Modelling and Predicting Volatility in Essential Food Prices Using ARIMA-GARCH Models

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ABSTRACT

The volatility of food prices poses significant challenges to food security, particularly in developing countries. Sudden changes in the prices of essential commodities, driven by factors such as climate change, market disruptions, and economic policies, can lead to economic instability and food insecurity. In Indonesia, significant fluctuations in staple commodity prices like rice, eggs, beef meat, chicken meat, chili, and sugar have been observed, influenced by climatic conditions, harvest yields, and import policies. Understanding these volatility patterns is crucial for effective policy formulation and economic planning. ARIMA and ARCH-GARCH models have been widely used to analyze food price volatility, demonstrating effectiveness in capturing price fluctuations in various agricultural commodities. This research aimed to model and predict the volatility of essential food prices in Indonesia using ARIMA-GARCH models. The study found that ARIMA models were suitable for chili (ARIMA(4,1,0)), eggs (ARIMA(0,1,3)), beef meat (ARIMA(5,2,0)), chicken meat (ARIMA(3,1,0)), and rice (ARIMA(2,1,0)), while the GARCH(1,1) model was the most appropriate for predicting sugar prices. Diagnostic tests indicated that while the ARIMA models fit the data well, residuals for most commodities showed significant deviations from normal distribution, suggesting potential heteroskedasticity. However, only sugar exhibited ARCH effects, indicating the need for GARCH models. High error metrics for chili and sugar suggest the need for more sophisticated modelling techniques, whereas lower errors for beef meat, chicken meat, and rice indicate more stable price patterns. These findings emphasize the importance of refining forecasting models, incorporating additional variables like weather conditions and policy changes, and exploring advanced models for high-volatility commodities. Regular monitoring and evaluation of models, coupled with stakeholder engagement, are crucial for managing price volatility and ensuring food security in Indonesia.

1. Introduction

The volatility of food prices poses significant challenges to food security, particularly in developing countries[1]. Food price volatility means sudden changes in the prices of essential commodities over a short period, driven by factors such as climate change, market disruptions, and economic policies. These fluctuations can severely impact both producers and consumers, leading to economic instability and food insecurity[2]. In Indonesia, food price volatility has been a persistent issue, with significant fluctuations observed in the prices of staple commodities[3]. Factors such as climatic conditions, harvest yields, and import policies have contributed to this volatility[4].

Essential commodities in Indonesia, such as rice[3], [5], [6], eggs[5], beef meat[5], chicken meat[3], [5], chili[5], [6], [7], [8], sugar[3], [5], play a crucial role in the country's food security and economic stability. Rice, a staple food, often sees price volatility due to climatic conditions and harvest yields, affecting millions of households[9]. Eggs, beef, and chicken meat are vital protein sources, with their prices influenced by feed costs and market demand[10]. Chili, a key ingredient in Indonesian cuisine, faces price fluctuations due to weather and pest issues[11]. Sugar, essential for various food products, is impacted by global market dynamics and domestic policies. Understanding the volatility in these commodities is crucial for effective policy formulation and economic planning.

ARIMA and ARCH-GARCH models have become the widely used methods for analysing food price volatility in recent years. Studies have demonstrated their effectiveness in capturing price fluctuations in various agricultural commodities, including rice, chicken, and sugar in Indonesia[3], as well as several export crops in Egypt[12]. Additionally, the hybrid ANN-GARCH model has effectively forecasted prices of rice, red chili, onion, and cayenne pepper in Jakarta[6]Research on China's soybean price using ARIMA-GJR-GARCH method further underscores the utility of these models.[13]. Overall, these methods provide robust tools for forecasting and managing price volatility in agricultural markets.

This paper aims to model and predict the volatility of essential food prices in Indonesia using ARIMA-GARCH models. The paper is structured as follows: Section 2 presents a literature review of methods used for forecasting, Section 3 details the data sources and data processing methods, Section 4 provides an analysis and discussion of the model results and volatility predictions for essential food prices, and Section 5 concludes with final remarks and suggestions for future research.

2. Literature Review

2.1 AutoRegressive Integrated Moving Average (ARIMA)

ARIMA model is a well-known statistical approach for time series forecasting, especially effective in analyzing and predicting financial and economic data. In recent years, the application of ARIMA models to volatility analysis has garnered significant attention, driven by the need for robust forecasting tools in uncertain economic environments[14].

The ARIMA model, formulated by Box and Jenkins in the 1970s, is defined by three parameters: p (autoregressive order), d (degree of differencing), and q (moving average order). This model is designed to capture autocorrelations within the data through these components:

- Autoregressive (AR) component: Reflects the correlation between a current observation and its previous values.
- Integrated (I) component: Indicates the differencing required to achieve stationarity in the time series.
- Moving Average (MA) component: Illustrates the connection between the current observation and previous forecast errors.

The general form of the ARIMA model is expressed as:

$$(1-\phi_1 L-\phi_2 L^2-\cdots-\phi_1 L^p)(1-L)^2 y_t=\left(1+\theta_1 L+\theta_2 L^2+\cdots+\theta_q L^q\right)\epsilon_t \quad (1)$$

where ϕ dan θ are parameters to be estimated, L is the lag operator, y_t is the time series, and ϵ_t is white noise[15].

In the context of volatility analysis, ARIMA models are often combined with Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models to capture both the mean and variance dynamics of time series data. This combination, often referred to as ARIMA-GARCH, is particularly effective in financial and economic applications where volatility clustering is present as demonstrated in the research by [12], [13] and this research.

2.2 Autoregressive Conditional Heteroskedasticity-Generalized Autoregressive Conditional Heteroskedasticity (ARCH-GARCH) model

ARCH model, introduced by Robert Engle[16], and its extension, the GARCH model, developed by Tim Bollerslev[17], are foundational techniques for modelling and forecasting time series volatility. These models excel at capturing time-varying volatility, a common feature in financial and economic data.

The ARCH model tackles the problem of time-varying variance by modeling the conditional variance based on past squared errors. The standard form of an ARCH(q) model is expressed as:

$$\sigma_t^2 = \alpha_0 + \alpha_1\epsilon_{t-1}^2 + \alpha_2\epsilon_{t-2}^2 + \cdots + \alpha_q\epsilon_{t-q}^2 \quad (2)$$

where σ_t^2 represents the conditional variance, ϵ_t is the error term, and α_i are the parameters to be estimated.

The GARCH model improves upon the ARCH model by including lagged values of the conditional variance. The basic form of a GARCH(p, q) model is given by:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q}\alpha_i\epsilon_{t-i}^2 + \sum_{j=1}^{p}\beta_j\sigma_{t-j}^2 \quad (3)$$

This approach enables the model to handle short-term disruptions and long-term volatility persistence. ARCH and GARCH models are especially useful for examining and forecasting volatility in financial markets, commodities, and macroeconomic variables. Their ability to capture volatility clustering—where high volatility periods are followed by low volatility periods—makes them essential tools for both researchers and practitioners.

3. Method

3.1. Data Sources

The food price data from Indonesia used in this study is secondary data sourced from the World Bank's data catalog (datacatalog.worldbank.org). The dataset comprises 209 observations, spanning from January 1, 2007, to May 1, 2024. It includes price information for six essetials commodities: chili, eggs, beef meat, chicken meat, rice, and sugar. For the purpose of analysis, the data is divided into training and testing sets. The training set is used to construct and fine-tune the models, while the testing set assesses their performance and predictive accuracy. This separation ensures that the models are evaluated on unseen data, offering a realistic measure of their capability to predict future price movements and volatility in Indonesia's food market.

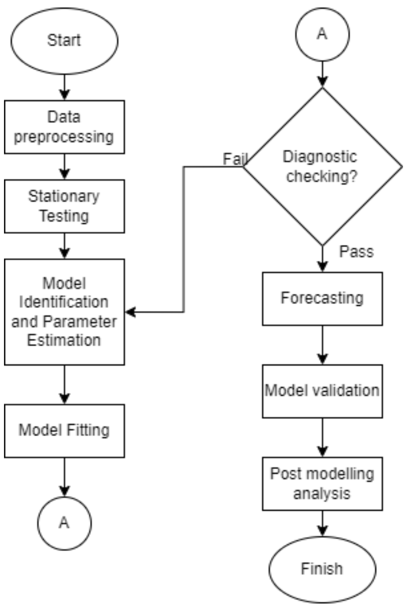

Fig. 1. Research flow

3.2. Analysis Procedure

The research procedures are illustrated in the flowchart Picture 1

4. Result And Discussion

The time series analysis of food prices in Indonesia shows distinct trends and volatility patterns across different commodities from January 1, 2007, to May 1, 2024. Most commodities, including chili, eggs, beef meat, chicken meat, rice, and sugar, exhibit an overall upward trend in prices, reflecting increasing demand and various market pressures. However, the degree of volatility varies significantly: chili and sugar prices display high volatility with frequent and sharp fluctuations due to factors like seasonal changes, market demand shifts, and external shocks. In contrast, eggs and rice demonstrate more stable price trends with minor fluctuations, indicating relatively stable market conditions and efficient production practices. Beef and chicken meat show moderate volatility, with noticeable price spikes in response to market dynamics such as supply chain disruptions and disease outbreaks.

Table 1. Box Cox Transformation

Commodity	Estimated λ	Lower CL (95%)	Upper CL (95%)	Rounded Value
Chili	-0,07	-0,43	0,30	0,00
Eggs	0,24	-0,22	0,70	0,00
Meat beef	0,5	0,13	1,07	0,5
Meat chicken	-0,09	-0,84	0,61	0,00
Rice	-0,16	-0,67	0,34	0,00
Sugar	-0,6	-1,13	-0,14	-0,5

After splitting the data, the first step is to test for stationarity in both variance and mean. The Box-Cox Transformation test results, as shown in Table 1, indicate the need to transform the data to stabilize variance and achieve stationarity. The ADF test results confirm that, after applying the specified differencing steps, the time series for each commodity becomes stationary in terms of mean, with p-values less than 0.05, indicating no further differencing is needed. This stationarity is crucial for reliable ARIMA modelling, as it assumes stationary input data. All commodities, except for beef meat, require one differencing step to achieve stationarity, while beef meat requires two steps. This underscores the importance of preprocessing in time series analysis to ensure the data meets the assumptions of the modelling techniques used. From the ACF and PACF plots in Picture 2, the ARIMA model parameters were determined for estimation. The significance of the estimated coefficients for various ARIMA models, along with their AIC and BIC values, is shown in Table 2.

For each commodity, significant parameters were subjected to diagnostic model tests to evaluate the residual values. The results of these diagnostic tests are presented in Table 3. The diagnostic test results show that the p-values for most models exceed the common threshold of 0,05. This suggests that the residuals do not exhibit significant autocorrelation, indicating that the models fit the data well concerning serial correlation. However, the Kolmogorov-Smirnov (KS) p-values are extremely low for all models, indicating that the residuals deviate significantly from a normal distribution. This suggests that while the models adequately address autocorrelation, there may still be issues with the distribution of the residuals that need to be addressed.

The results of the Kolmogorov-Smirnov (KS) test indicate significant deviations from a normal distribution in the residuals for all models. This indicates possible heteroskedasticity, meaning the variability of the residuals changes over time. To further investigate this issue, an ARCH (Autoregressive Conditional Heteroskedasticity) test was performed. The ARCH test results revealed that only the sugar commodity exhibited ARCH effects, indicating heteroskedasticity in its residuals. This implies that applying ARCH or GARCH models might be more appropriate for capturing the volatility in sugar prices and improving forecast accuracy. For the other commodities, the absence of ARCH effects suggests that their residuals do not exhibit time-varying volatility, and the current models are sufficient without the need for ARCH-GARCH adjustments.

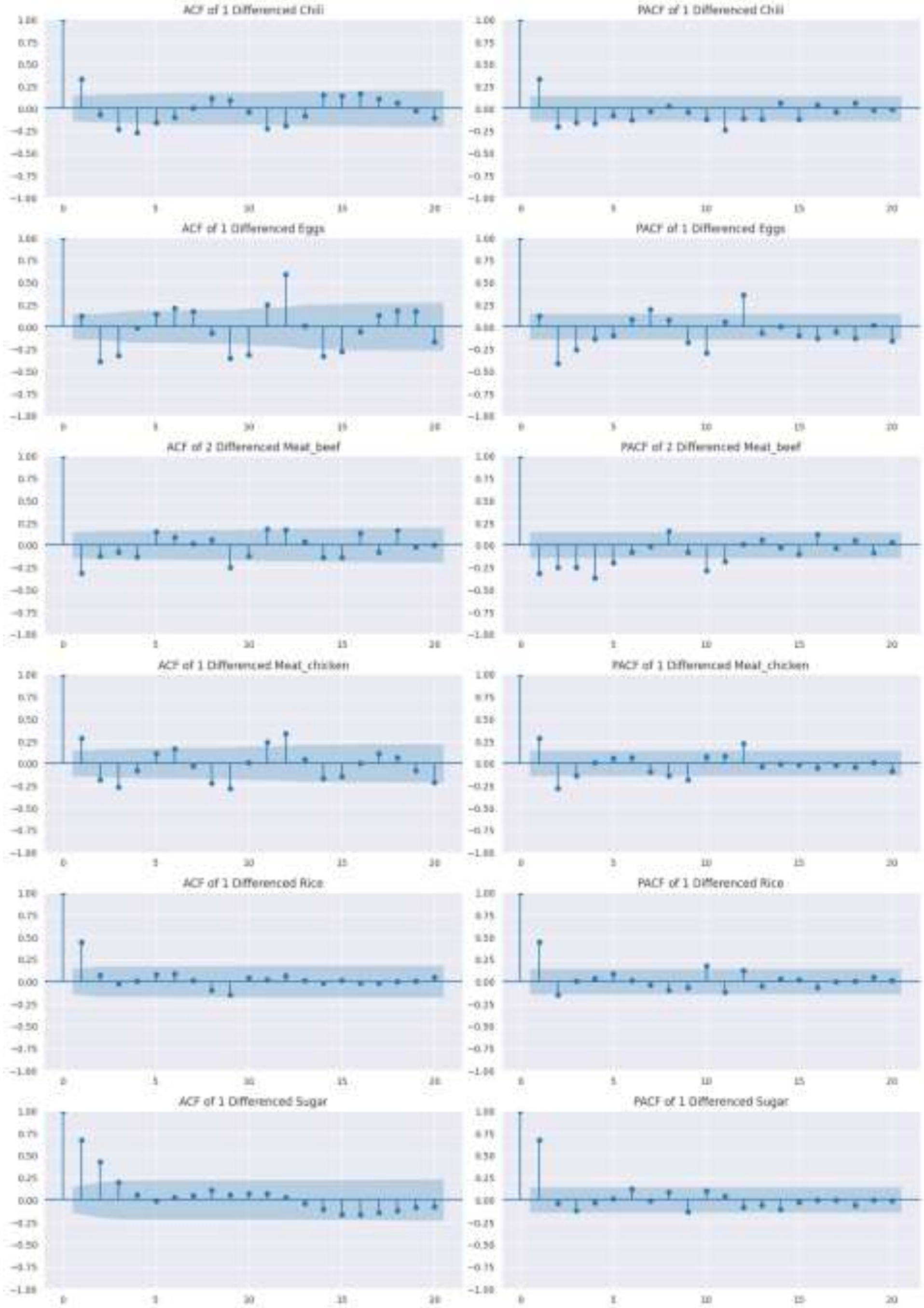

Fig. 2.ACF and PACF plot

Table 4 shows a comparison of various parameters for the estimation models using GARCH on sugar prices. This comparison includes AIC and BIC values of different GARCH models to determine the most suitable one for capturing the volatility and improving the forecast accuracy of sugar prices. Based on the comparison, the GARCH(1,1) model is chosen to predict sugar prices. Meanwhile, the most adequately fitted models to evaluate the price volatility of various commodities are as follows: ARIMA(4,1,0) for chili, ARIMA(4,1,1) for eggs, ARIMA(5,2,0) for beef, ARIMA(3,1,0) for chicken, and ARIMA(2,1,0) for rice.

Table 2. Comparison of ARIMA models

Commodity	ARIMA Model	Parameter	Estimation	p-value	AIC	BIC
Chili	(0,1,4)	ma(1)	-0,6832	-0,6832	-159,225	-143,288
		ma(2)	-0,4177	-0,4177		
		ma(3)	-0,0528	-0,0528		

Commodity	ARIMA Model	Parameter	Estimation	p-value	AIC	BIC
		ma(4)	0,1538	0,1538		
	(4,1,0)	ar(1)	-0,3406	-0,3406	-121,057	-105,12
		ar(2)	-0,3483	-0,3483		
		ar(3)	-0,2785	-0,2785		
		ar(4)	-0,2592	-0,2592		
	(4,1,4)	ar(1)	1,1930	1,1930	-164,680	-135,993
		ar(2)	-1,4348	-1,4348		
		ar(3)	1,1925	1,1925		
		ar(4)	-0,4424	-0,4424		
		ma(1)	1,8295	1,8295		
		ma(2)	-1,8272	-1,8272		
		ma(3)	0,8373	0,8373		
		ma(4)	0,0186	0,0186		
Eggs	(0,1,3)	ma(1)	-1,0586	0,001	-599,482	-586,733
		ma(2)	0,4219	0,0000		
		ma(3)	0,0019	0,0000		
	(3,1,0)	ar(1)	-0,4419	0,0000	-538,624	-525,875
		ar(2)	-0,504	0,0000		
		ar(3)	-0,401	0,0000		
	(3,1,3)	ar(1)	-0,2837	0,477	-613,103	-590,792
		ar(2)	-0,026	0,931		
		ar(3)	-0,4541	0,015		
		ma(1)	-0,6449	0,104		
		ma(2)	-0,7237	0,252		
		ma(3)	0,4105	0,16		
	(4,1,0)	ar(1)	-0,5693	0,0000	-556,263	-540,326
		ar(2)	-0,6618	0,0000		
		ar(3)	-0,5496	0,0000		
		ar(4)	-0,3284	0,0000		
	(4,1,3)	ar(1)	-0,2569	0,745	-610,818	-585,319
		ar(2)	-0,3187	0,471		
		ar(3)	-0,3954	0,266		
		ar(4)	-0,1733	0,232		
		ma(1)	-0,7047	0,376		
		ma(2)	-0,3544	0,756		
		ma(3)	0,1087	0,805		
Meat Beef	(0,2,1)	ma(1)	-0,9998	0,904	936,445	942,797
	(5,2,0)	ar(1)	-1,5585	0,0000	878,019	897,076
		ar(2)	-1,6077	0,0000		
		ar(3)	-1,3401	0,0000		
		ar(4)	-0,9475	0,0000		
		ar(5)	-0,4004	0,0000		
	(5,2,1)	ar(1)	-1,1684	0,0000	776,877	799,11
		ar(2)	-1,1019	0,0000		
		ar(3)	-0,9552	0,0000		
		ar(4)	-0,7791	0,0000		
		ar(5)	-0,3704	0,0000		
		ma(1)	-0,9999	0,0000		
Meat Chicken	(0,1,3)	ma(1)	-0,6404	0,304	-573,503	-560,753
		ma(2)	-0,3902	0,128		
		ma(3)	0,0313	0,696		
	(3,1,0)	ar(1)	-0,3179	0,0000	-539,805	-527,056
		ar(2)	-0,3848	0,0000		
		ar(3)	-0,36611	0,0000		
	(3,1,3)	ar(1)	1,2383	0,0000	-596,089	-573,777
		ar(2)	-1,2551	0,0000		
		ar(3)	0,277	0,004		
		ma(1)	-1,9827	0,005		
		ma(2)	1,99279	0,007		
		ma(3)	-0,9447	0,161		
Rice	(0,1,1)	Sma(1)	-0,783	0,0000	-850,398	-844,023
	(2,1,0)	ar(1)	-0,2201	0,0000	-847,944	-838,382
		ar(2)	-0,2777	0,0000		
	(2,1,1)	ar(1)	0,4967	0,0000	-885,401	-872,652

Commodity	ARIMA Model	Parameter	Estimation	p-value	AIC	BIC
		ar(2)	-0,1553	0,226		
		ma(1)	-0,9802	0,0000		
Sugar	(0,1,2)	ma(1)	-0,1977	0,0000	-2853,99	-2844,42
		ma(2)	-0,0939	0,0000		
	(1,1,0)	ar(1)	$6{,}59e^{-9}$	0,0000	-2853,67	-2847,29
	(1,1,2)	ar(1)	$-9{,}122e^{-12}$	0,0000	-2846,71	-2833,96
		ma(1)	$-9{,}123e^{-12}$	0,0000		
		ma(2)	$-2{,}362e^{-12}$	0,0000		

Table 3. Diagnostic Model Results

Commodity	ARIMA Model	Ljung box p-value	KS statistics	KS p-value
Chili	(4,1,0)	0,5379	0,3452	$1{,}149e^{-19}$
Eggs	(3,1,0)	0,0958	0,4478	$1{,}917e^{-33}$
	(4,1,0)	0,1190	0,4535	$2{,}420e^{-34}$
Meat Beef	(5,2,0)	0,0560	0,2073	$3{,}183e^{-7}$
	(5,2,1)	0,1007	0,1333	0,00301
Chicken	(3,1,0)	0,1080	0,4430	$1{,}065e^{-32}$
Rice	(0,1,1)	$2{,}36e^{-5}$	0,4778	$2{,}696e^{-38}$
	(2,1,0)	0,3751	0,4780	$2{,}512e^{-38}$
Sugar	(0,1,2)	0,8167	0,4998	$4{,}121e^{-42}$
	(1,1,0)	0,9152	0,4998	$4{,}118e^{-42}$
	(1,1,2)	0,0914	0,4998	$4{,}113e^{-42}$

Table 4. GARCH comparison

Commodity	**GARCH Model**	**AIC**	**BIC**
Sugar	(1,1)	-2901,96	-2889,19
	(1,2)	-2894,69	-2878,72
	(2,1)	-2892,62	-2876,65
	(2,2)	-2887,46	-2868,30

Finally, Table 5 shows a comparison of MSE, MAE, RMSE, and MAPE to assess model accuracy. The high error metrics for chili and sugar suggest significant volatility and the need for more sophisticated modeling techniques. Conversely, commodities like beef meat, chicken meat, and rice exhibit lower errors, indicating more stable and predictable price patterns. These findings emphasize the importance of continuously refining forecasting models and integrating additional variables to improve accuracy.

Table 5. Model Evaluation

Commodity	MSE	MAE	RMSE	MAPE(%)
Eggs	$3{,}46e^{8}$	15910,01	18608,61	29,94
Eggs	$2{,}15e^{7}$	4359,15	4640,08	14,87
Meat Beef	$5{,}11e^{7}$	6775,38	7150,33	5,12
Meat Chicken	$1{,}87e^{7}$	3017,50	4324,21	7,72
Rice	$4{,}76e^{6}$	1586,50	2182,04	10,99
Sugar	$4{,}83e^{6}$	1946,81	2198,49	12,12

5. Conclusions And Suggestions

This research analysed the volatility and trends in the prices of six key commodities in Indonesia: chili, eggs, beef meat, chicken meat, rice, and sugar, over the period from January 1, 2007, to May 1, 2024. By employing ARIMA and GARCH models, we identified the best-fit models for each commodity. The ARIMA models were suitable for chili (ARIMA(4,1,0)), eggs (ARIMA(4,1,0)), beef meat (ARIMA(5,2,0)), chicken meat (ARIMA(3,1,0)), and rice (ARIMA(2,1,0)), while the GARCH(1,1) model was the most appropriate for predicting sugar prices. High error metrics for chili and sugar suggest significant volatility, highlighting the need for more sophisticated modelling techniques for these commodities. In contrast, lower errors in beef meat, chicken meat, and rice indicate more stable and predictable price patterns.

To improve future research, continuously refine and update forecasting models with more recent data and include additional variables like weather conditions, policy changes, and global market trends. For high-volatility commodities like chili and sugar, explore advanced models such as multivariate GARCH or machine learning approaches. Ensure high-quality data collection and preprocessing to enhance reliability. Regularly monitor and evaluate models to quickly adapt to market changes. Use these insights to inform policymakers about potential price instability, allowing for proactive measures to stabilize the market and ensure food security. Engage with stakeholders to share findings and collaboratively develop effective strategies for managing price volatility.

References

[1] V. Erokhin and T. Gao, ‘Impacts of COVID-19 on Trade and Economic Aspects of Food Security: Evidence from 45 Developing Countries’, *Int J Environ Res Public Health*, vol. 17, no. 16, 2020, doi: 10.3390/ijerph17165775.

[2] H. Hamilton *et al.*, ‘Exploring global food system shocks, scenarios and outcomes’, *Futures*, vol. 123, p. 102601, 2020, doi: https://doi.org/10.1016/j.futures.2020.102601.

[3] I. Setiawati, Ardiansyah, and R. Taufikurohman, ‘Price volatility of staple food using ARCH-GARCH model’, *IOP Conf Ser Earth Environ Sci*, vol. 653, no. 1, p. 12146, Feb. 2021, doi: 10.1088/1755-1315/653/1/012146.

[4] Z. Rozaki, ‘COVID-19, Agriculture, and Food Security in Indonesia’, *Reviews in Agricultural Science*, vol. 8, pp. 243–260, 2020, doi: 10.7831/ras.8.0_243.

[5] A. Hermawan *et al.*, ‘The Impact of the COVID-19 Pandemic on the Prices Volatility of the Main Foodstuffs in Indonesia’, *Community empowerment, sustainable cities, and transformative economies*, pp. 669–687, 2022.

[6] M. Jannah, K. Sadik, and F. M. Afendi, ‘Study of Forecasting Method for Agricultural Products Using Hybrid ANN-GARCH Approach’, *J Phys Conf Ser*, vol. 1863, no. 1, p. 012052, 2021, doi: 10.1088/1742-6596/1863/1/012052.

[7] E. P. Lestari, S. D. W. Prajanti, W. Wibawanto, and F. Adzim, ‘ARCH-GARCH analysis: An approach to determine the price volatility of red chili’, *AGRARIS: Journal of Agribusiness and Rural Development Research*, vol. 8, no. 1, pp. 90–105, 2022.

[8] M. N. E. Brahmana and N. K. Hidayat, ‘Price Volatility Analysis of Red and Cayenne Pepper of Java Islands during Covid-19 Pandemic’, *Journal of Economics, Finance and Accounting Studies*, vol. 4, no. 4, pp. 11–18, 2022.

[9] A. W. Putra, J. Supriatna, R. H. Koestoer, and T. E. B. Soesilo, ‘Differences in local rice price volatility, climate, and macroeconomic determinants in the Indonesian market’, *Sustainability*, vol. 13, no. 8, p. 4465, 2021.

[10] M. Henchion, A. P. Moloney, J. Hyland, J. Zimmermann, and S. McCarthy, ‘Trends for meat, milk and egg consumption for the next decades and the role played by livestock systems in the global production of proteins’, *Animal*, vol. 15, p. 100287, 2021.

[11] T. Karyani, A. Susanto, E. Djuwendah, and H. Hapsari, ‘Red chili agribusiness and the risks faced by the farmers’, in *IOP Conference Series: Earth and Environmental Science*, IOP Publishing, 2020, p. 012002.

[12] H. Mahmoud Sayed Agbo, ‘Forecasting agricultural price volatility of some export crops in Egypt using ARIMA/GARCH model’, *Review of Economics and Political Science*, vol. 8, no. 2, pp. 123–133, 2023.

[13] Y. Xu, Z. Xia, C. Wang, W. Gong, X. Liu, and X. Su, ‘An Empirical Analysis of the Price Volatility Characteristics of China’s Soybean Futures Market Based on ARIMA-GJR-GARCH Model’, *Journal of Mathematics*, vol. 2021, no. 1, p. 7765325, 2021.

[14] V. I. Kontopoulou, A. D. Panagopoulos, I. Kakkos, and G. K. Matsopoulos, ‘A review of ARIMA vs. machine learning approaches for time series forecasting in data driven networks’, *Future Internet*, vol. 15, no. 8, p. 255, 2023.

[15] S. Makridakis and M. Hibon, ‘ARMA models and the Box–Jenkins methodology’, *J Forecast*, vol. 16, no. 3, pp. 147–163, 1997.

[16] R. F. Engle, ‘Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation’, *Econometrica*, pp. 987–1007, 1982.

[17] T. Bollerslev, ‘Generalized autoregressive conditional heteroskedasticity’, *J Econom*, vol. 31, no. 3, pp. 307–327, 1986