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Beef Price Volatility in Indonesia: Before, During, and After the COVID-19 Pandemic

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ABSTRACT

Indonesia's beef market has long exhibited structural volatility, which became more pronounced during major disruptions such as COVID-19. Analyzing these fluctuations across different periods is crucial for strengthening market resilience. This paper examines beef price volatility in Indonesia across three critical periods, before the pandemic (2017–2019), during the COVID-19 pandemic (March 2020 – June 2023), and after the pandemic (June 2023 onward), and identifies the key factors influencing it. Daily price data for beef, chicken meat, and eggs were obtained from the Indonesian Strategic Food Price Information Center (PIHPS) for 2017–2024 and analyzed using the GARCH (1,1) model and logarithmic regression with crisis dummy variables. The results show that beef price volatility increased significantly during the pandemic and remained high in the new normal period, confirming the long-term persistence of price shocks. Significant influencing factors include the COVID-19 pandemic, seasonal events (Ramadan and Eid al-Fitr), the price and volatility of chicken meat, and lagged beef imports from previous periods. The methodological contribution of this study lies in the use of daily data and a time-lag structure that captures short-term dynamics more accurately. These results underscore the need for structural reform, daily price monitoring systems, and adaptive market intervention to strengthen Indonesia's food security and market resilience.

Keywords: Beef; COVID-19; GARCH; Price stabilization; Price volatility

INTRODUCTION

The COVID-19 pandemic has emerged as a major global disruption that reshaped economic systems worldwide, including in Indonesia (Rela et al., 2022; Seshaiyer & McNeely, 2020; Whitehead & Kim, 2022). Beyond its public health impacts, the pandemic triggered structural shocks in national food systems (Khedhiri, 2023; Nurhidayah & Djalante, 2022; Yudha & Roche, 2023), including beef as a particularly vulnerable commodity due to its price sensitivity (Calvia, 2024; Surni et al., 2021).

Even before the COVID-19 pandemic, beef prices in Indonesia were highly volatile due to structural challenges, including heavy reliance on imports (accounting for 32.9% of total supply) (Ministry of Agriculture, 2022), fragile domestic supply chains, and exchange rate fluctuations (Hadi & Chung, 2022). The pandemic further exacerbated these vulnerabilities, as social restriction policies (called PPKM and PSBB in Indonesia) disrupted logistics, reduced beef production by 10.18%, and triggered price spikes of up to 19.9% in 2021 (Bai et al., 2022; Bairagi, Mishra, & Mottaleb, 2022). Notably, beef prices remained consistently higher than those of other protein sources, such as chicken meat and eggs, throughout the pandemic.

Price volatility patterns varied significantly across commodities. While chicken meat and egg prices followed similar trends, beef exhibited distinct fluctuations. Among the three, eggs displayed the highest volatility, with a Coefficient of Variation (*CV*) of 0.12, compared to chicken meat (0.07) and beef (0.06). The pandemic period intensified these fluctuations: beef's *CV* rose to 0.06—triple its pre- and post-pandemic stability level of 0.02. Similarly, chicken meat and eggs saw higher *CV*s during the pandemic (0.08 and 0.12, respectively) compared to pre-pandemic levels (0.07 for both) and post-pandemic declines (0.05 and 0.07). These findings underscore how large-scale restrictions and the transition to the "New Normal" amplified price instability across key food commodities. Given these dynamics, analyzing price volatility before, during, and after the pandemic is critical to understanding systemic vulnerabilities in Indonesia's beef supply chain. Such research can inform policies to enhance resilience against future shocks, ensuring more stable food prices and supply security.

While several studies have explored beef price volatility, they have often done so in isolation, focusing on specific dimensions such as domestic production (Komalawati, Asmarantaka, Nurmalina, & Hakim, 2019), import policy, regional market patterns (Komalawati, Asmarantaka, Nurmalina, & Hakim, 2021), or global connectivity (Tanaka & Guo, 2020). Few have investigated the full trajectory of volatility across three distinct periods, pre-pandemic, pandemic, and post-pandemic, using high-frequency (daily) data. In fact, the post-pandemic period (2023–2024) revealed a new pattern of volatility resulting from a combination of government interventions and economic recovery, which has yet to be systematically mapped.

This study addresses research gaps by applying a multidimensional analytical framework using the *GARCH* model to assess the impact of external shocks (e.g., the COVID-19 pandemic) relative to structural factors like import dependence and exchange rate. It also examines spillover effects from substitute commodities (chicken and eggs), using high-frequency daily data from the National Strategic Food Price Information Center (PIHPS) of Bank Indonesia (2017–2024) to capture short-term volatility often missed in aggregate datasets. Post-pandemic data (2023–2024) allows analysis of recovery-phase dynamics and policy impacts. The study aims to (1) analyze beef price volatility across pre-, during-, and post-pandemic periods, (2) measure the relative roles of pandemic-related and structural shocks, and (3) provide long-term policy recommendations for price stabilization.

Despite its comprehensive framework, this study has limitations, particularly the exclusion of climate-related variables due to unavailable daily-scale data, and a national-level focus aligned with macroeconomic indicators. Nonetheless, insights from global literature support interpretation of findings and policy relevance (Bozma, Urak, Bilgic, & Florkowski, 2023). Ultimately, this study enhances understanding of how external crises interact with structural vulnerabilities in shaping price volatility, highlighting that the pandemic amplified rather than caused instability. The use of high-frequency modeling emphasizes the need for anticipatory, multisectoral policy approaches aligned with resilient food system strategies (Montalbano & Romano, 2023; Namany, Govindan, & Al-Ansari, 2024).

RESEARCH METHOD

This study employs Heaton's (2004) secondary data research methodology by utilizing institutional administrative records. The primary data for analyzing price volatility consist of daily consumer-level price data from July 10, 2017, to December 31, 2024, sourced from the National Strategic Food Price Information Center (PIHPS) of Bank Indonesia (Table 1). To assess the influencing factors, additional monthly data from July 2017 to December 2024 were obtained from the Ministry of Trade, Bank Indonesia, and Statistics Indonesia (BPS) (Table 1). The entire dataset is segmented into three periods: pre-pandemic (July 2017–March 2020), pandemic (March 2020–June 2023), and post-pandemic (from June 2023 onward), based on key government policy milestones such as the declaration of the national public health emergency, the implementation of Large-Scale Social Restrictions, and the end of the pandemic period through Presidential Decree No. 17 of 2023 (Wahyuni, Pujiharto, Azizah, & Zulfikar, 2021). These temporal divisions allow for a more accurate analysis of price dynamics across different policy regimes.

TABLE 1. TYPES AND SOURCES DATA

No.	Data Types	Data Sources
1.	Daily beef prices at the consumer level	National Strategic Food Price Information Center (*called as PIHPS in Indonesia*) Bank Indonesia
2.	Daily chicken meat and egg prices at the consumer level	National Strategic Food Price Information Center (*called as PIHPS in Indonesia*) Bank Indonesia
3.	Exchange rate	Bank Indonesia
4	Inflation rate	Bank Indonesia
5.	Import of Beef	Central Bureau Statistics and Ministry of Trade
6.	Import of Feeder Cattle	Central Bureau Statistics
7.	Beef production	Central Bureau Statistics and National Food Agency

Daily price data gaps due to holidays and weekends were addressed using an interpolation technique developed by Insukindro (1990). Prior to analysis, the data were transformed using the natural logarithm function to reduce the influence of variability and stabilize the data (Raudys & Goldstein, 2022). Beef price volatility was estimated using the GARCH model introduced by Bollerslev in 1986 (Komalawati et al., 2019). Before applying the GARCH model, the Augmented Dickey–Fuller (*ADF*) test was applied to ensure the stationarity of the mean process (Hassani, Yeganegi, Khan, & Silva, 2020; Pallotta & Ciciretti, 2024), while allowing for potentially non-stationary or near-integrated behavior in the conditional variance during periods of structural shocks. This test is essential to avoid spurious regression results, which may lead to biased estimations. Non-stationary data were differenced until stationarity was achieved.

Following the stationarity test, the appropriate mean equation was determined using autoregressive (*AR*), moving average (*MA*), or Autoregressive Integrated Moving Average (*ARIMA*) models. Model selection was based on the lowest values of the Akaike Information Criterion (*AIC*) and Schwarz Criterion (*SC*), as well as the highest log-likelihood value. The *ARIMA* model was required to satisfy several criteria to be deemed valid, including random residuals, parsimony, statistically significant parameter estimates, fulfillment of the stationarity condition (i.e., *AR* and *MA* coefficients less than one), a convergent iteration process, and a low Mean Squared Error (*MSE*). The selected mean equation was then tested for heteroscedasticity using the *ARCH-LM* test (Lagrange Multiplier test for Autoregressive Conditional Heteroscedasticity). If the residuals exhibited heteroscedasticity, the model was subsequently estimated using the *GARCH (1,1)* model. This study employs the *GARCH (1,1)* model, which is widely used due to its ability to capture time-varying conditional variance (Yousef & Shehadeh, 2020). The selection of *GARCH (1,1)* is strongly supported by the characteristics of the beef price time series, which visually exhibits a volatility clustering effect, where the *GARCH (1,1)* model is the most parsimonious and effective specification for capturing this effect (Joukar & Nahmens, 2016). The *GARCH (1,1)* is specified as follows:

$$\sigma_t^2=\alpha_0+\alpha_1\varepsilon_{t-1}^2+\beta_1\sigma_{t-1}^2 \tag{1}$$

Where σ_t^2 represents the conditional variance in period t, α_0 is a constant, ε_{t-1}^2 is the squared residual from the previous period ($t-1$), and σ_{t-1}^2 the conditional variance in period $t-1$. Parameters α_1 and β_1 are the coefficient estimates of the *GARCH* terms, respectively. The coefficient α reflects the *ARCH* effect and indicates the magnitude of short-term price volatility or how quickly volatility responds to recent shocks (e.g., policy changes or supply disruptions) (Engle, 1982). The value of β measures the impact of past volatility on current conditional volatility (Tanaka & Guo, 2020). Higher β value will suggest long-lasting volatility persistence, meaning prices struggle to stabilize even after the crisis. A value of $\alpha+\beta$ close to one implies high volatility persistence over time.

It is important to emphasize that the interpretation of the *GARCH(1,1)* parameters in this study focuses on volatility persistence rather than strict covariance stationarity. During periods characterized by large structural shocks, such as the COVID-19 pandemic and the post-pandemic adjustment phase, the conventional stationarity condition ($\alpha + \beta < 1$) may not necessarily hold. In such contexts, values of $\alpha + \beta$ approaching or exceeding unity reflect prolonged volatility persistence and slow dissipation of shocks rather than model misspecification. Such volatility dynamics are commonly observed in markets affected by major structural changes, where non-stationary or near-integrated variance processes capture economically meaningful shifts in market conditions (Campos-Martins & Amado, 2025). Previous studies further show that commodity markets exposed to crisis-driven disruptions exhibit highly persistent volatility dynamics that are economically relevant for understanding market instability and informing policy responses, particularly during periods of heightened uncertainty (Khan, Kayani, Khan, Mughal, & Haseeb, 2023; Zavadska, Morales, & Coughlan, 2020). Accordingly, the *GARCH* model in this study is employed as a volatility characterization and policy-relevant analytical tool, rather than as a strict second-moment stationary process (Horváth, Trapani, & Wang, 2025). The *GARCH* model is estimated using the Maximum Likelihood method and processed with EViews 9.

To analyze the factors influencing beef price volatility in Indonesia, monthly data from July 2017 to December 2024 are used. The daily price and volatility data are aggregated into monthly data to enable further analysis. The relationship between influencing factors and volatility is estimated using a logarithmic regression model that include lagged endogenous and exogenous variables. The lagged variables included because agricultural markets require some periods to adjust from shocks in other markets or transport delays (Morales, 2018). The formulation of the model used to examine the determinants of beef price volatility is as follows:

$$\begin{aligned} ln(\sigma_t) = {} & \theta_0 + \theta_1 ln\,(P_{bt-1}) + \theta_2\, ln(\sigma_{t-4}) + \theta_3\, ln(\sigma_{t-24}) + \theta_4\, ln(IM_{t-1}) + \\ & \theta_5 ln(FC_{t-4}) + \theta_6\, ln(Q_{t-1}) + \theta_7 ln(ER_t) + \theta_8\, ln(IR_t) + \theta_9\, ln(P_{ct-1}) + \\ & \theta_{10} ln(P_{et-1}) + \theta_{11}\, ln(\sigma_{ct-1}) + \theta_{12}\, ln(\sigma_{et-1}) + \theta_{13} D_{ef} + \theta_{14} D_{ea} + \\ & \theta_{15} D_{pc} + \mu_t \end{aligned} \qquad (2)$$

Expected sign $\theta_1,\theta_7,\theta_8,\theta_9,\theta_{10},\theta_{11},\theta_{12},\theta_{13},\theta_{15}>0;\theta_2,\ \theta_3,\theta_4,\theta_5,\theta_6,\ \theta_{14}<0$

In this model, $ln(\sigma_t)$ represents the natural logarithm of beef price volatility in period t, calculated from daily price fluctuations aggregated into monthly data. $ln\ (P_{bt-1})$ is the natural logarithm of the beef price in the previous month, while $ln(\sigma_{t-4})$ and $ln(\sigma_{t-24})$ denote the natural logarithms of beef price volatility at 4-month and 24-month lags, respectively. $ln(IM_{t-1})$ refers to the natural logarithm of beef import volume in the previous month (tonnes/month), and $ln(FC_{t-4})$ represents the natural logarithm of feeder cattle imports four months earlier (head/month). $ln(Q_{t-1})$ is the natural logarithm of beef production in the previous month (tonnes/month). $ln(ER_t)$ indicates the natural logarithm of the exchange rate (IDR/USD), and $ln(IR_t)$ is the natural logarithm of the inflation rate (percent).

$ln(P_{ct-1})$ and $ln(P_{et-1})$ are the natural logarithms of chicken meat and egg prices in the previous month, respectively. $ln(\sigma_{ct-1})$ and $ln(\sigma_{et-1})$ denote the natural logarithms of chicken meat and egg price volatility in the prior month. The model also includes dummy variables: D_{ef} for Ramadan and Eid al-Fitr, D_{ea} for Eid al-Adha, and D_{pc} for the COVID-19 pandemic period. μt is the error term, and θ_1-θ_{15} are the estimated coefficients for each explanatory variable. This log-log model allows the interpretation of estimated coefficients as elasticities, showing the percentage change in beef price volatility resulting from a one-percent change in each independent variable. Estimation is conducted using Ordinary Least Squares (OLS) and processed with EViews 9 software.

RESULTS AND DISCUSSION

Beef Price Volatility and Determinant Factors

The prices of beef from 2017 to 2024, the prices of beef before, during, and after pandemic were then tested for stationarity using the Augmented Dickey-Fuller (ADF) test.

Table 2 presents the results of the unit root tests. Based on the table, most variables used in the volatility analysis were found to be stationary at first difference, except for price of beef after pandemic, as indicated by ADF test statistics that exceed the 1% critical value.

TABLE 2 RESULTS OF UNIT ROOT TESTS USING AUGMENTED DICKEY-FULLER (ADF) TEST

Variables	Level	First Difference	Critical values 1%
Beef price (P_b)	-1.84 (0.36)	-7.70 (0.00)	-3.51
Beef price before pandemic (P_{bp})	0.42 (0.98)	-24.45 (0.00)	-3.44
Beef price during pandemic (P_{pc})	2.02 (0.28)	-20.77 (0.00)	-3.44
Beef price post-pandemic (P_{pp})	-4.58 (0.00)	-13.44 (0.00)	-3.44

The stationarity test was followed by the determination of the appropriate mean model. Table 3 presents the best mean equations used to estimate beef price volatility for the overall period (2017–2024), as well as for the subperiods before, during, and after the COVID-19 pandemic. The results indicate that each time series segment required a different ARIMA specification. The best-fitting ARIMA model for the overall 2017–2024 beef price volatility data is ARIMA (2,1). For the pre-pandemic period, the best model is MA(1); for the pandemic period, it is ARIMA(2,2); and for the post-pandemic period, ARIMA(1,1) is the most suitable. All four ARIMA models were subsequently tested for heteroscedasticity using the ARCH-LM test, which produced significant probability values ($p < 0.01$). These results indicate the presence of ARCH effects in the residuals of the mean equations, confirming that the models are suitable for further volatility analysis using the GARCH approach.

TABLE 3. THE ESTIMATION RESULTS OF BEEF PRICE VOLATILITY ANALYSIS

	Price Volatility 2017-2024	Pre-pandemic price volatility	Pandemic period price volatility	Post-pandemic volatility price
Mean Model				
C	-0.00 (0.00)	11.75 (0.00)	11.70 (0.00)	11.86 (0.00)
AR(1)	1.02(0.00)		1.91 (0.00)	1.01 (0.00)
AR(2)			-0.91 (0.00)	
MA(1)	-0.89 (0.00)	0.86 (0.00)	-1.35 (0.00)	-0.31 (0.00)
MA(2)	-0.08 (0.00)		0.39 (0.00)	
GARCH Model				
C	4.31E-06 (0.00)	1.30E-07	8.47E-06 (0.00)	2.75E-07 (0.00)
α	3.82 (0.00)	0.76 (0.00)	1.89 (0.00)	0.08 (0.00)
β	0.11 (0.00)	0.34 (0.00)	0.07 (0.00)	0.86 (0.00)
$\alpha + \beta$	3.93	1.10	1.96	0.94
Log-likelihood	11435.82	3677.75	4972.50	2103.16
AIC	-8.71	-7.38	-8.24	-9.94
SIC	-8.70	-7.36	-8.21	-9.92
ARCH-LM test	0.23 (0.63)	0.77 (0.38)	0.12 (0.72)	0.00 (0.98)

Note: α is the ARCH effect (short-term shock responsiveness); β is the GARCH effect (volatility persistence); $\alpha + \beta$ is the degree of long-term volatility persistence; (…) is the probability values

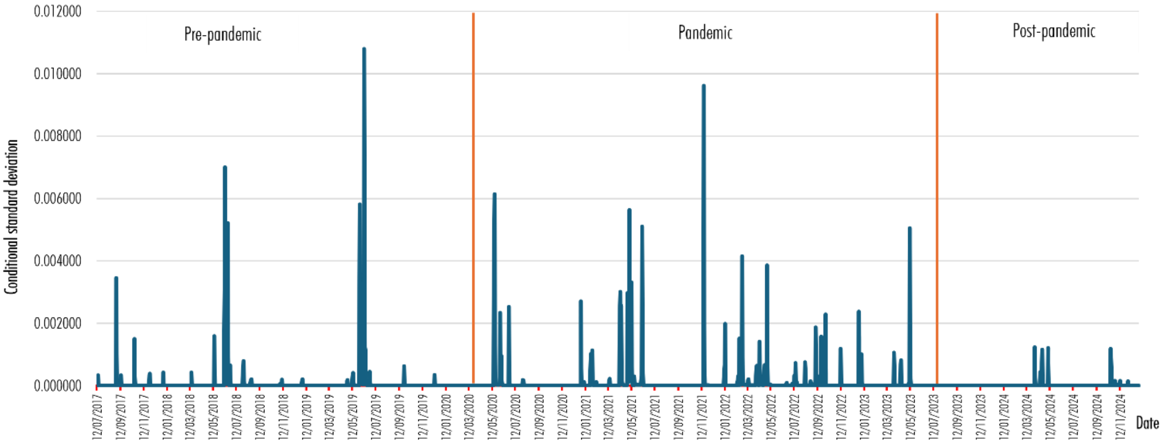
Table 3 also presents the estimated parameters of the GARCH (1,1) models for beef price volatility across the full period (2017–2024), as well as the pre-, during-, and post-pandemic periods. The ARCH-LM test conducted on the GARCH (1,1) model returned non-significant F-statistic and Chi-square values ($p > 0.10$), indicating no remaining ARCH effects and confirming that the model is well-specified.

The estimation results of the GARCH (1,1) model over the entire period (2017–2024) indicate the ARCH coefficient (α), which captures the short-term responsiveness of volatility to new shocks, is relatively large (α = 3.82), suggesting that beef prices were highly sensitive to unexpected disturbances during this period. This shock sensitivity was particularly pronounced during the pandemic period, when α increased to 1.89, reflecting strong short-term volatility responses associated with sudden supply chain disruptions and trade restrictions. Prior to the pandemic, the estimated α value was more moderate (α = 0.76), indicating relatively lower sensitivity to short-run shocks. In the post-pandemic period, α declined substantially (α = 0.08), implying that immediate price reactions to new shocks weakened. However, this does not necessarily indicate lower overall volatility, as volatility persistence remained high through the dominance of the GARCH component (β). Across the full sample and during the pre-pandemic and pandemic periods, the predominance of α relative to β is consistent with volatility dynamics driven mainly by exogenous shocks rather than gradual variance accumulation, particularly during the height of market disruptions in 2020–2022. These results highlight the importance of distinguishing between short-term shock effects (α) and long-term volatility persistence (β) when interpreting GARCH-based volatility dynamics.

The GARCH coefficient (β) represents the impact of past conditional variance on current volatility (Tanaka & Guo, 2020). This study finds that the post-pandemic period is characterized by a β value approaching 1, suggesting that price volatility remained persistent even after the initial shock had subsided. Moreover, during the post-pandemic period, α was lower than β, implying that variance persistence played a more dominant role than immediate external market shocks in influencing beef price movement.

The sum of α and β reflects the degree of long-term volatility persistence. Among the four estimated models, only the post-pandemic period exhibited $\alpha + \beta$ values approaching 1, indicating near-integrated volatility persistence. This finding aligns with previous studies by Zavadska et al. (2020), which suggest that values of $\alpha + \beta$ close to 1 imply a high risk of prolonged volatility. It suggests persistent volatility, meaning prices remain unstable post-crisis or beef prices may stay volatile in the long-term (Komalawati et al., 2019) due to structural weaknesses like import dependency and supply chain inefficiencies (Shobur et al., 2025). The high level of volatility persistence in beef is consistent with the findings of (Pipit, Pranoto, & Evahelda, 2019).

The results of the volatility estimation are illustrated in Figure 1, which shows the movement of beef price volatility in Indonesia from July 10, 2017 to December 31, 2024. The graph represents daily beef price volatility as the conditional standard deviation (i.e., the square root of the conditional variance). The pattern shown in Figure 1 is consistent with the GARCH model estimation results discussed above: beef price volatility was considerably higher during the pandemic period compared to the pre-pandemic (2017–2020) and post-pandemic (2023–2024) periods.



Note: Volatility is measured using conditional standard deviation and the values range from 0.00000486 to 0.01079, with most observations concentrated below 0.000007; orange line shows the border of period

FIGURE 1. DAILY BEEF PRICE VOLATILITY IN INDONESIA

TABLE 4. FACTORS AFFECTING BEEF PRICE VOLATILITY IN INDONESIA

Variables	Coefficient	Probability value
Constanta	-13.06	0.84
Beef prices	-1.18	0.79
Beef price volatility t-1	-0.20*	0.06
Beef price volatility t-24	0.10	0.30
Imported beef t-1	0.46	0.11
Imported feeder cattle t-4	-0.21	0.46
Production t-1	-0.21	0.68
Exchange rate	-5.23	0.30
Inflation rate	0.44	0.30
Chicken meat prices t-1	8.25**	0.01
Egg prices t-1	-2.98	0.20
Chicken meat price volatility t-1	1.98**	0.02
Egg price volatility t-1	0.13	0.70
Ramadan and Eid al-Fitr	1.30**	0.01
Eid al-Adha	-1.04*	0.06
COVID-19 pandemic	1.60***	0.00
R-squared	**0.62**	
Adjusted R-squared	**0.50**	
S.E. of regression	**1.14**	
F-statistic	**5.38**	
Prob(F-statistic)	**0.00**	
Durbin-Watson stat	**1.84**	

*Note: Dependent variable = beef price volatility at period t; ***, **, * = significant at 0.01, 0.05, and 0.1 respectively*

Table 4 presents the factors influencing beef price volatility, with an R-squared value of 0.6173. This indicates that approximately 61.73% of the variation in beef price volatility in

Indonesia can be explained by the independent variables included in the model. The moderate R-squared value reflects the inherent complexity of the factors that drive price volatility, which often involve a wide range of dynamic, interrelated, and mutually exclusive phenomena that cannot be captured by a single or limited set of variables (Algieri, 2021; Kieu, Luu, & Yoon, 2020). In addition, the adjusted R-squared result of 0.5024 suggests that around 50.24% of the variation in the dependent variable (beef price volatility) can be explained by the independent variables, after adjusting for the number of explanatory variables used in the regression.

The analysis confirms that the COVID-19 pandemic significantly increased beef price volatility in Indonesia (coefficient = 1.60; $p < 0.01$), primarily due to disruptions in supply chains, consumption shifts, and economic stress, consistent with studies in Turkey (Bozma et al., 2023) and the U.S. (Ramsey, Goodwin, Hahn, & Holt, 2021), although not all studies agree, likely due to differing data coverage (Hermawan et al., 2022). The R-squared value of 0.617 indicates that the independent variables in the model explain approximately 61.7% of the variation in beef price volatility, while the remaining proportion is attributable to other factors not included in the model.

Seasonal events also play a role: volatility spikes during Ramadan and Eid al-Fitr (coefficient = 1.30; $p < 0.05$) due to demand surges (Komalawati et al., 2019), while Eid al-Adha reduces volatility (coefficient = −1.04; $p < 0.10$) through increased beef supply, aligning with (Dewia, Nurmalina, Adhi, & Brümmer, 2017). Volatility is also influenced by historical trends and substitution effects (Javadi, Ghahremanzadeh, & Soumeh, 2024; Zumbach, 2010). Previous price volatility and the price and volatility of chicken (Anwar et al., 2023; Xie, Zhu, Liu, Ye, & Liu, 2024) at lag $t-1$ (coefficient = 1.98; $p < 0.05$) significantly affect beef volatility, indicating strong inter-commodity linkages. A negative effect at lag $t-4$ reflects market adjustment tied to cattle fattening cycles (Komalawati et al., 2019), while lag-24 volatility is not significant.

Discussion

Beef price volatility is typically driven by climate-related production shocks (Godde, Mason-D'Croz, Mayberry, Thornton, & Herrero, 2021), shifting consumption patterns (Magalhaes et al., 2023), and currency fluctuations (Hadi & Chung, 2022). The pandemic exacerbated these issues, amplifying volatility. Import policy instability and global market uncertainty (Du & Dong, 2023) often have longer-lasting impacts than health crises alone. Unpredictable price swings threaten food security and political stability, as evidenced in Ethiopia and Ghana (Wossen, Berger, Haile, & Troost, 2018).

This study confirms persistent beef price volatility post-pandemic, with low α but $\beta \approx 1$ in GARCH models. Heavy reliance on Australian imports intensified shocks and price surges of 19.9% (2021) and 24% (2022) followed Australia's post-drought recovery directly impacted Indonesia, a major importer of Australian beef. Strategic solutions include import diversification, domestic production strengthening (e.g., feedlots), and strategic reserves. Pandemic restrictions significantly disrupted supply chains ($p < 0.05$) (Monge & Lazcano, 2022), revealing fragile logistics and fragmented information systems (Peel, 2021). Recommendations include digital traceability and regional logistics hubs (Ijaz et al., 2021; Sumrow, Hudson, Sarasty, Carpio, & Bratcher, 2024).

Other contributors to volatility include spillover effects from substitute commodities like chicken and eggs (Hermawan et al., 2022), indicating consumer sensitivity and cross-commodity linkages. Lagged effects (four-period lag of beef price volatility) and seasonal events like Ramadan affect beef prices, justifying a seasonal intervention calendar to coordinate geographically targeted actions. Domestic production showed weak response to price signals ($p > 0.15$), underscoring the need for resilience-focused policies (price guarantees). The pandemic exposed systemic vulnerabilities, calling for machine learning-based early warning systems and scenario-based policy simulations. Though GARCH (1,1) captured volatility persistence (Adj. $R^2 = 0.5024$), future research should explore non-linear models, spatial econometrics, and non-pandemic shocks (geopolitics, climate), as well as expand the scope to other key food commodities such as rice, cooking oil, chili, and seafood, to evaluate whether similar volatility patterns apply across markets.

CONCLUSION

This study finds that the COVID-19 pandemic served as a major shock that significantly increased beef price volatility in Indonesia. However, volatility did not subside in the post-pandemic period, indicating that structural weaknesses, particularly import dependency and inefficient supply chains, are the dominant drivers of persistent price instability. The pandemic acted more as an amplifier than a root cause, reflecting persistent volatility dynamics rather than transitory shocks.

Volatility was also shaped by seasonal demand surges (Eid al-Fitr, Eid al-Adha), substitution effects from other protein sources (chicken), and delayed responses from domestic production. The prolonged nature of volatility highlights a vulnerability within Indonesia's beef supply chain that requires urgent structural reforms beyond reactive crisis responses.

Policy actions must therefore focus not only on crisis mitigation but also on long-term resilience. These include the development of a real-time price monitoring system, strategic import diversification, and investment in domestic production infrastructure. Seasonal price stabilization programs and predictive analytics using big data should be institutionalized to anticipate future shocks and safeguard food security.

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Authors' Contributions: AFM: conceptualization ideas, collecting data, processing and analyzing data, writing original manuscript, editing the manuscript; KK: research design, conceptualization ideas, processing and analyzing data, reviewing and editing the manuscript; AS: research design, conceptualization ideas, finalizing and reviewing the manuscript.

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