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Tea Price Dynamics in the Kolkata Market: An Asymmetric ARMAX-EGARCH Approach with Seasonal Regressors

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Abstract

Forecasting prices of agricultural commodity is challenging due to long-term trends, seasonal fluctuations, and market volatility. The present study investigates the behaviour of monthly tea prices in the Kolkata market, which is also known as India's principal tea trading hub. To fulfill the objectives of the study, we have used tea prices from January 1960 to April 2026. Several forecasting models, including Seasonal Naïve (SNaïve), Exponential Smoothing (ETS), and Seasonal ARIMA (SARIMA), were evaluated. SARIMA achieved the best performance among the linear alternatives (RMSE: 0.2132 and MAPE: 6.0545). However, residual diagnostics uncovered prominent volatility clustering and conditional heteroskedasticity, demonstrating that linear models fail to capture the market's true risk structure (Lag 4, Lag 8 and Lag 12 with p=0.001). To address these limitations, an integrated ARMAX-EGARCH (1,1) model with monthly seasonal dummy variables and a Skewed Student-t distribution was developed. The proposed framework simultaneously captures serial dependence, recurring seasonal patterns, asymmetric market responses, and heavy-tailed price movements. The empirical results show structural seasonal changes, enduring volatility memory, and significant heavy-tailed risk factors. The model reveals a significant asymmetric leverage impact, indicating that negative price shocks generate over double the volatility of positive shocks. The findings demonstrate that incorporating asymmetric volatility dynamics significantly improves the understanding and forecasting of tea price behavior. The proposed approach provides a reliable risk-adjusted forecasting tool that can support decision-making by producers, traders, agribusiness firms, and policymakers operating in volatile agricultural markets.

Keywords: ARMAX-EGARCH; Forecasting; Seasonal effects; Tea prices; Volatility clustering

JEL Classification: C150, C22, C58, G170

Introduction

Understanding the behavior of prices of agricultural commodity is a fundamental yet challenging issue in agricultural economics (Hegde *et al*., 2020; Geetha *et al*., 2024). For a highly traded crop like tea (*Camellia sinensis*), prices do not just move at random; they carry deep structural patterns, from long-term trends driven by shifting consumer demand to sharp, short-term spikes caused by seasonal harvest cycles (Mila *et al.*, 2021; Kumbasaroglu, 2026). In India, the Kolkata market serves as the primary tea trade hub. The prices established as a benchmark that directly influences global supply chains, national agribusiness strategies, and the livelihoods of millions of small farmers. Because the stakes are so high, building reliable models to forecast these prices is essential for managing market risk and structuring sound agricultural policies (Mishra & Dash, 2024; Alao *et al*., 2023).

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For decades, researchers analyzing agricultural markets have relied heavily on traditional linear models like ARIMA and its seasonal counterpart, SARIMA. These models assume that market volatility is constant over time-a property known as homoskedasticity. While convenient for calculation, this assumption rarely holds true in real-world spot markets. Agricultural trading is constantly disrupted by unpredictable shocks, such as sudden weather anomalies, changes in trade tariffs, or seasonal harvest surpluses (Seeley, 2025). Driven by these disruptions, the market exhibits volatility clustering—a phenomenon where high-turbulence periods stick around, followed by periods of relative calm (Yuan *et al*., 2020; Abeje, 2021). When a time series exhibits this type of changing variance-known as Autoregressive Conditional Heteroskedasticity (ARCH) effects-standard linear models struggle. Ignoring these variations leads to biased error estimates, which produce unrealistic forecast intervals that completely miscalculate actual market risk.

To address these limitations, this study evaluates a comprehensive forecasting pipeline using historical monthly tea prices from the Kolkata market, spanning more than six decades from January 1960 through April 2026. While initial linear mean modeling and baseline symmetric GARCH models fail to clear residual dependencies, we resolve these vulnerabilities by building an integrated, asymmetric ARMAX-EGARCH framework. By transforming the target series into log-returns, introducing an exogenous seasonal monthly dummy matrix, and employing a Skewed Student-error distribution, we simultaneously capture deterministic seasonal cycles, asymmetric leverage shocks, and heavy tail risks.

Data Sources and Methodology

The present study was carried out in Kolkata tea market situated in West Bengal. The behaviour of tea prices in Kolkata was studied for the period 1960 to 2026. The multi-decadal dataset encompasses 66 years and four months of continuous records (January 1960 to April 2026). The data was partitioned into an ex-post validation split: a training dataset (starting from January 1960 to April 2025) and a hold-out test dataset (starting from May 2025 to April 2026) (Figure 1). To fulfil the objectives of the study, secondary data were collected. The study is based on the data monitored and collected by World Bank. The data were analyzed using tabular methods and statistical techniques relevant to the study like time-series analysis.

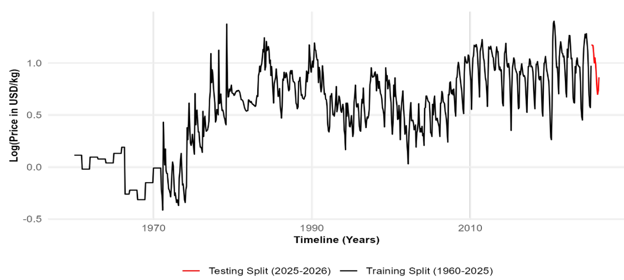

Figure 1: Training-Testing Split of the Dataset

Analytical framework

Testing for unit roots and stationarity

Before applying any time series model, we must ensure the data is stationary to avoid drawing misleading or spurious conclusions. We verify the stochastic properties of the tea price series Y_t using two complementary tests: the Augmented Dickey-Fuller (ADF) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. The ADF test checks for the presence of a unit root (indicating non-stationarity) by running the following regression:

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \sum_{i=1}^{k} \delta_i \Delta Y_{t-i} + \epsilon_t$$

Here, δ represents the first-difference operator ($\Delta Y_t = Y_t - Y_{t-1}$), α is a deterministic drift constant, t represents a linear time trend, and is the optimal number of lags chosen via the Akaike Information Criterion (AIC). The null hypothesis (H_0:γ = 0) states that the series is non-stationary.

Conversely, the KPSS test flips the assumption, testing the null hypothesis that the series is inherently stationary around a deterministic trend (H_0:σ^2_ε=0). It calculates a score statistic based on the cumulative residuals:

$$\text{KPSS} = \frac{\sum_{t=1}^{T} S_t^2}{T^2\sigma^2}$$

In this formula, $S_t = \sum_{i=1}^{t} e_i$ is the cumulative sum of the residuals from a stationarity regression, and σ^2 estimates the long-run variance. To stabilize multi-decadal variance and mitigate scale expansion across the 1960–2026 horizon (Figure 2, 3 and 4), the data is modeled as a log-return series x_t, expressed as:

$$x_t = \Delta \ln(Y_t) = \ln(Y_t) - \ln(Y_{t-1})$$

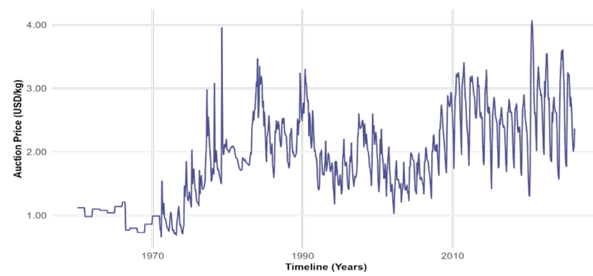

Figure 2: Monthly Kolkata tea prices (1960-2026)

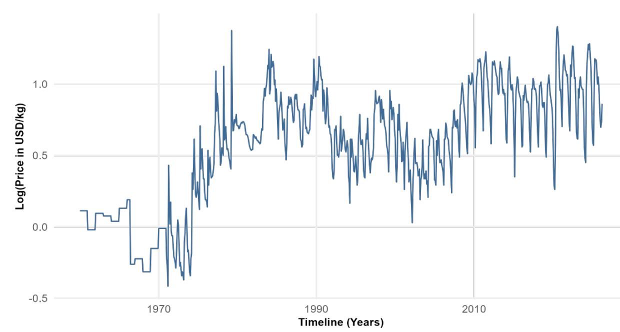

Figure 3: Log-Transformed tea price series

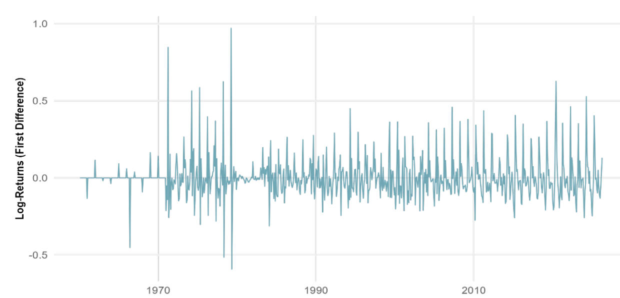

Figure 4: Log-return series

Seasonal Naïve (SNaïve) model

To establish a non-parametric baseline that captures pure seasonal repetition without parameter optimization, the Seasonal SNaïve (SNaïve) model is introduced. This framework assumes that the best predictor of a future value is the observed value from the exact same season of the previous period. Using standard lag operator notation (L), where represents the seasonal period (m = 12 for monthly price data), the model can be written as:

$$y_t = y_{t-m} + \varepsilon_t \text{ or, equivalently, } (1 - L^m)yt = \varepsilon_t$$

Here, the operator $1 - L^m$ acts as a seasonal differencing mechanism that directly maps the current price y_t to its lag from one year prior, while ε_t represents the residual forecast error. Unlike parametric models, the SNaïve framework contains no autoregressive (ϕ, Φ) or moving average ($\theta\varsigma$) polynomial operators, nor does it include a drift constant (c). It assumes that short-term regular relationships and seasonal patterns across years are perfectly rigid (Figure 5), serving as a vital benchmark to evaluate whether more complex linear frameworks add significant predictive value.

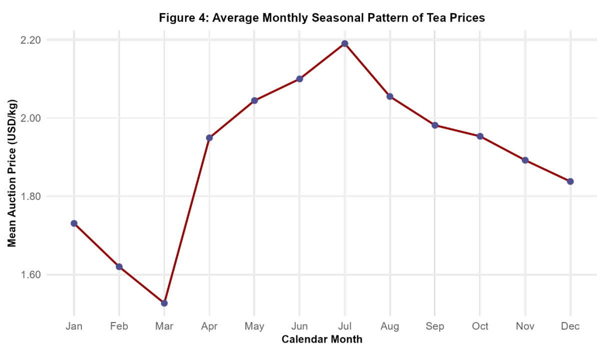

Figure 5: Average monthly seasonal pattern of Tea prices

Volatility Diagnostics: Testing for ARCH effects

To prove whether standard linear models are sufficient or if we need a more advanced approach, we extract the residuals (ε_t) from our best mean model and test them for conditional heteroskedasticity using Engle's Lagrange Multiplier (LM) test. This test looks for patterns in the volatility by running an auxiliary regression on the squared residuals:

$$\epsilon_t^2 = \omega_0 + \sum_{i=1}^{p} \alpha_i \, \epsilon_{t-i}^2 + v_t$$

The null hypothesis assumes homoskedasticity-meaning that the residuals are completely stable and have no predictable variance patterns (H_0:α_1=α_2 = --- = α_p= 0). The test statistic relies on the R^2 value generated by this secondary regression:

$$\text{ARCH-LM} = T \cdot R^2 \sim \chi^2(p)$$

If the resulting test statistic is statistically significant, we reject the null hypothesis. This confirms powerful volatility clustering and mandates the deployment of a conditional variance engine (Dessie *et al*., 2023; Mubarok *et al*., 2024; Zahira and Zainuddin, 2023), which provides mathematical confirmation that ARCH effects exist, meaning a traditional linear ARIMA model alone is inadequate for our data.

An Integrated ARMAX-EGARCH Framework

To overcome remaining linear autocorrelation and handle asymmetric volatility shocks, we implement an integrated Autoregressive Moving Average with Exogenous Regressors (ARMAX) mean equation combined with an Exponential GARCH (EGARCH) variance model.

Mean Equation (ARMAX)

To absorb the structural calendar effects that standalone seasonal filters fail to clear, we construct a deterministic seasonal matrix containing 11 binary monthly dummy variables ($D_{i,t}$). The conditional mean is modeled as an process: (Marc, 2022; Silva *et al*., 2022; Uyar and Ağcakoca, 2020).

$$x_t = \mu + \phi_1 x_{t-1} + \theta_1 \varepsilon_{t-1} + \sum_{i=1}^{11} \delta_i \, D_{i,t} + \varepsilon_t$$

Where accounts for the baseline monthly drift, ϕ_1 is the regular autoregressive parameter, θ_1 is the moving average parameter, and δ_i represents the regression coefficients assigned to each month from January through November. December serves as the omitted baseline reference month to avoid the dummy variable trap.

Variance Equation (EGARCH (1,1))

To address asymmetric "leverage effects"-where price drops and price spikes generate distinct magnitudes of market volatility-the conditional variance (σ^2_t) is modeled using an specification (Dinku and Worku, 2022; Dinga *et al*., 2023). By modeling the natural log of variance ($\text{In}(\sigma^2_t)$), the system bypasses non-negativity parameter constraints: (Enumah & Adewinbi, 2023; Yıldırım & Bekun, 2023).

$$\ln(\sigma_t^2) = \omega + \alpha_1(|z_{t-1}| - E|z_{t-1}|) + \gamma_1 z_{t-1} + \beta_1 \ln(\sigma_{t-1}^2)$$

Where is the baseline log-variance constant, captures the magnitude of symmetric ARCH shocks, β_1 scales the persistence of volatility memory, γ_1 and tracks the asymmetric leverage parameter. The standard error innovation is defined as $\varepsilon_t = \sigma_t z_t$.

Innovation Density (Skewed Student-test)

Agricultural price adjustments exhibit heavy tails (fat tails) and directional bias due to acute supply shocks (Girgin, 2023). We resolve this by assuming zt follows a standardized Skewed Student-t (sstd) distribution parameterized by a skewness factor (ξ) and a shape/degrees-of-freedom factor (ν). The system parameter estimation is executed by using Maximum Likelihood using automated numerical optimization engines (Ardia *et al*., 2019).

Results and Discussion

The descriptive statistics for the 796 observations of tea price (USD), reflects a relatively stable market with a slight upward bias and thinner-than-normal tails, a baseline structural assessment typical in tea market econometrics (Priyadharshini, 2021). The prices span a range of 3.41, moving from a minimum of 0.66 to a maximum of 4.07, while a low standard error (SE=0.03) indicates high precision in the sample mean estimate. The distribution features a mild right-skewness ("Skewness"=0.24), suggesting a small concentration of higher price spikes, which is highly characteristic of agricultural commodity markets prone to weather or supply shocks (Sahu *et al*., 2024). Furthermore, the negative kurtosis ("Kurtosis"=-0.61) reveals a platykurtic distribution, meaning the price data has a flatter peak and lighter tails than a standard normal curve; this aligns with real-world statistical deviations where perfect normality is rare, indicating fewer extreme price fluctuations or outlier shocks during this specific observed period (Table 1).

Baseline linear performance matrix

The baseline linear performance matrix reveals that the model outshines all purely linear alternatives. It yields the lowest error variance and minimizes absolute percentage deviations under the single-digit threshold (Table 2). However, visual diagnostics on the forecast values obtained from the fitted SARIMA (1,1,1)(1,1,1) fail to capture the actual pattern exists in the data set (Figure 7).

Pre-Upgrade ARCH diagnostics

Engle's ARCH-LM test was performed on the linear residuals to evaluate the potential presence of conditional heteroskedasticity.

The test statistics are highly significant at the 1 per cent level across all tested lag intervals, systematically rejecting the null hypothesis of homoskedasticity. This confirms powerful volatility clustering and mandates the deployment of a conditional variance engine also supported by Figure- 8, 9, 10 and 11.

Maximum likelihood estimation of the upgraded ARMAX-EGARCH model

To rectify the residual structural deficiencies, the optimized model was estimated by using full-sample, Maximum Likelihood along with Skewed Student-innovations and the same are represented in Table 4. Estimated EGARCH Conditional Volatility are also plotted in Figure 12 representing the volatility clustering.

Table 1: Descriptive statistics of tea prices in Kolkata market

Observations	Min	Max	Range	Skewness	Kurtosis	Se
796	0.66	4.07	3.41	0.24	−0.61	0.03

Table 2: Out-of-sample forecasting validation matrix

Candidate Models	RMSE	MAE	MAPE (%)	MASE
Seasonal SNaïve	0.3837	0.3217	12.1362	1.134
ETS state space model	0.2156	0.1775	6.8049	0.6258
Non-seasonal ARIMA (1,1,1)	0.3517	0.2869	12.0782	1.0113
Seasonal ARIMA (1,1,1)×(1,0,1)$_{12}$	0.2132	0.1643	6.0545	0.5791

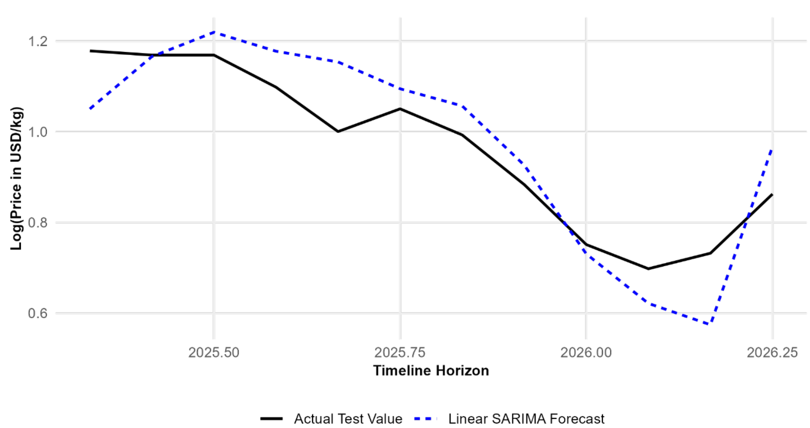

Figure 6: SARIMA forecast versus actual values for testing period

Table 3: ARCH-LM test on standalone linear residuals

Lag	Chi-Square statistic	*df*	*p*-Value
Lag 4	44.1242	4	< 0.001
Lag 8	44.7854	8	< 0.001
Lag 12	187.032	12	< 0.001

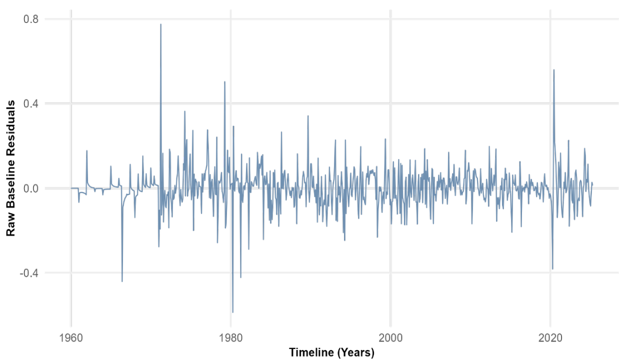

Figure 7: Residual time plot of the SARIMA model

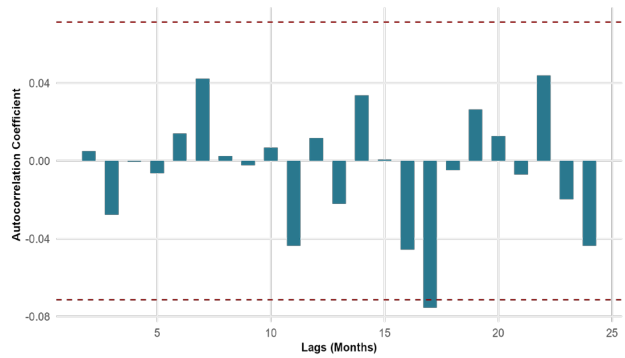

Figure 8: ACF of the SARIMA residuals

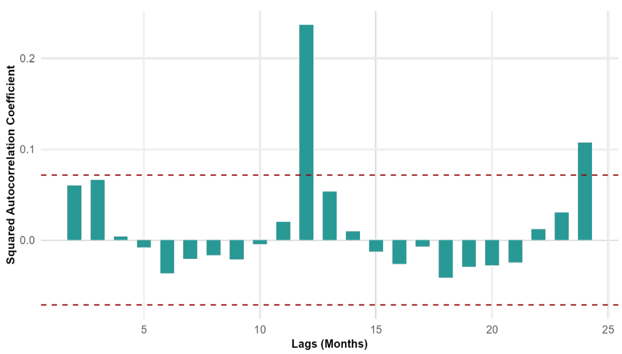

Figure 9: ACF of squared SARIMA residuals (ARCH Diagnostic)

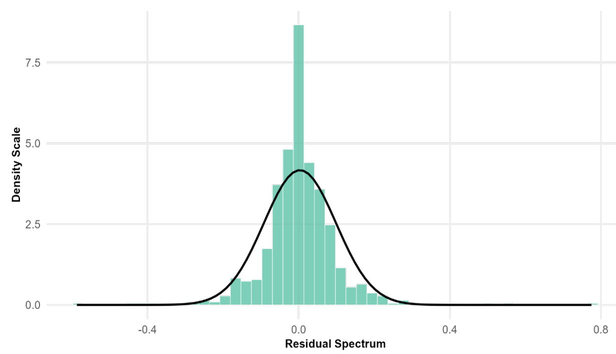

Figure 10: Distribution of SARIMA residuals (Histogram with density)

Mathematical Specification of the Empirical Variance Component

$$\mathrm{In}(\sigma^2_t) = -0.0026+0.3493(|z_{t-1}|-E|z_{t-1}|) -0.1433z_{t-1} + 0.9999\ \mathrm{In}(\sigma^2_{t-1})$$

The estimated asymmetry parameter (γ_1=–0.1433, p<0.001) confirms a stark leverage effect in the Kolkata tea trade. When positive returns occur ($z_{t-1} > 0$), the absolute impact on variance is ($\alpha1+\gamma1$) = 0.2060. Conversely, when negative return shocks occur ($z_{t-1} < 0$), the impact increases to ($\alpha1-\gamma1$) 0.4926. This proves that downward price corrections trigger more than double the market volatility and stakeholder anxiety than matching upward movements.

The persistence term ($\beta1$=0.9999) reveals an exceptionally strong volatility memory, meaning that price destabilization driven by climatic anomalies or trade disruptions will take multiple subsequent cycles to decay.

Distributional Characteristics

The skewness parameter (ξ=1.2190, p <0.001) highlights a heavy right-skew, signaling a prone distribution toward acute positive outlier price spikes (Gupta *et al.*, 2023). The shape parameter (v = 2.0100) sits near its theoretical minimum boundary, demonstrating severe leptokurtosis ("fat tails") (Lu *et al.*, 2023). This statistically confirms that extreme market shocks occur far more frequently than standard normal Gaussian parameters are capable of predicting.

Post-Estimation Residual Diagnostics

To ensure model adequacy, the standardized and squared standardized residuals were subjected to Ljung-Box portmanteau testing across 12 monthly lags (Rubio *et al.*, 2023) which are reported in Table 5 (Ahmar et al., 2025; Adams and Olives, 2025).

Table 4: Maximum likelihood parameter estimates of ARMAX-EGARCH model

Component	Parameter	Coefficient	SE	*z*-value	*p*-value
Mean Equation (ARMAX)	Intercept (μ)	-0.00130	0.00000	-19113.460	< 0.001
	Regular AR (ϕ_1)	0.99560	0.00003	34385.927	< 0.001
	Regular MA (θ_1)	-1.00000	0.00005	-19183.309	< 0.001
	January seasonal dummy ($mxreg_1$)	-0.01600	0.00000	-44137.650	< 0.001
	February seasonal dummy ($mxreg_2$)	0.00310	0.00001	615.162	< 0.001
	March seasonal dummy ($mxreg_3$)	0.00140	0.00000	492.413	< 0.001
	April seasonal dummy ($mxreg_4$)	0.00510	0.00000	2513.489	< 0.001
	May seasonal dummy ($mxreg_5$)	0.00440	0.00000	1084.064	< 0.001
	June seasonal dummy ($mxreg_6$)	0.00510	0.00000	1817.938	< 0.001
	July seasonal dummy ($mxreg_7$)	0.00530	0.00001	723.389	< 0.001
	August seasonal dummy ($mxreg_8$)	0.00100	0.00000	258.018	< 0.001
	September seasonal dummy ($mxreg_9$)	0.00000	0.00002	-0.752	0.452
	October seasonal dummy ($mxreg_{10}$)	0.00430	0.00001	763.501	< 0.001
	November seasonal dummy ($mxreg_{11}$)	0.00200	0.00000	558.473	< 0.001
Variance equation (EGARCH)	Volatility constant (ω)	-0.00260	0.00000	-591.017	< 0.001
	ARCH shock parameter (α_1)	0.34930	0.00002	21477.044	< 0.001
	GARCH persistence parameter (β_1)	0.99990	0.00009	11184.739	< 0.001
	Asymmetry / Leverage parameter (γ_1)	-0.14330	0.00130	-113.168	< 0.001
Distributional metrics	Student-t skew factor (ξ)	1.21900	0.00120	1028.573	< 0.001
	Student-t shape factor (v)	2.01000	0.00020	12309.091	< 0.001

Note: December serves as the omitted baseline reference month for the conditional mean seasonal matrix.

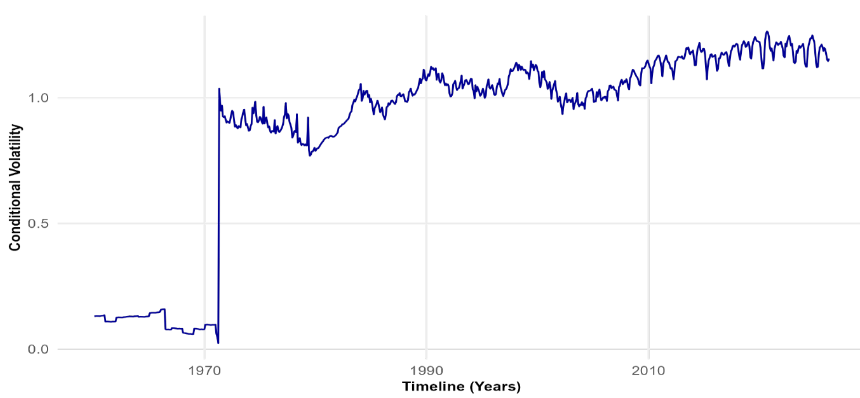

Figure 11: Estimated EGARCH conditional volatility (σ_t)

Table 5: Post-estimation residual diagnostics

Diagnostic Check Type	Test Statistic	*p*-Value
Ljung-box test on standardized residuals	8.1666	0.7720
Ljung-box test on squared residuals	0.0386	1.0000

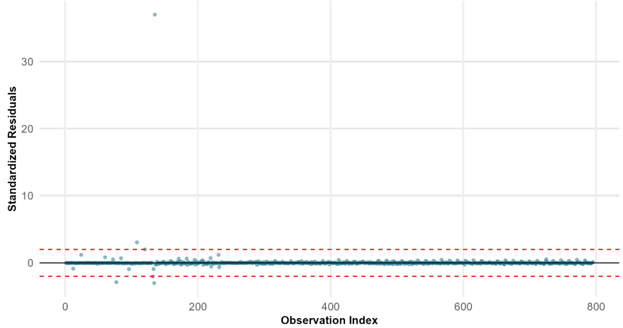

Figure 12: Standardized residual diagnostic panel

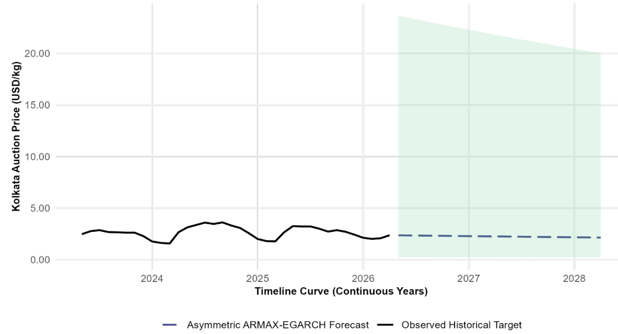

Figure 13: Tea Price Forecast with 95% Confidence Intervals (24-Months)

The Ljung-Box test on the standardized residuals yields a highly insignificant test statistic (Q(12) = 8.1666, p=0.772), failing to reject the null hypothesis of independent errors. This confirms that the inclusion of explicit monthly exogenous regressors paired with the parsimonious ARMAX process successfully neutralized the linear serial correlation (Figure 13) (Mishra & Dash, 2024; Alao *et al*., 2023).

Furthermore, the Ljung-Box test on the squared standardized residuals yields a test statistic of 0.0386 with a p-value of 1.000 (Singh et al., 2024; Wang et al., 2025). This indicates a complete failure to reject the null hypothesis of homoskedasticity, proving that the asymmetric EGARCH specification has completely accommodated the time-varying variance structures (Srihari *et al*., 2024; Teker *et al*., 2024). Collectively, these diagnostics confirm that the model's residuals behave strictly as a white noise process, establishing the structural integrity and validity of the resulting 24-month ex-ante forecasts showing an almost a constant line (Figure 14) as reported by a number of researchers like, Zhao *et al*., 2024; Michańków *et al*., 2023; Song *et al*., 2023.

Conclusions and Policy Implications

This study developed a robust forecasting pipeline for spot prices of tea in the benchmark Kolkata auction market using over six decades of monthly data. While traditional linear frameworks like SARIMA map directional patterns efficiently, they fall short when handling time-varying risk structures and extreme price shocks.

By building an integrated ARMAX-EGARCH(1,1) framework under a Skewed Student- distribution, we solved these structural issues. Our final model successfully cleared all remaining residual dependencies (Q p = 0.7720; Q_2 p = 1.000). The empirical results reveal structural seasonal variations, persistent volatility memory (β_1), and severe heavy-tailed risks (ν=2.0100). Crucially, the model uncovers a strong asymmetric leverage effect (γ_1= – 0.1433), demonstrating that negative price shocks generate more than double the volatility of positive shocks. These findings provide agribusinesses and policymakers with a reliable, risk-adjusted forecasting window to manage market instability and secure smallholder livelihoods.

References

Abeje T 2021. Modeling Price Volatility for Selected Agricultural Commodities in Ethiopia: The Application of GARCH Models. Available at SSRN: https://ssrn.com/abstract=3912501 or http://dx.doi.org/10.2139/ssrn.3912501.

Adams S O and Olives P I 2025. Modelling and Forecasting of Crude Oil Price Return Volatility from 2006-2023: An Application of the GARCH Models. *Journal of Science and Technology* **17**:94-107. https://doi.org/10.30880/jst.2025.17.01.010

Ahmar A S, Alfairus M Q and Nursya'bani N 2025. Sustainable energy risk management: An integrated exponential smoothing and ARCH-GARCH framework for probabilistic forecasting. *Development and Sustainability in Economics and Finance* **8:**100087. https://doi.org/10.1016/j.dsef.2025.100087

Alao R O, Alhassan A, Alao S, Olanipekun I O, Olasehinde-Williams G O and Usman O 2023. Symmetric and asymmetric GARCH estimations of the impact of oil price uncertainty on output growth: evidence from the G7. *Letters in Spatial and Resource Sciences* **16**: 5. https://doi.org/10.1007/s12076-023-00325-z

Ardia D, Bluteau K and Rüede M 2019. Regime changes in Bitcoin GARCH volatility dynamics. *Finance Research Letters*, **29**: 266-271. https://doi.org/10.1016/j.frl.2018.08.009

Dessie E, Brhane T, Mohammed A and Walelign A 2023. Agricultural commodity price volatility models and prediction performance of GARCH family models. *Horn of African Journal of Business and Economics (HAJBE)* **6**:150-171. https://journals.ju.edu.et/index.php/jbeco/article/view/5174/1836

Dinga B, Claver J H, Cletus K K and Che S F 2023. Modeling and predicting exchange rate volatility: Application of symmetric GARCH and asymmetric EGARCH and GJR-GARCH models. *Journal of the Cameroon Academy of*

Sciences **19**: 155-178. https://dx.doi.org/10.4314/jcas.v19i2.6

Dinku T and Worku G 2022. Asymmetric GARCH models on price volatility of agricultural commodities. *SN Business & Economics* **2**: 181. https://doi.org/10.1007/s43546-022-00355-7

Enumah N K. and Adewinbi H S 2023. An analysis of the exchange rate volatility in Poland using the GARCH, GJR-GARCH and EGARCH models. *Earthline Journal of Mathematical Sciences* **11**: 287-302. https://doi.org/10.34198/ejms.11223.287302

Geetha V, Gomathy C K, Sai B P V H N and Kiran C S 2024. Price forecasting of agricultural commodities. *AIP Conference Proceedings* 3028, 020015-1–020015-9. AIP Publishing LLC. https://doi.org/10.1063/5.0212568

Girgin Y 2023. *Modeling Exchange Rate Volatility using Arma-garch Aproach with Non-gaussian Distributions.* M.Sc. Thesis, submitted to Middle East Technical University, Turkey.

Gupta R, Ji Q, Pierdzioch C and Plakandaras V 2023. Forecasting the conditional distribution of realized volatility of oil price returns: The role of skewness over 1859 to 2023. *Finance Research Letters*, **58**: 104501. https://doi.org/10.1016/j.frl.2023.104501

Hegde G, Hulipalled V R and Simha J B 2020. A study on agriculture commodities price prediction and forecasting. In: *2020 International Conference on Smart Technologies in Computing, Electrical and Electronics (ICSTCEE), Bangaluru, India,* pp. 316-321. 10.1109/ICSTCEE49637.2020.9277401

Kumbasaroglu H 2026. Global Tea Production Forecasting Using ARIMA Models: A Multi-Country Time-Series Analysis (1961–2028). *Sustainability* **18**: 1005. https://doi.org/10.3390/su18021005

Lu L, Lei Y, Yang Y, Zheng H, Wang W, Meng Y, ... and Zha L 2023. Assessing nickel sector index volatility based on quantile regression for Garch and Egarch models: Evidence from the Chinese stock market 2018–2022. *Resources Policy* **82**: 103563. https://doi.org/10.1016/j.resourpol.2023.103563

Marc T 2022. Optimal ARMAX model order identification of dynamic systems. *London Journal of Engineering Research* **22**: 1-22. https://journalspress.uk/index.php/LJER/article/view/407

Michańków J, Kwiatkowski Ł and Morajda J 2023. Combining deep learning and GARCH models for financial volatility and risk forecasting. https://doi.org/10.48550/arXiv.2310.01063

Mila F A, Noorunnahar M, Nahar A, Acharjee D C, Parvin M T and Culas R J 2021. Modelling and forecasting of tea production, consumption and export in Bangladesh. *Current Applied Science and Technology* **22**. DOI: 10.55003/cast.2022.02.22.009

Mishra A and Dash A K 2024. Return volatility of Asian stock exchanges; a GARCH DCC analysis with reference of Bitcoin and global crude oil price movement. *Journal of Chinese Economic and Foreign Trade Studies* **17**: 29-48. https://doi.org/10.1108/JCEFTS-01-2024-0009

Mubarok A F, Komalawati K and Setiadi A 2024. ARCH/GARCH analysis: estimating beef price volatility in Indonesia. *Jurnal Ilmiah Manajemen Kesatuan* **12**: 391-398. DOI: 10.37641/jimkes.v12i2.2455

Priyadharshini, M. (2021). An Empirical Study on Forecasting Production and Price of Tea in India. *Asian Journal of Agricultural Extension, Economics & Sociology*, **39**: 150–160. https://doi.org/10.9734/ajaees/2021/v39i1130736

Rubio L, Palacio Pinedo A, Mejía Castaño A and Ramos F 2023. Forecasting volatility by using wavelet transform, ARIMA and GARCH models. *Eurasian Economic Review* **13**: 803-830. https://doi.org/10.1007/s40822-023-00243-x

Sahu, N., Nayan, R., Panda, A., Varun, A., Kesharwani, R., Das, P., *et al.* 2024. Impact of Changes in Rainfall and Temperature on Production of Darjeeling Tea in India. *Atmosphere*, **16**: 1. https://doi.org/10.3390/atmos16010001

Seeley M 2025. The Reaction of Agricultural Commodity Prices to the Russia-Ukraine Conflict: Evidence from An Event Study, EGARCH Volatility Analysis, and GVAR Modelling. *EGARCH Volatility Analysis, and GVAR Modelling.* Available at SSRN: https://ssrn.com/abstract=5213636 or http://dx.doi.org/10.2139/ssrn.5213636

Silva V L G D, Oliveira Filho D, Carlo J C and Vaz P N 2022. An approach to solar radiation prediction using ARX and ARMAX models. *Frontiers in Energy Research*, **10**: 822555. https://doi.org/10.3389/fenrg.2022.822555

Singh R K, Singh Y, Kumar S, Kumar A and Alruwaili W S 2024. Mapping risk–return linkages and volatility spillover in BRICS stock markets through the lens of linear and non-linear GARCH models. *Journal of Risk and Financial Management* **17**: 437. https://doi.org/10.3390/jrfm17100437

Song Y, Tang X, Wang H and Ma Z 2023. Volatility forecasting for stock market incorporating macroeconomic variables based on GARCH-MIDAS and deep learning models. *Journal of Forecasting* **42**: 51-59. https://doi.org/10.1002/for.2899

Srihari G, Kusuma T, Chetanraj D B, Kumar J S and Aluvala R 2024. Predictive modeling of return volatility in sustainable investments: An in-depth analysis of ARIMA, GARCH, and ARCH techniques. *Investment Management & Financial Innovations* **21**: 213-228. doi:10.21511/imfi.21(1).2024.17

Teker D L, Teker S and Gümüştepe E D 2024. Backcasting Bitcoin volatility: ARCH and GARCH approaches. *PressAcademia Procedia* **20**: 14-16. https://doi.org/10.17261/Pressacademia.2024.1918

Uyar H and Ağcakoca E 2020. Artic Determination of Dynamic Characteristics the Structure with ARX and ARMAX Estimation Methods. *Sakarya University*

Journal of Science **24**: 460-471. https://doi.org/10.16984/saufenbilder.612826

Wang Z, Xing T and Wang X 2025. Economic uncertainty and stock market asymmetric volatility: Analysis based on the asymmetric GARCH-MIDAS model. *International Journal of Emerging Markets* **20**: 3488-3511. https://doi.org/10.1108/IJOEM-05-2023-0841

Yıldırım H and Bekun F V 2023. Predicting volatility of bitcoin returns with ARCH, GARCH and EGARCH models. *Future Business Journal* **9**: 75. https://doi.org/10.1186/s43093-023-00255-8

Yuan X, Tang J, Wong W K and Sriboonchitta S 2020. Modeling co-movement among different agricultural commodity markets: A Copula-GARCH approach. *Sustainability* **12**: 393. https://doi.org/10.3390/su12010393

Zahira A N and Zainuddin A 2023. Application of ARCH/GARCH models in analysis of price volatilities local, imports (USA), and world. *J-PEN Borneo: Jurnal Ilmu Pertanian* **6**. https://jurnal.borneo.ac.id/index.php/j-pen/article/view/3620/2460

Zhao P, Zhu H, Ng W S H and Lee D L 2024. From GARCH to neural network for volatility forecast. In: *Proceedings of the AAAI Conference on Artificial Intelligence* **38**: 16998-17006. https://doi.org/10.1609/aaai.v38i15.29643

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