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# Sugar Price Volatility in India's Food–Energy Nexus: Evidence from Ethanol Blending, Sugarcane Pricing and Climate Factors.

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**Abstract**
The Indian sugar industry is moving from a food commodity market to an integrated food–energy market with the growing implementation of the Ethanol Blended Petrol (EBP) programme. Price stability for sugar is crucial to the interests of farmers, consumers and industry, but market uncertainty has arisen due to ethanol diversion, climate variability and policy interventions. This analysis uses monthly retail sugar price data for the period June 2016 to May 2026 across three major Indian states, Karnataka, Maharashtra and Uttar Pradesh, to understand seasonal behaviour, volatility dynamics and the drivers of retail sugar price volatility. The methods include analysis of seasonal price trends, Augmented Dickey–Fuller (ADF) and ARCH–LM tests, as well as eGARCH (1,1) models, to estimate the persistence of volatility and asymmetric price responses. The findings show strong volatility persistence and asymmetric effects in Maharashtra and Uttar Pradesh, while price behaviour is comparatively stable in Karnataka. Simultaneously, the effects of ethanol blending percentage, sugarcane Fair and Remunerative Price (FRP), temperature and rainfall were also assessed using a multiple regression model. Ethanol blending has a significant effect on price volatility, while higher FRP has the opposite effect. The findings highlight the importance of balanced food–fuel policies, stable sugarcane pricing mechanisms, and evidence-based market management for improving sugar market stability during India's ongoing food–energy transition.

## Introduction

Agriculture is a key sector for food security, employment generation in rural areas, industrialization, and sustainable environment. Sugarcane (*Saccharum officinarum L.*) has become a strategic crop among the major agricultural crops due to its various economic, industrial and environmental use. In addition to its sugar production, sugarcane is an essential raw material for production of bioethanol, cogeneration of electricity, production of bio-based chemicals, paper and animal feed production. Therefore, the crop has now gained significance in the field of bioeconomy and will also play a role in the transition towards renewable energy, assisting in the fight against climate change and ensuring sustainable development (15, 30).

India has a significant role in the global sugar economy as the second largest producer of sugarcane and one of the largest producers and consumers of sugar in the world. Sugar industry is one of the most crucial agro-based industries of the country, providing employment to the sugar cane farmers who cut and pick sugar cane, transport it and process it or engage in allied activities (10, 23). The National Policy on Biofuels has ushered in the Ethanol Blended Petrol (EBP) Programme, which has spurred the growth of ethanol production with attractive procurement policies, investment incentives and increased production capacity. With this the dependency on crude oil has decreased for India and also created the new opportunity for the sugar industry to contribute to India's green energy transition (5, 24).

Ethanol production has revolutionised the sugar industry with its high impact on the food–fuel linkages in the Indian sugar industry. The diversion of sugarcane juice and molasses for ethanol impacts the sugar availability, sugar stocks and market dynamics. Focus on ethanol production helps to generate optimum profits to the mills and farmers. (4,12,31). Moreover, the policy measures and climatic fluctuations influence sugar prices. The government interventions like Fair and Remunerative Price (FRP), export restrictions, buffer stock operations and ethanol procurement policies have a great impact on production of sugar, market arrivals, and domestic supply conditions (5,23,29). Similarly, various climatic factors that affect the yield, recovery and harvesting conditions of sugarcane production, impacting the availability of sugar and its prices.



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Unlike other studies that have studied sugar price volatility or ethanol markets separately, this study analyzes and evaluates the impact of ethanol blending, FRP and climatic variables on the retail sugar price volatility in the three major sugar-producing states of India using a combination of seasonal analysis, eGARCH volatility modelling and regression analysis.

Objectives:

To examine the seasonal pattern and volatility dynamics of retail sugar prices across major sugar-producing states of India.

To assess the effect of ethanol blending, sugarcane fair and remunerative price (FRP), temperature and rainfall on retail sugar price volatility.

## Methodology

### Data Sources

In this research, the seasonal behaviour, volatility dynamics and factors driving retail sugar price volatility of three major sugar-producing states of India, Maharashtra, Uttar Pradesh and Karnataka, which contribute 60 to 70 per cent of India's sugar production, are examined. The last ten years of monthly data for sugar prices at the retail level were taken for the period from June 2016 to May 2026 from the Department of Consumer Affairs, Government of India. Ethanol Blending Percentage data were analysed from the Ministry of Petroleum and Natural Gas (MpNG), and Sugarcane Fair and Remunerative Price (Sugarcane FRP) data were collected from the Commission for Agricultural Costs and Prices (CACP). The monthly data of temperature and rainfall were obtained from the Indian Meteorological Department (IMD). These variables were chosen due to their direct impacts on sugar supply, cost of production, and market behaviour.

In order to achieve the first objective, descriptive statistics and seasonal decomposition techniques were initially used for the analysis of the seasonal behaviour and distributional characteristics of retail sugar prices. The stationarity test was performed by the Augmented Dickey–Fuller (ADF) test to ensure stationarity before estimating the volatility, and the ARCH–LM test was used to check for autoregressive conditional heteroskedasticity (ARCH) of the time series. The agricultural commodity prices were found to be generally volatility clustered and time-varying in variance, which led to the use of the ARFIMA–eGARCH (1,1) model to estimate volatility persistence and asymmetric responses to market shocks. The eGARCH model allows volatility to respond differently to positive and negative price shocks and also does not impose any restrictions on the conditional variance being positive, which is especially useful for agricultural commodity markets.

The second objective was met by using the multiple linear regression model to find out the factors influencing the volatility of the retail price of sugar. The dependent variable was retail sugar price volatility and the explanatory variables were ethanol blending percentage, Sugarcane Fair and Remunerative Price (FRP), average monthly temperature and monthly rainfall. The variables were chosen to reflect their importance in agricultural commodity markets from economic theory and previous studies.

### Analytical Tools

### Volatility Modelling

Volatility was estimated by first modelling the mean equation of the retail sugar price return series using an Autoregressive Moving Average (ARMA) model:

$$R_t = \mu + \sum_{i=1}^{p} \phi_i R_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t$$

where $R_t$ is the return at time $t$, $\mu$ is the constant term, $\phi_i$ and $\theta_j$ are the autoregressive and moving average coefficients, respectively, and $\varepsilon_t$ is the random error term.

The conditional volatility of sugar prices was then estimated using the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model proposed by Bollerslev (1986). The GARCH(1,1) variance equation is given by:

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

where $\sigma_t^2$ denotes the conditional variance at time $t$, $\varepsilon_{t-1}^2$ is the squared residual from the previous period, and $\sigma_{t-1}^2$ is the lagged conditional variance. The parameters $\alpha_1$ and $\beta_1$ measure the impact of recent shocks and the persistence of past volatility, respectively. The persistence of volatility is assessed by the sum $(\alpha_1+\beta_1)$; values close to one indicate highly persistent volatility shocks (Enders, 2014).

Model adequacy was evaluated using the Ljung–Box Q test for serial correlation, the ARCH–LM test for remaining ARCH effects, the Sign Bias and Engle–Ng tests for asymmetric responses to positive and negative



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shocks, and the Nyblom stability test to examine parameter stability over time (Francq & Zakoïan, 2010). All analyses were performed using **RStudio**.

**Regression Analysis**

Multiple linear regression analysis was employed to examine the influence of ethanol blending percentage, sugarcane Fair and Remunerative Price (FRP), temperature, and rainfall on retail sugar price volatility using monthly data for the last ten years. The analysis was performed using **Microsoft Excel**, with retail sugar price volatility as the dependent variable.

The regression model is expressed as:

$$PV_t = \beta_0 + \beta_1 EB_t + \beta_2 FRP_t + \beta_3 TEMP_t + \beta_4 RAIN_t + \varepsilon_t$$

where:

$PV_t$= Retail sugar price volatility
$EB_t$= Ethanol blending percentage
$FRP_t$= Sugarcane Fair and Remunerative Price
$TEMP_t$= Average monthly temperature (°C)
$RAIN_t$= Monthly rainfall (mm)
$\beta_0$= Intercept
$\beta_1$–$\beta_4$ = Regression coefficients
$\varepsilon_t$= Random error term

The regression coefficients measure the direction and magnitude of the effect of each explanatory variable on retail sugar price volatility.

**Results And Discussion**

**Analysis of Retail Sugar Price Trends and Seasonality**

The descriptive statistics of monthly retail sugar prices and price returns for the four regions of Karnataka, Maharashtra, Uttar Pradesh and All India (average) are displayed in Table 1 for the period from June 2016 to May 2026. The mean retail prices of sugar were in the range of ₹39.29 per kg in Karnataka to ₹40.48 per kg in Uttar Pradesh and ₹40.98 per kg in the country indicating a comparatively similar price level across the major sugar producing states. The price variability is maximum in Karnataka and Maharashtra with a standard deviation of ₹3.07 per kg and ₹2.99 per kg, respectively, and lowest in Uttar Pradesh with ₹2.79 per kg, indicating relatively more price stability in Uttar Pradesh.

**Table 1: Descriptive statistics of retail prices and price returns of each state with the all-India average**

| Descriptive Statistics | Karnataka Price | Price returns | Maharashtra Price | Price returns | Uttar Pradesh Price | Price returns | All India Avg. Price | Price returns |
|---|---|---|---|---|---|---|---|---|
| **Mean** | 39.29 | 0.13 | 39.76 | 0.15 | 40.48 | 0.12 | 40.98 | 0.13 |
| **Standard Error** | 0.28 | 0.08 | 0.27 | 0.07 | 0.26 | 0.06 | 0.28 | 0.05 |
| **Median** | 39.03 | 0.08 | 39.73 | 0.05 | 40.96 | 0.05 | 41.1 | 0.09 |
| **Mode** | 37.94 | -0.36 | 37.04 | -0.03 | 40.86 | -0.01 | 39.5 | 0.46 |
| **Standard Deviation** | 3.07 | 0.84 | 2.99 | 0.73 | 2.79 | 0.66 | 3.03 | 0.55 |
| **Sample Variance** | 9.41 | 0.71 | 8.93 | 0.54 | 7.76 | 0.44 | 9.19 | 0.3 |
| **Kurtosis** | 1.61 | 2.27 | 3.95 | 10.91 | 1.32 | 5.02 | 1.7 | 6.97 |
| **Skewness** | -0.81 | -0.05 | -1.4 | 2 | -0.95 | 0.61 | -0.87 | 0.67 |
| **Range** | 16.05 | 5.78 | 17.24 | 6.27 | 13.78 | 5.06 | 15.65 | 4.89 |
| **Minimum** | 28.72 | -3.17 | 27.62 | -1.79 | 30.85 | -2.24 | 30.55 | -2.13 |
| **Maximum** | 44.77 | 2.61 | 44.86 | 4.48 | 44.63 | 2.82 | 46.2 | 2.76 |
| **Sum** | 4675.57 | 15.82 | 4731.87 | 17.38 | 4817.7 | 13.89 | 4876.71 | 15.78 |
| **Count** | 120 | 120 | 120 | 120 | 120 | 120 | 120 | 120 |



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It was observed that the average monthly prices returned were relatively small ranging from 0.12% to 0.15%, reflecting slow fluctuations in retail prices of sugar over the period studied. Negative skewness for retail prices in the sample points suggests that retail prices in the sample points were more likely to exceed the mean than to fall below the mean, while the high kurtosis values for price returns for the sample points in Maharashtra and Uttar Pradesh suggests that extreme price increases and decreases in the sample points are more likely to occur than other price changes and that the price changes are more likely to cluster around the highest prices than the lowest prices. The descriptive statistics show moderate regional differences in retail sugar prices and some initial evidence of non-normality and volatility change over time, supporting the use of more sophisticated models of volatility like the eGARCH model.
The monthly retail prices trend of sugar in Karnataka, Maharashtra and Uttar Pradesh in June 2016 to May 2026 is presented in figures 1-3.

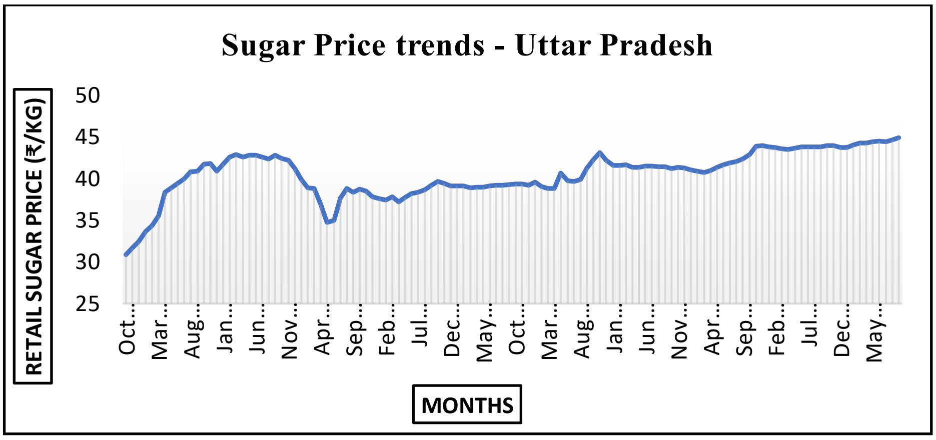


**Fig. 1: Monthly Retail Sugar Prices in Uttar Pradesh (2016–2026)**

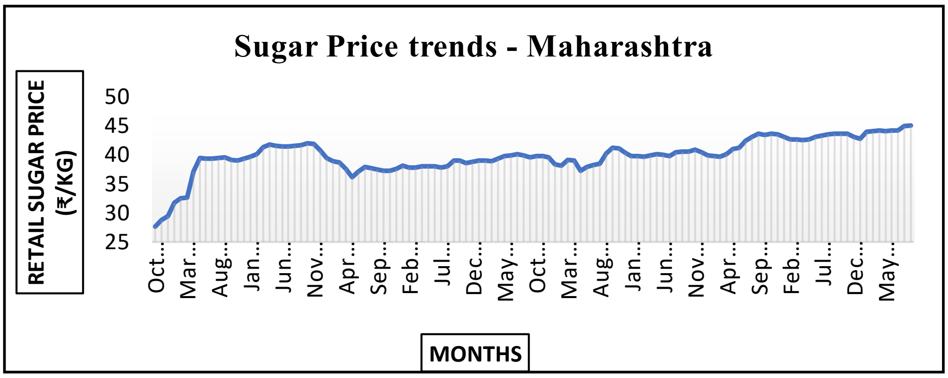


**Fig. 2: Monthly Retail Sugar Prices in Maharashtra (2016–2026)**

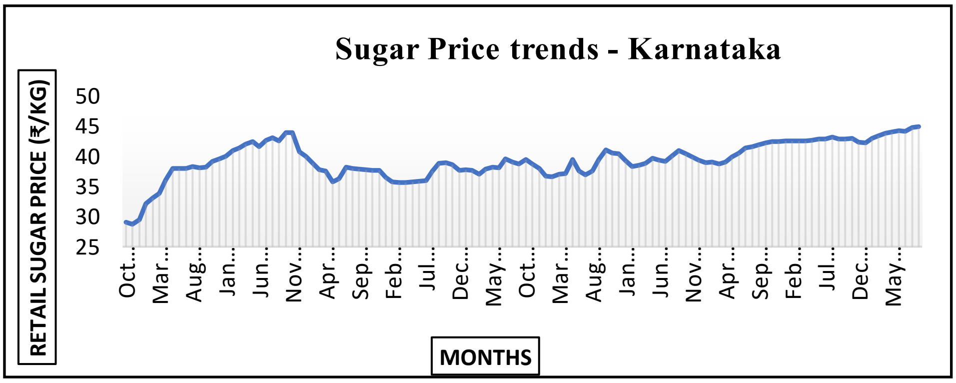


**Fig. 3: Monthly Retail Sugar Prices in Karnataka (2016–2026)**



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The overall retail price of sugar showed an increase in all three states which was attributed to the rise in production costs, frequent revision of the Fair and Remunerative Price (FRP) of sugarcane, rising transportation and energy costs and variations in domestic and global market conditions (5,11,23,27).
The pattern of increase was the same in most states, but not all, and the dollar values of the price changes varied. The cyclical fluctuations were relatively higher in Maharashtra and Karnataka, reflecting their high responsiveness to the fluctuations in the sugarcane production and climatic factors and market interventions. In contrast, due to State advised Prices which support the marketing of sugarcane in Uttar Pradesh, that displayed comparatively stability in sugar retail prices, which reflects its larger production base and big milling infrastructure (23,27,29). The differences in the retail prices of sugar across the regions indicate that the production structure and state-level policy measures are important factors in shaping the retail price behaviour of sugar.
In all three states, a definite seasonal pattern was noticed and this coincided with the sugarcane harvesting and crushing cycle. Sugar prices were found to have fallen in general across the board in the crushing season (October/November to March/April) because of the availability of sugar, and to have risen during the off-season (June–September) as the stocks become low in the market and fresh production is stopped. Relative smoothness in seasonal movements was observed for Uttar Pradesh due to its relatively longer crushing season and staggered operation of mills. In earlier research on price behaviour, similar kind of findings were discussed, which identify harvesting schedules, production cycles in India (11,27).
The observed trend also suggests that there is a crucial structural change taking place in India's sugar economy. With the increase in ethanol production, comes an extra demand for sugarcane, which has been creating an extra demand for the crop and transforming the sector from a traditional food commodity system to an integrated food–energy economy. As a result, the price of sugar is now more and more shaped by production policies in the agriculture sector and renewable energy policies. Hence, building market intelligence, climate-resilient production, mechanised harvesting, and balanced ethanol diversion policy will be vital to facilitate market stability, provide better farm income, and progress toward the goal of Viksit Bharat 2047 (1,4,12).

**Sugar Price Volatility, Volatility Clustering and eGARCH Analysis**

**Sugar Price Volatility**

Besides seasonality, volatility is observed in the following figures 4,5 & 6, State-wise price returns, as sharp downward and upward movements in the price series, like between September 2016 and September 2017, indicate short-term shocks in the market for a brief period, which could be due to policy changes, ban on export or oversupply. Around months March 2023 – Jan 2024, all three states experience a subsequent period of higher prices, possibly due to adjustment and disruption in the sugar markets after the pandemic (11,27,34).

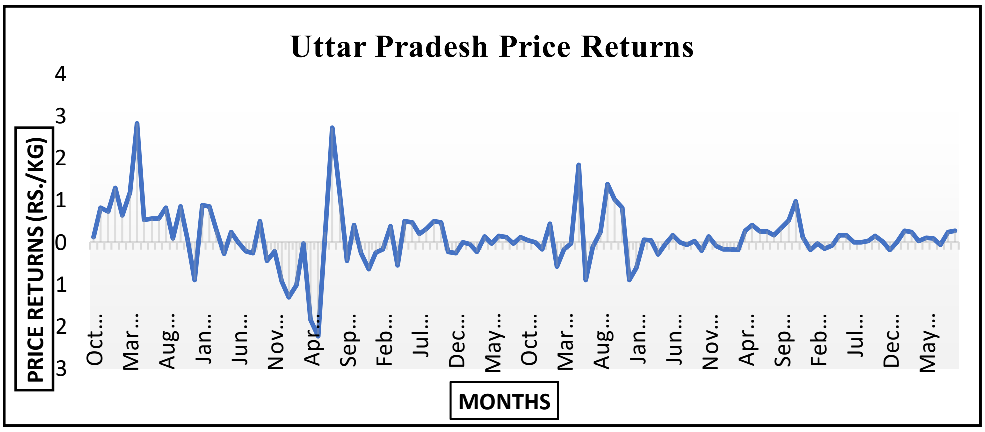


**Fig. 4: Sugar Price Volatility of Uttar Pradesh (2016–2026)**



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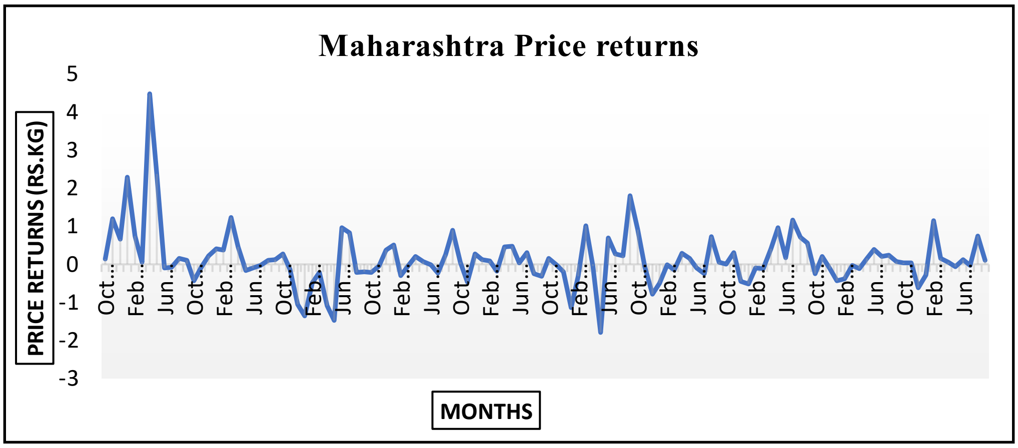


**Fig. 5: Sugar Price Volatility of Maharashtra (2016–2026)**

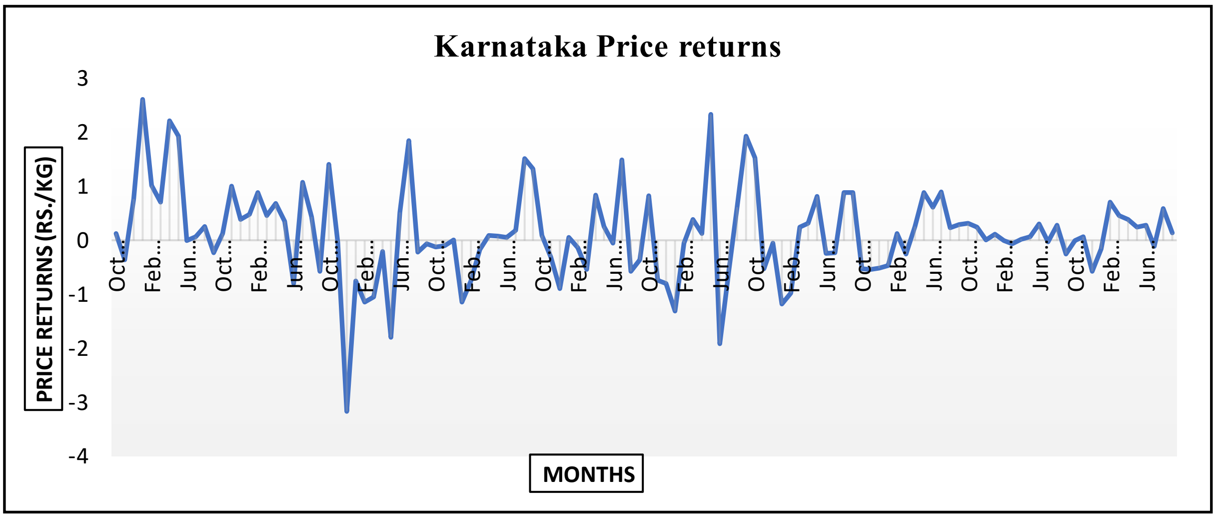


**Fig. 6: Sugar Price Volatility of Karnataka (2016–2026)**

In comparing the states, Karnataka and Maharashtra exhibit similar cyclical patterns suggesting that they form part of a similar sugar market market system in western India with similar responses to rainfall, production variation and policy. But there is a difference between the two, with Uttar Pradesh indicating less volatility and greater stability. These inter-state differences highlight the need to take into account the regional variations in the production capability, industrial structure and policy support while studying the sugar price movement (26,29). However, despite all these differences, all three states have shown a positive overall price trend, indicating that structural factors, including the rising cost of production, labour shortages, and increased domestic demand, are responsible for the sugar price trend rising steadily during the past 10 years (8).
The suitability of volatility modelling was checked with the help of the statistical characteristics of the data, whose results are presented in Table 2, by applying the tests of Shapiro–Wilk, Augmented Dickey–Fuller (ADF), and ARCH–LM. All three states had p-values of less than 0.05 when testing for normality using the Shapiro–Wilk test, suggesting non-normal distributions with heavy tails which are widely observed in agricultural commodity prices. All of the return series were found to be stationary ($p < 0.05$) by the ADF test, which was a prerequisite for time-series modelling. The ARCH–LM test also showed that there are significant ARCH effects in Maharashtra ($p = 0.0075$) and Uttar Pradesh ($p = 0.0248$) indicating the presence of conditional heteroskedasticity and volatility clustering. The ARCH effect was found to be absent in Karnataka ($p = 0.1963$) which indicated the relatively stable variance over time. The results support the use of eGARCH model in Maharashtra and Uttar Pradesh where the volatility is time varying (2,13).



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**Table 2: Preliminary Diagnostic Tests**

| Test | Karnataka | Maharashtra | Uttar Pradesh | Interpretation |
|---|---|---|---|---|
| Shapiro-wilk (P-value) | <0.001 | <0.001 | <0.001 | Non-normal distribution |
| ADF (P value) | 0.01 | 0.02 | 0.01 | Stationary |
| ARCH - LM (P value) | 0.196 | 0.007 | 0.025 | ARCH effect present in Maharashtra and Uttar Pradesh |

**Sugar Price Volatility Clustering**

The all preliminary diagnosting tests are done after that, there is a need to follow the steps to analyse the price volatility clustering of different states in India with the help of GARCH model.

In the above fig.4, it is observed that the retail prices of sugar in Karnataka state exhibit clustering in the volatility of the price series, small changes in prices are followed by small changes further (like Oct'24 (109) to Nov'24 (110) and May'25 (116) to Jun'25 (117) ), and large changes in prices are followed by large changes further (like Nov'15 (1) to Dec'15 (2) and Feb 2016 (5) to March 2016 (6) ).

In the above fig. 5, it is observed that there is a clustering of volatility of the retail price of sugar in Maharashtra state with small changes in prices followed by small changes further (Like happened in Oct'24 (109) to Nov'24 (110) and Apr'25 (115) to May'25 (116) ) and large changes in prices followed by large changes (Like happened in Jan'16 (4) Feb'16 (5) and Sept'21 (72) to Oct'21 (73) ).

In the above fig.6 it is observed that small changes in the sugar retail price per kg in Uttar pradesh state (Like Jan'20 (52) to Feb'20 (53) and Jul'24 (106) to Aug'24 (107)) are followed by small changes further (Like Jan'20 (52) to Feb'20 (53) and Jul'24 (106) to Aug'24 (107) ) and large changes followed by large changes further (Like Jan'18 (34) to Aug'18 (35) and Sept'21 (72) to oct'21 (73) ).

**eGARCH Model Analysis**

As the important ARCH effects are identified in Maharashtra and Uttar Pradesh, an ARFIMA–eGARCH (1,1) model was estimated to analyse the persistence of volatility and asymmetric response to retail sugar prices. It is especially suitable model for the eGARCH model that can account for asymmetric market shocks as well as long memory and volatility without non-negativity constraint for the conditional variance (12).

From the estimated results (Table 3), it is observed that the parameter β of GARCH was positive and highly significant for both the two states, namely, Maharashtra (β = 0.826) and Uttar Pradesh (β = 0.954), which shows that there is high volatility persistence. The higher value of β coefficient in Uttar Pradesh suggests that shocks to volatility remain longer as compared to Maharashtra, suggesting market disturbances subside slowly. These results are consistent with earlier ones which found that markets for agricultural commodities remain volatile on a persistent basis because of production uncertainty and policy interventions (2,13,27).

**Table 3: Estimated eGARCH (1,1) Parameters**

| Parameters | Maharashtra | Uttar Pradesh |
|---|---|---|
| μ | 0.00225*** | 0.00094 |
| AR(1) | –0.270*** | NS |
| MA(1) | 0.742*** | 0.522*** |
| α | NS | Marginal |
| β | 0.826*** | 0.954*** |
| γ | 0.668*** | 1.082*** |

Note: NS = Not Significant, *** = Significant at 1% level.

In both cases (Maharashtra and Uttar Pradesh), the leverage parameter (γ) was also positive and statistically significant (γ = 0.668 and 1.082 respectively), which meant that there was evidence of asymmetric volatility. The analysis also indicated that positive price shocks resulted in higher volatility in the future than negative price shocks, indicating that increases in sugar prices lead to higher market uncertainty. This asymmetry is probably linked to shortages in supply, diversion of ethanol for various purposes, changes in the export policy, and the expectations of future availability of sugar(2,13). The moving average component was significant in both the states and the autoregressive component was significant only in Maharashtra, which, in both cases, implies that



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short run market shocks continue to have an impact on subsequent price changes and in the former case, the autoregressive component was relatively high, thereby implying relatively strong short run market adjustment. The estimated models were adequate as confirmed by the diagnostic tests (Table 4). The Ljung–Box test showed no significant autocorrelation in the residuals, and the ARCH–LM test confirmed that there were no further ARCH effects after fitting the model. Additionally, the Nyblom stability test revealed the parameters estimated were stable over the measurement period.

**Table 4: Model Diagnostic Tests**

| Test | Maharashtra | Uttar Pradesh | Conclusion |
|---|---|---|---|
| Ljung - Box | Pass | Pass | No residual autocorrelation |
| ARCH - LM | Pass | Pass | No remaining ARCH effect |
| Nyblom Stability | Stable | Stable | Parameters stable |

**Table 5. Multiple Regression Results for Factors Affecting Retail Sugar Price Volatility**

| Variables | Coefficient (β) | Standard Error | t-value | p-value | Significance | Expected Effect |
|---|---|---|---|---|---|---|
| Constant | 6.748 | 1.398 | 4.827 | <0.001 | *** | — |
| Ethanol Blending (%) | 0.16 | 0.034 | 4.637 | <0.001 | *** | Positive |
| Sugarcane Fair and Remunerative Price (FRP) | –0.029 | 0.006 | –5.021 | <0.001 | *** | Negative |
| Temperature (°C) | 0.02 | 0.018 | 1.122 | 0.264 | NS | Positive |
| Rainfall (mm) | –0.001 | 0.001 | –1.963 | 0.052 | * | Negative |

**Table 6: Model Summary**

| Model Statistics | Value |
|---|---|
| Number of observations (n) | 120 |
| Multiple R | 0.451 |
| $R^2$ | 0.204 |
| Adjusted $R^2$ | 0.176 |
| Standard Error of Estimate | 0.497 |
| F-statistic | 7.347 |
| Model Significance (p-value) | <0.001 |

**Regression Analysis of Factors Affecting Retail Sugar Price Volatility**

The influence of ethanol blending percentage, Sugarcane Fair and Remunerative Price (Sugarcane FRP), Average monthly temperature and monthly rainfall on the retail sugar price volatility was estimated using multiple linear regression. The conditional volatility series was obtained from the eGARCH model, and used as the dependent variable. The overall regression model was statistically significant ($F = 7.35$, $p < 0.001$), suggesting that the explanatory variables explain a significant amount of the variation in the retail sugar price volatility.



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The coefficient of determination ($R^2 = 0.204$) shows that the selected explanatory variables explain about 20.35% of the variation in retail sugar price volatility, and the adjusted coefficient of determination (Adjusted $R^2 = 0.176$) shows that the explanatory power is moderate, considering the number of explanatory variables. Explanatory power is quite modest but that is typical of agricultural commodity price studies because the volatility of such markets is subject to a great deal of economic, institutional, climatic and international variability. In addition to the variables used in this study, sugar production domestically, buffer stocks, international sugar prices, crude oil prices, sugar trade policies, sugar market expectations and exchange rate fluctuations can also explain the volatility of retail sugar prices (11,13,27).

**Effect of Ethanol Blending on Retail Sugar Price Volatility**

Retail sugar price volatility showed a highly significant positive relationship with ethanol blending percentage ($\beta = 0.160$, $t = 4.64$, $p < 0.001$) which is one of the strongest determinants identified in the present study. The positive sign means that increasing ethanol blending has a significant positive relationship with the volatility of retail sugar prices.

This is a result of the structural change in India's sugar industry in the context of the Ethanol Blended Petrol (EBP) Programme. The more sugarcane juice and molasses used for ethanol production, the less available for use in the domestic market for sugar. These supply changes add to the short-term sugar supply volatility, leading to more retail price volatility.

This result is consistent to (13), who concluded that sugar and ethanol markets are closely tied and that sugar price behaviour is closely related to developments in energy markets. Similarly, (12,31) noted considerable volatility transmission between sugar and ethanol markets in Brazil, and that the expansion of biofuels has increasingly led to the development of a food–fuel linkage. Thus, ethanol blending in the context of renewable energy development and energy security is beneficial, but it also adds to the uncertainty in the energy market of sugar, and thus, demands a well-balanced food–fuel policy.

**Effect of Sugarcane Fair and Remunerative Price (FRP)**

Sugar cane Fair and Remunerative Price (FRP) was also negatively related with retail sugar price volatility with highly significant value ($\beta = -0.029$, $t = -5.02$, $p < 0.001$). The negative sign indicates that the price volatility of sugar in the retail sector goes down with the rise in FRP.

A remunerative procurement price offers income security to the farmers and stabilizes sugarcane cultivation which will enable sugar mills to maintain a constant supply of raw material.

The results of (5) which emphasize the critical role that government pricing strategies and regulatory measures play in reducing cyclical swings and guaranteeing stability in the Indian sugar business, are supported by this study. As a result, FRP serves as both an efficient market stabilization tool and an agricultural assistance strategy.

**Effect of Temperature**

The coefficient of temperature ($\beta = 0.020$) was estimated and found to be positively but not significantly related to retail sugar price volatility for the study period ($p = 0.264$).

While temperature affects growth of sugarcane, sucrose accumulation, duration of crop and its productivity, the effect on retail sugar prices seems to be mitigated due to irrigation infrastructure, better varieties, mechanisation and modernisation in crop management. Therefore, the variability in retail prices of sugar was not large enough to be responsible for the large differences in temperature.

According to (15,22,28,29), the adoption of technology breakthroughs and adaptive agricultural practices also significantly reduced the direct impact of temperature variability on sugarcane production or market pricing.

**Effect of Rainfall**

The rainfall showed a negative coefficient ($\beta = -0.001$), with minor statistical significance ($p = 0.052$). The negative correlation suggests that better rainfall would lead to increased productivity for sugarcane, and therefore more stable supply sugar would lead to reduced price volatility for sugar in the retail market.

But the poor statistical significance indicates that variations in retail sugar prices cannot be explained solely by variations in rainfall. It is subject to much influence from the distribution of rainfall, availability of irrigation, groundwater supply, crop management, and production conditions in the region.

The findings are consistent with those of (18,19,20,35), who discovered that climatic factors can influence agricultural commodity prices mainly through interactions with production systems and policy interventions.

**Limitations of the Study**

There are some limitations of this study that need to be taken into consideration when interpreting the results. The analysis is restricted to the top three sugar producing States in India and monthly retail sugar prices data for the



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study period is only used. The analysis did not include some important variables like international sugar prices, crude oil price, wholesale sugar price and export policy changes. All these may contribute to the volatility of sugar prices. Hence, future research can be conducted with greater geographical scope, frequency of data collection, and more market and policy variables, which will give a more complete picture of sugar price behaviour.

**Recommendations**

**Implement a Dynamic Policy for Ethanol Diversion:**
Create an adaptable ethanol diversion system that balances ethanol output and sugar availability based on market conditions and domestic sugar reserves. This would help India meet its renewable energy goals while reducing excessive price volatility.

**Boost Price Stabilization with Market Monitoring and FRP:**
Retail sugar price variations can be minimized and farmer income security can be enhanced by periodically revising the Fair and Remunerative Price (FRP) in conjunction with real-time monitoring of sugar production, stockpiles, and market prices.

**Promote sustainable sugarcane cultivation in a climate resilient way:**
Efficient irrigation systems, drought-tolerant sugarcane varieties and precision agriculture in crop production for the adoption of technologies and strategies for climate smart farming to reduce risk of weather variability.

**Develop AI Based Sugar Market Intelligence Systems:**
Develop AI and machine learning based digital tools and platforms for timely alerts regarding price volatility, sugar production and supply-demand mismatch, for better decision making by policy makers, sugar mills and agricultural farmers.

**Enable the Integrated Sugar–Bioenergy Value Chain:**
Promote investments in mechanization, modernization of milling infrastructure, digital supply chain management, and bio-refineries for boosting production efficiency, value addition, profitability of farmers, and sustainable development of agriculture and green energy sector to realize the vision of Viksit Bharat 2047.

**Conclusion**

This study investigated the trends, seasonal volatility and volatility of retail sugar prices in Maharashtra, Uttar Pradesh and Karnataka using eGARCH model and also analyzed the effect of ethanol blending, Sugarcane Fair and Remunerative Price (FRP), temperature and rainfall on the volatility of retail sugar prices using multiple regression analysis. The results indicated that the prices of sugar remained volatile and were not symmetric across the country, especially in Maharashtra and Uttar Pradesh.

The regression results indicated that ethanol blending had a significant effect on the increase in price volatility and that FRP had an effect in stabilizing the prices of gasoline and diesel while climatic variables had relatively small direct impacts. The study emphasizes the importance of balanced food–fuel policies, climate-smart production systems, and digital market intelligence for food to achieve price stability, a robust sugar–bioenergy industry, and empower India's green energy transition and Viksit Bharat 2047.

Overall, the results indicate that for India to move towards a bioenergy economy for sugar, coordinated policies in the food-energy sector are needed that promote the development of ethanol and keep the price of sugar stable in the market, while maintaining sustainable incomes for farmers.

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**Author's Contributions**

VA designed the study, collected the data from different authorised sources and analyzed the data, interpreted the results, and prepared the initial draft of the manuscript. The manuscript was carefully read by KS and HB who gave them valuable suggestions for improving the quality of the manuscript. They participated in the design of the research, data collection, data analysis, and interpretation of the results. All authors reviewed and approved the final version of the article, and have agreed to take responsibility for the accuracy and integrity of the work.

**Compliance with ethical standards**

**Conflict of interest:** The authors declare no conflict of interest.

**Ethical Issues:** None.

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