions that must respond to rapidly evolving market conditions.

However, many studies, particularly those conducted at the national level or involving multiple food commodities, continue to rely on low-frequency price series such as monthly averages. This reliance tends to smooth over short-term fluctuations and obscures the rapid price adjustments that characterise highly perishable or frequently traded food commodities. For instance, recent analyses of volatility in Indonesia's strategic food commodities—including rice, chili, shallots, garlic, and cooking oil—are based on monthly national price data, limiting their ability to capture high-frequency dynamics (Matondang et al., 2023). Likewise, broader work examining volatility spillovers across Indonesia's provinces employs monthly rural producer-price data, which, while valuable for understanding spatial transmission patterns, does not account for daily or intra-week volatility that households and traders experience in real time (Theresia et al., 2025).

The scarcity of high-frequency, multi-commodity datasets stands in clear contrast to the increasing relevance of short-term shocks in global food markets. International evidence shows that volatility can intensify or spread rapidly across markets in response to policy actions such as export bans or changes in import regulations, effects that unfold far more quickly than monthly datasets are able to capture (Brander et al., 2023). As a result, despite meaningful progress in Indonesia's food price literature, the continued reliance on low-frequency data limits our ability to observe the real-time volatility that households and traders actually face. This gap also constrains our understanding of how short-term shocks move through different commodities, supply chains, and local markets.

This limitation is further compounded by the scarcity of subnational, high-frequency analyses that use advanced econometric tools to capture regional variation. Studies conducted at the national level, or those relying on aggregated indices, are not well suited to guide local policy because they overlook the substantial differences in market structures, supply chains, and consumption patterns across Indonesia's provinces. Recent research shows that demand elasticities and the welfare impacts of price shocks vary greatly across regions, meaning that policy conclusions drawn from national aggregates may misrepresent the actual vulnerabilities experienced by specific communities (Hamzah et al., 2023). Without empirical frameworks that combine high-frequency volatility measures with region-specific behavioural responses, policymakers lack the analytical tools needed to translate volatility forecasts into actionable risk thresholds for staple foods at the local level. As a result, interventions often remain reactive rather than preventative, limiting their effectiveness in protecting

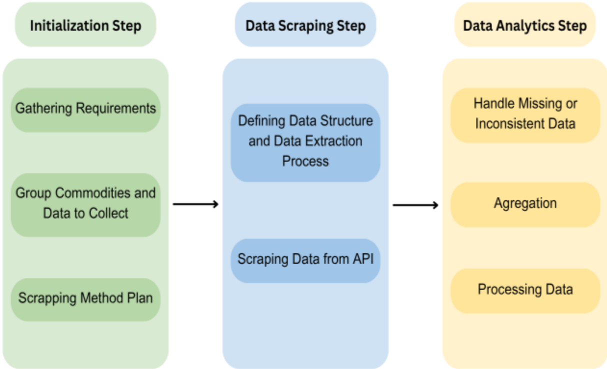

Figure 2. Data Aggregation Framework
Source : Processed by Author

household welfare during periods of sharp price instability.

Methodologically, machine learning techniques have become increasingly intertwined with econometric practice, particularly when handling high-dimensional datasets. These methods facilitate variable selection, regularisation, and robust predictive modelling, and they have enabled real-time economic monitoring through approaches such as nowcasting, which leverage search engine data, online behaviour, or satellite imagery to infer short-term economic conditions. In parallel, distributed computing frameworks significantly expand researchers' ability to process large datasets. Bluhm and Cutura (2022), for example, demonstrate how Apache Spark can parallelise econometric tasks ranging from microeconomic regressions to time-series modelling, dramatically reducing computation time and lowering the barriers for researchers with limited resources to work with terabyte-scale data.

The present study adopts this big-data paradigm by scraping more than one million daily price observations from Bank Indonesia's PIHPS (Price Monitoring Survey) system. While the raw scraped data encompass a wide variety of food commodities across East Java, this research focuses specifically on five key staple food commodities—Red Bird's Eye Chili Pepper, Medium Rice, Powdered Milk (400 g), Free-Range Chicken Meat, and Commercial Chicken Eggs—to analyse volatility behaviour using a high-frequency dataset. We estimate GARCH models to characterise time-varying volatility and compute one-day 95 percent Value-at-Risk thresholds to define maximum allowable daily price drops and rises. By uniting high-frequency big-data collection, sophisticated volatility modelling, and risk-based guardrails, this research offers a replicable, subnational methodology that addresses the identified gaps and enhances the precision and responsiveness of food-price stabilisation policies.

C. RESEARCH METHODS

The data aggregation framework presents the overarching research framework, which unfolds in three sequential stages. The Initialization stage establishes the study's scope and data requirements, defining the five target commodities and specifying the daily price series to be collected. In the Data Scraping stage, an automated crawler extracts over 1,446 observations per commodity from the East Java provincial government's online price portal, yielding a high-frequency "big-data" repository. The Data Analytics stage then transforms the raw series, aligning timestamps, handling missing values and outliers, and computing log-returns for econometric modeling. This structured pipeline ensures that the subsequent GARCH(1,1) estimation and Value-at-Risk calculations rest on a robust, granular, and timely daily price dataset.

Data

Data collection followed a three-stage research framework, beginning with an automated web-scraping step directed at the Pusat Informasi Harga Pangan Strategis Nasional (National Strategic Food Price Information Center) portal. This process harvested daily price quotes for Red Bird's Eye Chili Pepper, Medium Rice, Bendera Powdered Milk (400 g), Free-Range Chicken Meat, and Commercial Chicken Eggs in East Java. Leveraging big-data techniques, the scraper captured over 1447 daily observations per commodity, far exceeding traditional monthly series, and stored them in a structured database for subsequent analysis. This high-frequency dataset enhances temporal granularity and supports near–real-time monitoring of price movements, enabling more responsive volatility modeling than is possible with lower-frequency data. Such web-scraped price data have been shown to improve the timeliness and accuracy of consumer-price measurements (Cavallo & Rigobon, 2016).

The choice of these specific commodities was deliberate. They represent dietary cornerstones for the majority of Indonesian households and are significant components of household expenditure, particularly for low-income families. Rice is the primary staple, while eggs and chicken are the most accessible sources of animal protein. Chili is a fundamental ingredient in Indonesian cuisine, and its price fluctuations are often a primary driver of short-term food price inflation (Mariyono, 2017).

Consequently, monitoring the price stability of these specific items is critical for assessing overall food security and public welfare, making them ideal subjects for a study on inflation and policy intervention (Purba et al., 2021). After collection, the raw price series underwent standardised cleaning procedures, including timestamp alignment, outlier detection, and the treatment of missing entries, prior to the computation of log returns. Missing observations were addressed using linear interpolation, which maintains the continuity of the time series and prevents the introduction of artificial shocks that can arise from mean or median based imputation. This approach is widely used in high frequency price datasets and ensures that the resulting series is suitable for volatility modelling.

GARCH Model Specification and Mean Equation

This study employs a quantitative approach to model and forecast the volatility of selected commodity prices. The methodology follows a structured process encompassing data preparation, model specification, competitive model estimation, and rigorous diagnostic validation. The entire analysis is conducted using the R programming language, primarily leveraging the rugarch package (Ghalanos, 2022). The dataset consists of daily prices for five key commodities: Red Bird's Eye Chili Pepper, Medium Rice, Bendera Brand Powdered Milk, Free-Range Chicken Meat, and Commercial Chicken Eggs. Financial time series, such as commodity prices, are typically non-stationary and their variance is not constant over time (Brooks, 2019). To address this and obtain a stationary series suitable for volatility modeling, the daily prices P_t were transformed into continuously compounded percentage returns, commonly known as log-returns r_t .
The log-return at time t is calculated as :

$$P_t = ln\,(\frac{P_t}{P_{t-1}}) = ln(P_t) - ln(P_{t-1}) \qquad (1)$$

This transformation is standard practice in financial econometrics as log-returns exhibit more desirable statistical properties, such as stationarity, and their distribution is closer to a normal distribution, although often with heavier tails (Tsay, 2010).

To capture the time-varying volatility and volatility clustering observed in the commodity returns, the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) framework was employed. A complete GARCH model consists of a mean equation and a variance equation. The mean equation aims to capture any linear dependencies or serial correlation present in the returns series. Based on preliminary analysis, an Autoregressive model of order 1 (AR(1)) was specified for the conditional mean. The equation is:

$$r_t = \mu + \phi_1 r_{t-1} + \varepsilon_t \quad (2)$$

where :

- μ is the constant mean.
- ϕ_1 is the autoregressive coefficient capturing the effect of the previous period's return
- ε_t is the error term (or shock) at time t

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \quad (3)$$

where :

- ω = constant that represent the long-run average variance
- α = the impact of shocks in the previous period
- β = the persistence of past volatility

Furthermore, a key feature of financial returns is leptokurtosis, meaning their distribution has "fat tails" and a higher peak compared to a normal distribution. This implies that extreme price movements are more frequent than a normal distribution would suggest. To adequately capture this characteristic, the standardized residuals (z_t) are assumed to follow a Student's t-distribution instead of a normal distribution (Bollerslev, 1987).

Competing GARCH Models and Model Selection

To identify the most appropriate model for each commodity's return series, three distinct GARCH specifications were estimated and compared. All models use a GARCH(1,1) structure for the variance equation, which has been shown to be sufficient for modeling volatility in most financial time series (Hansen & Lunde, 2005). To identify the most appropriate volatility structure, three competing specifications were estimated, starting with the standard GARCH (sGARCH) model as a baseline (Bollerslev, 1986). The sGARCH model is symmetric, meaning it assumes that positive and negative shocks of the same magnitude have an identical effect on future volatility and is used to capture general volatility clustering. However, financial markets often exhibit asymmetric responses to news, a phenomenon the sGARCH model cannot capture.

To address this limitation, two asymmetric models were also tested. The Exponential GARCH (eGARCH) model, proposed by Nelson (1991), is specifically designed to capture the "leverage effect," where negative news increases volatility more than positive news, offering greater flexibility by modeling the logarithm of the variance. Similarly, the GJR-GARCH model also accounts for the leverage effect but does so by using a different mechanism that introduces an additional component to the volatility forecast that is only activated in response to negative shocks (Glosten, Jagannathan, & Runkle, 1993). By comparing these three models, the analysis can empirically determine which structure best describes the volatility dynamics of each specific commodity.

Model Selection and Validation

For each commodity, the three fitted models (sGARCH, eGARCH, GJR-GARCH) were formally compared using information criteria. The Akaike Information Criterion (AIC) (Akaike, 1974) and the Bayesian Information Criterion (BIC) (Schwarz, 1978) were calculated. These criteria balance model fit (measured by the log-likelihood) with model parsimony by penalizing for the number of estimated parameters. The model exhibiting the lowest BIC value was selected as the optimal model for a given commodity series, as BIC tends to select simpler models, reducing the risk of overfitting (Brooks, 2019).

After identifying the best-fitting model for each commodity, a comprehensive set of diagnostic tests was performed on the model's standardized residuals to ensure its adequacy. The key diagnostic checks included:

1. Ljung-Box Test on Standardized Residuals: To test for any remaining serial correlation in the residuals. The null hypothesis is the absence of autocorrelation.
2. Ljung-Box Test on Squared Standardized Residuals: To test for any remaining ARCH effects. Failure to reject the null hypothesis suggests that the GARCH model has successfully captured the volatility dynamics.
3. Sign Bias Tests: To check if the direction (sign) of the shocks, as well as their magnitude, can predict future volatility beyond the model's specification, thereby testing for any uncaptured asymmetric effects.

A model is considered valid and robust if its standardized residuals closely approximate the theoretical assumptions of being independent and identically distributed.

Value at Risk (VaR) Modeling

Following the selection of the optimal GARCH model for each commodity, this study proceeds to quantify the one-day-ahead market risk using the Value at Risk (VaR) framework. VaR is a widely accepted industry standard that measures the maximum potential loss on a portfolio over a given time horizon for a specified confidence level (Jorion, 2007). This analysis employs a parametric GARCH-based approach to calculate VaR, which leverages the detailed volatility dynamics captured by the previously fitted models. This method is considered superior to simpler models as it accounts for time-varying volatility and the fat-tailed nature of financial returns (Engle & Manganelli, 2004). The calculation was performed for two distinct scenarios for each commodity : the standard downside VaR to quantity potential losses, and a symmetric upside Var to quantity potential gains.

For each commodity, the fitted GARCH model generates a one-step-ahead forecast of the expected log return and its standard deviation. The estimated Student's t–distribution parameters, notably the degrees-of-freedom shape, are then used to obtain the 5th-percentile quantile of the forecasted distribution. Combining that quantile with the forecasted mean and volatility yields the one-day-ahead, 95 percent Value-at-Risk for each commodity's log returns, which represents the largest expected adverse price movement under normal conditions.

The equation for the one day ahead 95 percent Value at Risk is given by :

$$VAR_{0.95} = -(\hat{\mu}_{t+1} + \hat{\sigma}_{t+1} \quad q_{0.05}) \qquad (4)$$

where $\hat{\mu}_{t+1} + \hat{\sigma}_{t+1}$ are the GARCH forecast of the mean and standard deviation, and $q_{0.05}$ is the 5th percentile of the fitted Student's t-distribution. The results are negated by convection so that VAR appeases a positive loss figure. (Brooks, 2019).

To provide a symmetric view of risk and opportunity, an upside Value-at-Risk was also calculated, estimating the minimum gain expected over the next trading day at a 95 percent confidence level. This follows the same steps as the downside VaR, using the one-step-ahead forecasts of the conditional mean and standard deviation from the fitted GARCH model. The 95th-percentile quantile of the Student's t-distribution is then obtained to represent an extreme positive outcome. Mathematically, the upside VaR is expressed as :

$$VARUP_{0.95} = \hat{\mu}_{t+1} + \hat{\sigma}_{t+1} \quad q_{0.95} \tag{5}$$

where $\hat{\mu}_{t+1} + \hat{\sigma}_{t+1}$ are the forecasted mean and standard deviation, and $q_{0.95}$ is the 95th percentile of the fitted distribution.

D. RESULTS AND DISCUSSION

GARCH Model Selection for Staple Food Commodity Price Volatility

This section presents and discusses the empirical findings from the GARCH modeling of staple food commodity prices in East Java. It begins with the model selection process, followed by an in-depth interpretation of the estimated GARCH parameters, an analysis of Value at Risk (VaR), and a discussion of observed price volatility patterns. The findings are then contextualized within existing literature and their implications for market stakeholders and policymakers in East Java are explored.

Table 1. GARCH Model Selection

Commodity	sGARCH AIC	sGARCH BIC	gjrGARCH AIC	gjrGARCH BIC	eGARCH AIC	eGARCH BIC	Selected
Red Bird's Eye Chili Pepper (kg)	–4.571679	–4.549772	–4.570299	–4.544742	–4.572143	–4.546585	sGARCH
Medium Rice (kg)	–10.514140	–10.492230	–10.525850	–10.500290	–10.477450	–10.451900	gjrGARCH
Bendera Powdered Milk (400 g/box)	–11.966900	–11.945000	–11.985510	–11.959950	–13.023400	–12.997850	eGARCH
Free-Range Chicken Meat (kg)	–9.837286	–9.815379	–9.841277	–9.815719	–9.886106	–9.860549	eGARCH
Commercial Chicken Eggs (kg)	–8.218078	–8.196171	–8.217129	–8.191571	–8.231827	–8.206269	eGARCH

Source : Author`s calculation

To accurately capture the volatility dynamics of each staple food commodity, this study tested three distinct GARCH family models: the standard GARCH (sGARCH), the Glosten-Jagannathan-Runkle GARCH (GJR-GARCH), and the Exponential GARCH (eGARCH). The sGARCH model captures symmetric volatility responses, while the GJR-GARCH and eGARCH models account for asymmetric effects, such as the leverage effect, where negative news (price drops) has a greater impact on volatility than positive news of the same magnitude (Hosu, Sarkodie, & Bekun, 2021)

Descriptive of table 1 and table 2 is:

- Red Bird's Eye Chili Pepper shows the highest mean price variability, with an average of Rp45,839/kg, a standard deviation of Rp6,742, and a maximum exceeding Rp60,000.
- Medium Rice remains relatively stable, with a mean price of Rp10,248/kg and the lowest standard deviation (Rp210), confirming its position as a government-controlled commodity.
- Bendera Powdered Milk (400g**)** averages Rp52,157/pack with very low volatility, reflecting strong supply chain stability.
- Free-Range Chicken Meat averages Rp35,623/kg, with occasional spikes linked to seasonal demand.
- Commercial Chicken Eggs average Rp25,319/kg, with moderate fluctuations (SD Rp1,148), indicating both consumer affordability concerns and producer vulnerability.

The selection of the most appropriate model for each commodity's return series was based on a formal comparison using the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). Both criteria evaluate the goodness-of-fit of a model while penalizing for complexity (number of parameters), thus guarding against overfitting. The model with the lowest AIC and/or BIC value is considered the most parsimonious and best-fitting model (Zaher, 2022).

The choice of sGARCH for chili pepper suggests its volatility responds symmetrically to shocks. In contrast, the selection of GJR-GARCH for rice and eGARCH for milk, chicken, and eggs indicates the presence of significant asymmetric effects in these markets. This finding is consistent with literature showing that staple food markets often react more strongly to negative shocks, such as poor harvests or policy uncertainty, than to positive ones (Gardebroek, 2004). The selected models were then carried forward for the Value at Risk analysis.

Parameter Estimations and Volatility Persistence

Following model selection, the analysis of parameter estimates offers critical insights into each commodity's volatility dynamics. A central concept is volatility persistence or "stickiness," measured by the sum of th#e ARCH (α_1) and GARCH (β_1) coefficients. A sum approaching one indicates that volatility shocks decay only very slowly, while a sum exceeding one implies an Integrated GARCH effect, where shocks have permanent consequences (Engle & Bollerslev, 1986).

Table 2. Parameter Estimation

Commodity	μ	AR(1)	ω	α_1	β_1	$\alpha_1+\beta_1$	Shape
Red Bird's Eye Chili Pepper (kg)	–0.001400	0.557042	0.000312	0.6192	0.3798	0.999	2.643888
Medium Rice (kg)	0.000033	0.022872	0	0.507433	0.667998	1.175431	2.591187
Bendera Powdered Milk (400 g/box)	0.000001	–0.000152	–0.024413	–0.011106	0.998391	0.987285	2.100001
Free-Range Chicken Meat (kg)	0.000005	–0.005619	–0.336176	0.074275	0.969586	1.043861	2.1
Commercial Chicken Eggs (kg)	–0.000391	0.536199	–0.715343	0.030208	0.929445	0.959653	2.406488

Source : Author`s calculation

For Medium Rice and Free-Range Chicken Meat, the sum of α_1 and β_1 exceeds one, at 1.175 and 1.044 respectively. This explosive persistence suggests that shocks to these markets fundamentally alter the level of price uncertainty in the long term. Such non-stationary variance behavior signals that once volatility rises, it remains elevated indefinitely unless countered by significant policy or market changes (Adhilaga & Hapsari, 2021).

Red Bird's Eye Chili Pepper demonstrates extremely high but stationary persistence, with an $\alpha_1 + \beta_1$ sum of 0.999. Bendera Powdered Milk and Commercial Chicken Eggs also exhibit high clustering, with sums of 0.987 and 0.960 respectively. Although these values lie below unity, their proximity indicates that shocks in these markets have prolonged effects on volatility that decay very slowly, underscoring the importance of timely policy interventions to prevent extended periods of market instability (Sukiyono & Rochdiani, 2020).

Overall, while all five commodities display significant volatility clustering, only Medium Rice and Free Range Chicken Meat show evidence of permanent volatility shocks. The persistence of these shocks points toward underlying structural inefficiencies that limit the ability of these markets to absorb disruptions quickly. In the case of rice, Indonesia's discretionary trade policies, including ad hoc import decisions, frequent tariff adjustments, and the practice of insulating domestic prices from world market movements, have been shown to increase rather than reduce domestic volatility (Martin et al., 2024). These policy driven interventions often interrupt the natural adjustment process and create uncertainty for both traders and consumers. Beyond policy related factors, the rice supply chain itself is long, fragmented, and heavily dependent on interprovincial flows. The presence of state logistics institutions with significant market influence can further slow the transmission of price information. This aligns with evidence that retail rice prices in Indonesia respond strongly to fluctuations in import volumes, stock management practices, and distribution bottlenecks, indicating that structural frictions impede timely market adjustment (Diawati et al., 2025).

For Free Range Chicken Meat, similar structural challenges help explain the persistence of volatility. The poultry sector in Indonesia is characterized by a vertically concentrated production system in which a small number of large integrators control breeding, feed, and downstream distribution. Such concentration can limit competition, restrict supply chain flexibility, and delay the market response to shocks. The broader empirical literature also shows that weak institutional quality and limited regulatory effectiveness tend to amplify the duration of food price disturbances, particularly when supply or

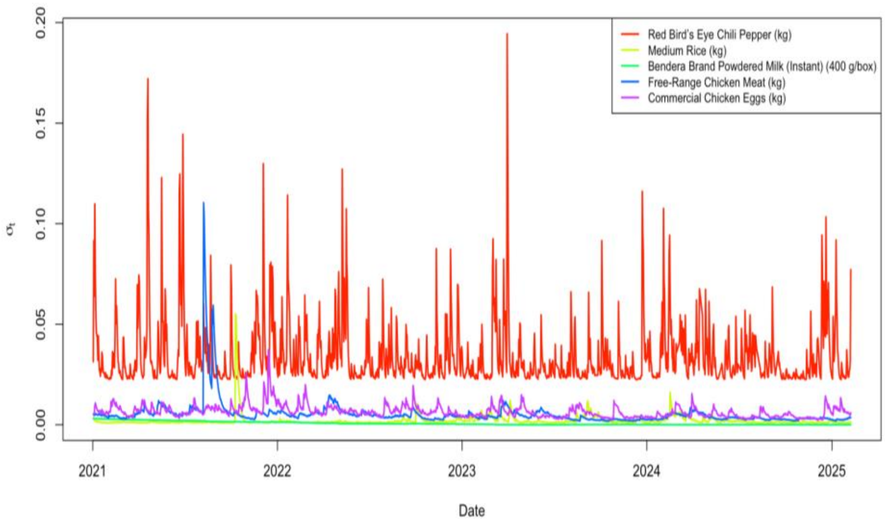

Figure 4: Conditional Volatility of Commodities
Source : Author`s calculation

chains are sensitive to input costs and coordination failures (Abaidoo et al., 2023). Taken together, these structural, institutional, and supply chain related factors provide a plausible explanation for why rice and chicken markets exhibit more persistent volatility than the other commodities examined, and why shocks in these markets tend to produce longer lasting consequences for consumers and producers.

Conditional Change of Volatility

A crucial validation of this study is the alignment between the estimated parametric risks and the observed conditional volatility changes over the study period. A comparison with historical market data demonstrates a strong correspondence between the model's volatility forecasts and the real-world price fluctuations experienced by the public. This consistency indicates that the GARCH models effectively capture the market's absorption of policy impacts. For instance, the high volatility spikes predicted for chili peppers throughout 2021-2025, and for free-range chicken meat and medium rice during 2022, reflect periods where policy interventions may have been sub-optimal unable to fully mitigate external shocks (Bellemare, 2015).

Conversely, commodities such as Bendera powdered milk and commercial chicken eggs exhibit significantly lower conditional volatility, suggesting that stabilization policies by the East Java Provincial Government have been largely successful. This stability implies a market equilibrium has been achieved, balancing the interests of producers and consumers (Minot, 2014). However, it is important to add a note of caution regarding medium rice. While the government has successfully suppressed price volatility, this should be complemented with robust supply-side policies. A sole focus on price control without enhancing productivity and supply chain efficiency can inadvertently put downward pressure on the Farmer's Terms of Trade (FTT), potentially compromising the long-term welfare and sustainability of rice farmers (Sitompul & Sembiring, 2022).

Value at Risk Thresholds for East Java Commodities

The Value at Risk (VaR) analysis reveals distinct levels of price volatility across the five commodities, highlighting where policy intervention may be most critical. Based on the one-day-ahead forecasts for the period of January 1, 2021, to February 2, 2025, the findings suggest a prioritized approach to price stabilization efforts.

Table 3. Value at Risk Thresholds Results

Commodity	Max Daily Drop (%)	Max Daily Rise (%)
Red Bird's Eye Chili Pepper (kg)	2.549	10.14
Medium Rice (kg)	0.159	0.165
Bendera Powdered Milk (400 g/box)	0.0035	0.0036
Free-Range Chicken Meat (kg)	0.210	0.211
Commercial Chicken Eggs (kg)	0.348	0.881

Source : Author`s calculation

The commodity demanding the most significant control efforts is Red Bird's Eye Chili Pepper. It exhibits the highest market risk, with a maximum potential daily price drop of 2.5% and a maximum potential daily price rise of 10.14%. Given its average price of Rp45,839 across three market types in East Java, these thresholds translate into significant monetary values. Specifically, a daily price increase exceeding Rp4,648/kg or a decrease greater than Rp1,146/kg warrants immediate intervention. Such measures are crucial for protecting public purchasing power, as extreme price instability in essential food items has direct negative consequences for food security (Tse, 2021).

The second priority for price management is Commercial Chicken Eggs, a critical and affordable source of protein for the public. While less volatile than chili, its price stability is a persistent challenge. The analysis indicates a maximum daily drop of 0.35% and a maximum daily rise of 0.88%. With an average price of Rp25,319, a relatively high figure for the island of Java, these percentages correspond to a potential daily decrease of Rp89 and an increase of Rp223. Moderate intervention is advised at these thresholds to maintain a delicate balance between farmer welfare, which is threatened by sharp price drops, and consumer affordability, which is eroded by price hikes (Adanacioglu & Yercan, 2021).

In contrast, the other three commodities demonstrate substantially lower volatility and therefore require less aggressive price control strategies. The analysis found a maximum daily drop and rise of 0.21% and 0.211% for free-range chicken meat, 0.16% and 0.17% for medium rice, and just 0.0035% and 0.0036% for Bendera powdered milk, respectively. The inherent stability of these commodities suggests that market forces are sufficient for price regulation, allowing policy resources to be focused on higher-risk products. The application of GARCH-based VaR models proves effective in differentiating these risk levels, providing an empirical basis to inform more targeted and efficient policy-making (Umar, Suleman, & Jarbolov, 2021).

E. CONCLUSION

This study examines price volatility in five key food commodities in East Java Province and finds that measured, data driven policy interventions are essential for maintaining economic stability and safeguarding public welfare. The combined use of GARCH modelling and Value at Risk (VaR) analysis provides three central insights.

First, the volatility estimates show that chili pepper is the primary driver of short-term inflation within the volatile foods category. Its price fluctuations are substantially more pronounced than those of medium rice, powdered milk, free range chicken meat, and commercial chicken eggs. This highlights the importance of a cautious and evidence-based approach to balancing supply and demand to maintain purchasing power for consumers.

Second, the persistence indicators reveal a more structural challenge. Medium rice and free-range chicken meat display persistence values greater than one, which means the markets for these commodities are not shock absorbent. Any disruption, regardless of magnitude, increases future price uncertainty on a permanent basis. This indicates the presence of deep structural constraints in production and distribution systems that cannot be addressed by short term price interventions alone.

Third, the VaR results show that chili pepper carries the highest daily risk magnitude and is therefore a principal source of acute inflationary pressure. Its extreme potential price swings require rapid, tactical policy responses. In contrast, price stabilization efforts for rice appear more successful at the consumer level, though these benefits must be balanced with the need to maintain fair incentives and protections for producers.

Based on these findings, this research recommends several strategic actions for the East Java Provincial Government and relevant stakeholders. A VaR based tolerance band scheme should be adopted to guide timely and proportionate policy intervention when daily price movements exceed defined upper or lower thresholds. This mechanism encourages a controlled degree of market flexibility while protecting both consumers and producers from harmful extremes. For structurally vulnerable commodities such as chili, long term solutions are required, including the expansion of urban farming networks and the strengthening of integrated supply chain systems across production, post harvest management, and distribution. Finally, intervention efforts should be spatially targeted, focusing on areas that consistently display high volatility, such as the Gerbangkertosusila region and the eastern "Horseshoe" area. These locations face unique structural and logistical challenges and therefore require tailored approaches to achieve more equitable provincial price stabilization.

Although this study provides an evidence-based framework for understanding volatility behaviour and designing risk responsive interventions, several limitations must be acknowledged. The VaR thresholds are derived from historical price patterns and may not fully capture the impact of rare or extreme systemic shocks, such as pandemics, geopolitical disruptions, or large-scale supply chain failures. In addition, the univariate GARCH models used here do not account for potential volatility spillover effects between commodities, which may be important in highly interconnected food systems. Future research could address these limitations by employing multivariate GARCH models or dynamic correlation frameworks to examine cross commodity volatility transmission, incorporating climate risk indicators, or evaluating the effectiveness of tolerance band interventions through simulation or pilot policy trials. Expanding the analysis to other provinces or national level data may also help assess whether the patterns observed in East Java are consistent across Indonesia's diverse regional markets.

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