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Assessing temporal price dynamics of tomatoes in Jabalpur District of India

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Abstract

Tomato prices in Jabalpur exhibit significant seasonal fluctuations and high volatility, necessitating accurate detection of price patterns to inform effective policy and market interventions. Seasonal indices reveal peak prices during June (1.23) & July (1.48), driven by high perishability and monsoon disruptions, and troughs from December (0.91) to February (0.81) due to post-harvest supply. The fitted linear trend model ($R^2 = 0.5304$) evidenced a statistically significant upward trajectory, indicating an average increase of ₹10.42/quintal per month (₹125.04/quintal annually), higher-order polynomial models like quadratic ($R^2 = 0.5504$) and cubic ($R^2 = 0.5599$) yielded only marginal improvements in model fit, and overall, all deterministic trend models failed to adequately capture the pronounced stochastic behaviour inherent in agricultural commodity prices. A log-linear model (adj. $R^2 = 0.7311$), estimating a Compound Annual Growth Rate (CAGR) of 15.83%, highlights both long-term price growth and the importance of variance stabilization. Structural breaks, notably in April-May 2020 and April 2022, correspond with COVID-19 related disruptions and market realignments after COVID respectively. Given the superior variance stabilization with logarithmic transformation and the inadequacy of deterministic models, stochastic trend approaches such as ARIMA are recommended for precise forecasting.

Keywords: Compound Annual Growth Rate (CAGR), Cuddy-Della Valle Index, structural breaks, tomato price, seasonal indices, trend analysis, log-linear model

1. Introduction

The essential vegetable staples-tomatoes, onions, and potatoes-collectively known as 'TOP' commodities, serve as primary drivers of India's food price inflation and Consumer Price Index movements. These commodities exhibit pronounced seasonal patterns with respect to price fluctuations. This seasonality, primarily driven by crop production and harvesting cycles, significantly contributes to food price inflation in India. The 'TOP' commodity group has been found to account for a large proportion, ranging from 50 to 70%, of the overall variance in food inflation, underscoring its importance in India's inflationary dynamics (Pratap *et al.*, 2021) ^[10]. This **volatility** through its effects on overall inflation figures has far-reaching implications for both consumers and producers in the agricultural sector. Tomato (*Solanum lycopersicum*) is a horticultural crop of family Solanaceae, which is a culinary staple in all parts of the world. Tomatoes are a good source of several vitamins and minerals, such as vitamin C, potassium, vitamin K, and folate. As per historical data, tomatoes show higher price volatility (0.21) compared to onions (0.19) and potatoes (0.10), (NABARD, 2023) ^[8]. Tomatoes, being highly perishable with short crop duration, demonstrate substantial seasonal price fluctuations, though these episodes tend to be transient. Tomato prices are particularly volatile, often influenced by environmental factors such as irregular rainfall patterns and droughts, which can lead to supply shortages. Tomato price hikes have consistently made headlines in newspapers across several years. For instance, tomato prices skyrocketed by 352% in one month (Business Standard, July 7, 2023), tomato prices soared to Rs 250 per kg in Delhi, Rs 200 in Mumbai (The Economic Times, July 10, 2023) and tomato prices crashed to Rs 2 per kg in Maharashtra's Narayangaon market (The Indian Express, September 20, 2023).

While in 2021, Tomato prices in Tamil Nadu soared past ₹100, govt stepped in with subsidised variety (Hindustan Times, November 24, 2021).

Within this context, tomato price fluctuations have been particularly impactful, illustrating the dual challenges faced by consumers and farmers. For consumers, sudden spikes in tomato prices can lead to increased food expenditure, potentially forcing households to adjust their consumption patterns or reduce spending in other areas. India holds the position of the world's second-largest producer of tomatoes, following China. As of 2021, the country's annual tomato production is approximately 21 million tonnes, which accounts for roughly 11% of global tomato output. Madhya Pradesh boasts the highest production of tomatoes in India, often competing with states like Andhra Pradesh and Karnataka for the top spot. According to the Directorate of Marketing and Inspection (2021), Madhya Pradesh held the top position in tomato production, with production of 2,805.07 thousand metric tonnes in the year 2020-21, followed by Andhra Pradesh (2,450.67 thousand metric tonnes). The tomato market in Jabalpur, Madhya Pradesh, plays an essential role in the regional and national supply chain due to its production volume and distribution capabilities. Understanding and analysing the temporal patterns in the tomato price series of the Jabalpur market facilitates the prediction of broader trends in the Indian tomato market, while offering valuable insights into underlying inflationary dynamics. This is particularly vital for meeting the demands of modern times and ensuring sustainable incomes for farmers. Strategic policies aimed at improving tomato production can enable farmers to schedule production effectively, optimize harvesting techniques, and develop efficient storage plans, ultimately stabilising price. Various studies have emphasized the importance of detecting price patterns for effective policy formulation and agricultural market management. Vasciaveo *et al.* (2013) ^[15] examined price co-movement between U.S. and Italian markets for wheat, corn, and soybean. Using cointegration and structural break tests, they find U.S. agri-prices drive Italian markets, with oil prices influencing U.S. trends. Anoopkumar (2014) ^[2] investigated intra-year price instability in Indian crops like cardamom and rubber, linking short-term volatility to seasonal supply cycles that adversely affect farmer incomes. Sendhil *et al.* (2023) ^[14] assessed rice and wheat market integration in India using cointegration and error correction models. The study reveals moderate wholesale-retail linkage and inefficiencies in price transmission. Santhosh Kumar *et al.* (2024) ^[13] explored soybean price dynamics in Gautampura using trend analysis, seasonal indices, CAGR, and CDVI. Findings highlight notable price instability and structural shifts driven by climatic and policy factors.

2. Materials and Methodology

2.1 Data

The secondary time series data analysed in this study pertains to computed monthly tomato prices and arrivals from agricultural markets (Mandis) in Jabalpur district, Madhya Pradesh, India, spanning the period from June 2011 to June 2024. The dataset was sourced from the AGMARKNET platform, an official initiative by the Department of Agricultural Marketing and Inspection under the Ministry of Agriculture, Government of India, accessible at <https://agmarknet.gov.in>. The study focuses on the Jabalpur district, encompassing key agricultural markets such as

Sihora, Shahpura, Patan, and the Jabalpur Fruits and Vegetables Market.

2.2 Time Series Decomposition

A time series is conceptualized as a realization of a stochastic process $\{X_t, t \in Z\}$, where each observation X_t represents a random variable indexed by discrete time. The comprehensive decomposition of time series reveals multiple interacting components through two fundamental approaches: additive and multiplicative decomposition models. In the additive decomposition model, the time series is represented as a linear combination of components, where the trend component T_t captures long-term directional movement, typically modeled as a deterministic or stochastic function of time. The seasonal component S_t represents periodic recurring variations, mathematically expressed as a periodic function with fixed frequency. Cyclical components C_t capture medium-term fluctuations, while the irregular component I_t encapsulates residual randomness. This model is mathematically expressed as:

$$X_t = T_t + S_t + C_t + I_t$$

Alternatively, the multiplicative decomposition model presents a more complex interaction between components, where the time series is represented as a product of its constituent elements:

$$X_t = T_t \cdot S_t \cdot C_t \cdot I_t$$

The multiplicative model becomes particularly useful when the magnitude of seasonal and cyclical variations changes proportionally with the trend. Unlike the additive model, which assumes constant variance, the multiplicative model allows for dynamic scaling of components, capturing more nuanced patterns of change.

2.3 Seasonal Index

Seasonal Index is a statistical method used to quantify periodic variations in time series data. The core objective is to decompose a time series into its trend, seasonal, and irregular components. The methodology begins by calculating a centered moving average to smooth out seasonal fluctuations, represented by the equation.

$$MA_t = \frac{1}{n} \sum_{i=-(n/2)}^{n/2} X_{t+i}$$

Where MA_t represents the moving average at time t and n is the number of periods in the moving average window. Subsequently, seasonal ratios are computed by dividing the original time series values by their corresponding moving averages, expressed as.

$$SR_t = \frac{X_t}{MA_t}$$

These ratios are then aggregated by seasonal period, calculating the average seasonal index using the formula,

$$SI_s = \frac{\sum_t SR_t[s]}{k}$$

Where, k represents the number of years in the dataset and $SR_t[s]$ is the seasonal ratio for season s at time t . To ensure

the seasonal indices are meaningful, they are normalized to sum to the total number of seasons, using the equation

$$NSI_s = SI_s \times \frac{m}{\sum SI_s}$$

Where m is the number of seasons. This process effectively explains seasonal variations, revealing the underlying seasonality and allowing for more accurate forecasting and removal of seasonal effects for analysis of long term patterns in the time series data.

2.4 Trend Models

Trend models such as Linear trend model $Y_t = \beta_0 + \beta_1 t + \varepsilon_t$, where $\varepsilon_t \sim i.i.d. WN(0, \sigma^2)$ capture constant rates of change using ordinary least squares estimation. Polynomial models such as quadratic $Y_t = \beta_0 + \beta_1 t + \beta_2 t^2 + \varepsilon_t$ and cubic $Y_t = \beta_0 + \beta_1 t + \beta_2 t^2 + \beta_3 t^3 + \varepsilon_t$ forms accommodate non-linear relationships with turning points and complex S-shaped curves respectively. Exponential growth models of form, $Y_t = \beta_0 e^{\beta_1 t} \varepsilon_t$ are linearized through logarithmic transformation (log-lin form) to capture exponential growth patterns with constant percentage rates (Hamilton, 1994).

2.5 Compound Annual Growth Rate (CAGR)

Compound Annual Growth Rate (CAGR) measures the mean annual growth rate over specified period longer than one year via an exponential growth model expressed as,

$$P_t = a_0(1 + b)^t$$

where P_t represents the price at time t , a_0 denotes the constant term, and b represents the growth rate. To facilitate estimation using ordinary least squares, the equation was transformed into specified log-lin form, $\ln P_t = \ln a_0 + t \ln(1 + b)$. This logarithmic transformation enables linear regression analysis while preserving the exponential nature of price growth patterns.

2.6 Time Series Instability Index

To evaluate price series instability, the Cuddy-Della Valle Index (CDVI) methodology was employed. This approach quantifies instability through the formula:

$$CDVI = CV \times \sqrt{(1 - R^2)}$$

Where $CDVI$ represents the instability index (%), CV denotes the coefficient of variation (%), and R^2 is the coefficient of multiple determination. The index provides a comprehensive assessment of market instability that accounts for both the degree of variation and the explanatory power of the underlying trend model, where lower values ($< 15\%$) indicate consistent trends and higher values suggest volatile patterns, thereby determining the reliability of trend projections throughout the study period.

2.7 Quantile-Quantile (Q-Q) plot

The Q-Q plot compares the quantiles of two datasets or compares a dataset against a theoretical distribution (i.e. Normal distribution). If the distributions are similar, the points will approximately lie on a straight line.

2.8 Bai-Perron Methodology for Multiple Structural Breaks Detection

The Bai-Perron methodology (Bai & Perron, 1998; 2003) [3] identifies multiple structural breaks in time series data through endogenous detection without prior specification of

break locations. The method employs a linear regression model with multiple structural breaks:

$$y_t = X'_t \beta_j + u_t, \quad t = T_{j-1} + 1, \dots, T_j \text{ and } j = 1, \dots, m + 1$$

Where y_t is the dependent variable, X_t is a vector of explanatory variables, β_j are segment-specific coefficients, u_t is the i.i.d. error term, T_j are unknown break dates, and m is the number of structural breaks creating $m + 1$ regimes.

The estimation procedure minimizes the sum of squared residuals (SSR) across all possible sample partitions subject to minimum segment size constraints $\varepsilon \in (0, 0.5)$ using dynamic programming. The framework provides several tests including the $SupF$ test for no breaks ($H_0: m = 0$) using $\sup_{m \leq M} \sup F(m)$, sequential $SupF(l + 1|l)$ tests, Double Maximum tests ($UDmax$ and $WDmax$), and employs BIC and Schwarz Criterion for optimal number of breaks selection.

3. Results and Discussion

The time series plot of the monthly average tomato arrivals and prices in Jabalpur district is illustrated in the Figure 1. The time plot of the monthly tomato price series reveals a clear upward trend, indicating a general increase in tomato prices over the years. In contrast, the monthly tomato arrival series exhibits a downward trend, possibly due to a reduction in agricultural land area dedicated to tomato cultivation and disruptions in weather patterns. The tomato price series exhibits considerable temporal volatility, with heightened fluctuations observed during the period spanning 2020 to 2024. Following a period of relative stability between 2011 and 2016, the tomato prices demonstrate significant volatility, with pronounced peaks observed during the 2022-2023 period. The monthly tomato arrival quantities exhibit temporal variability like the tomato price series. However, the series demonstrates noteworthy peaks around 2011-2012, suggesting periods of heightened arrival volumes and in the post-2020 period, the arrival quantities are lower compared to the earlier years. The tomato arrival quantities exhibit a relatively stable pattern with strong seasonal patterns, observed post-2020, indicative of consistent market conditions due to planting and harvesting cycles and minimal supply-side fluctuations. Notably, the post-2020 period is characterized by stability in arrival quantities, coinciding with the noted increase in price volatility.

The descriptive statistics presented in Table 1 and the accompanying box plot in Figure 2 show that the average monthly tomato price is Rs. 879.59 per quintal, with average arrivals around 44.08 tonnes. The data demonstrates substantial variability, with the highest recorded tomato price being Rs. 3,630.43 per quintal in July 2023 and the lowest being Rs. 299.63 per quintal in February 2017. Similarly, the maximum tomato arrivals were 281.87 tonnes in September 2012, while the minimum was 0.2 tonnes in May 2024. The data suggests an inverse relationship between tomato arrivals and prices, where periods of high arrivals coincide with lower prices, and vice versa. The monthly tomato arrival series demonstrates a substantially greater relative dispersion compared to the price series, as evidenced by the coefficient of variation. The skewness value of price series of 1.668056 indicates significant positive asymmetry, suggesting the presence of an extended right tail in the distribution. The excess kurtosis measure of 2.97237 indicates that the distribution is leptokurtic, with a sharper peak and thicker tails compared to the normal distribution. This suggests a

significant deviation from normality. The Jarque-Bera test statistic of 135.04 strongly rejects the null hypothesis of normality, providing robust evidence of a significant departure from a normal distribution. The dataset's longer right tail indicates the presence of frequent outliers, which is further validated by the five outliers observed in the Box-plot of the price series in Figure 2. The arrival series demonstrates positive skewness (2.416) and leptokurtosis (excess kurtosis

of 6.635), both indicative of a significant deviation of this series as well from normality. This is further substantiated by the elevated Jarque-Bera statistic of 454.67, strongly rejecting the null hypothesis of normality. The high degree of variability in the monthly tomato prices, as evidenced by the substantial standard deviation of 650.3188, underscores the need to apply logarithmic transformation to the price series in order to stabilize the variance.

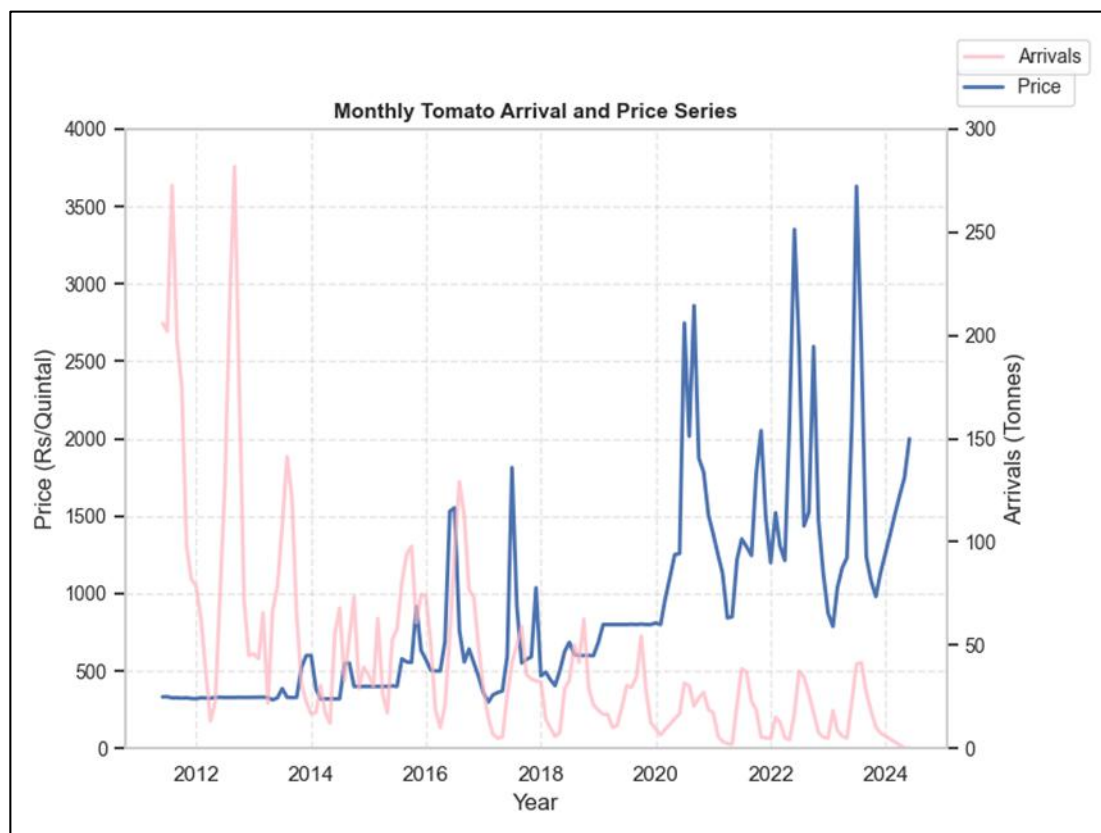


Fig 1: Monthly average tomato arrival and price series plot

Table 1: Descriptive statistics of tomato price and arrival series of Jabalpur District

Statistics	Original Price Series	Log Transformed Price Series	Arrival Series
Min	299.63	5.703	0.20
1st Quartile	386.2	5.956	13.28
Median	607.14	6.409	28.81
Mean	879.59	6.556	44.08403
3rd Quartile	1220.0	7.107	55.54
Max	3630.43	8.197	281.87
Standard Deviation	650.3188	0.6504925	50.23671
Coefficient of Variation (CV)	0.7393	0.09921	1.1396
Skewness	1.668056	0.4441703	2.416811
Kurtosis	2.97237	-0.8686185	6.635363
Jarque-Bera χ^2	135.04	9.8913	454.67
Jarque-Bera p-value	$< 2.2 \times 10^{-16}$	0.007114	$< 2.2 \times 10^{-16}$
5th Percentile	322.0128	5.77459	4.433524
95th Percentile	2093.81	7.646722	148.1156
Interquartile Range (IQR)	833.75	1.150121	42.25794

The lower standard deviation and coefficient of variation in the log-transformed price series indicate that the logarithmic transformation effectively stabilized the variance, which is a crucial prerequisite for time series modelling. Furthermore, the log-transformed price series displays a Jarque-Bera test statistic of 9.8913, suggesting a closer approximation to

normality after the transformation. However, residual non-normality persists, as evidenced by the deviations observed in the Q-Q plot in Figure 3. A logarithmic transformation of the monthly price series has been employed in this study for variance stabilization

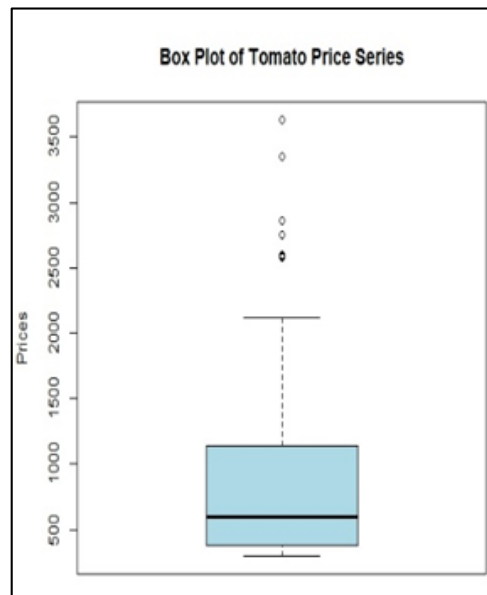


Fig 2: Box plot of tomato price series

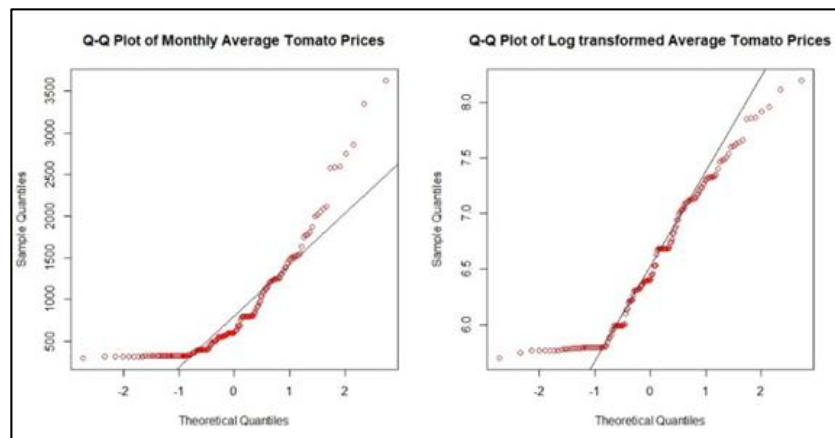


Fig 3: Q-Q plot of original tomato price series and log transformed tomato price series

The decomposition of the monthly tomato price series, displayed in Figure 4, follows a multiplicative approach due to increasing variance of the price series. The upward trend observed in tomato prices aligns with the trajectory of overall inflation in the economy. Inflationary pressures amplify the base cost of perishable commodities like tomatoes, leading to an inherent upward trend in their price series. Seasonal variations in tomato prices are deeply rooted in agricultural cycles influenced by planting and harvesting patterns, as well as climatic variables such as rainfall patterns. The seasonal

component of Price series decomposition plot (Figure 4) shows recurring seasonal patterns, with prices peaking during mid-year months, which suggests that seasonal cycles strongly influence tomato prices irrespective of external shocks or trend. Superimposed on these long-term and seasonal patterns are random fluctuations triggered by extreme events such as unseasonal heavy rainfall, droughts, or pest infestations. For instance, anomalous monsoon patterns in recent years have disrupted supply chains, exacerbating scarcity and inflating prices to unprecedented levels.

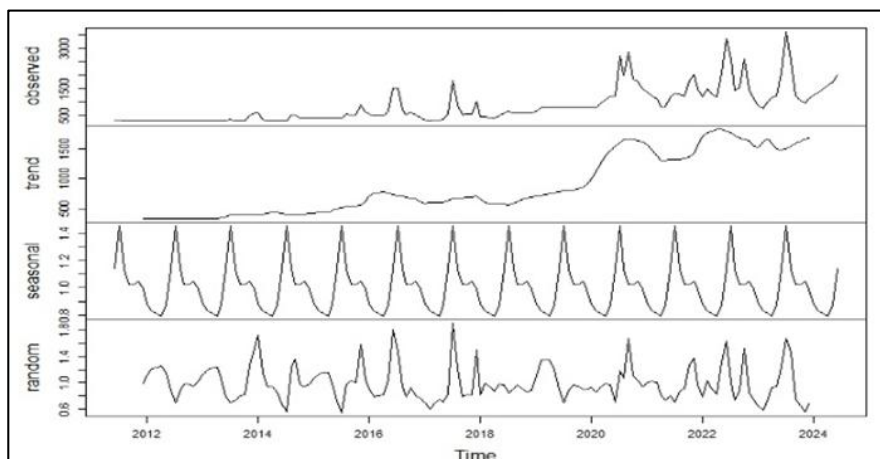


Fig 4: Multiplicative decomposition plot of tomato price series

The seasonal plot in the Figure 5 illustrates the fluctuations in the log transformed price variable across months from 2011 to 2024. Notably, there are distinct peaks in the mid-year months, particularly around July, indicating that prices tend to increase in the middle of the year across multiple years. The observed prices in July are, on average, 48.1% higher than the annual average price as indicated by the highest seasonal index (Table 2) observed in July (1.48141). July, followed by June (1.23302) exhibit a pronounced surge in prices that may correspond to supply-demand imbalances due to the off-season during these early monsoon months (Reddy *et al.*, 2018). August (1.09611) through December (0.91473) demonstrate indices close to unity, suggesting moderate deviations from the annual average price. Specifically, August shows a residual effect of the mid-year peak, while October (1.00351) marks the tapering off of the peak price seasonality. This transitional behaviour likely reflects supply-side adjustments or delayed market responses to weather

disruptions such as delayed rainfalls causing crop damages and storage and logistics issues.

Table 2: Monthly seasonal indices for tomato prices

Month	Seasonal Index
January	0.80996
February	0.81159
March	0.82352
April	0.82253
May	0.95532
June	1.23302
July	1.48141
August	1.09611
September	1.00351
October	1.03940
November	0.99098
December	0.91473

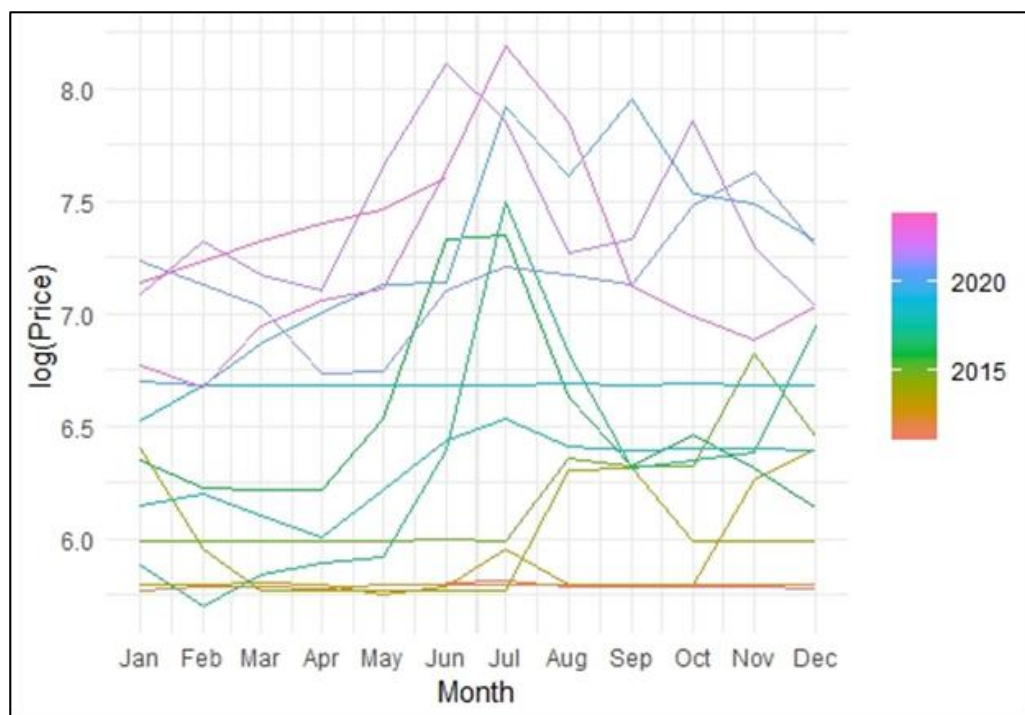


Fig 5: Seasonal plot of log transformed price series

The lowest seasonal index values are observed during the winter months through December (0.91473) to February (0.81159) due to post harvest effects. Also, lowest medians and narrower IQRs appear during January to March (Figure 6), suggesting greater market stability and possibly peak harvest periods. February, despite having a similar median to January, includes fewer extreme values, reinforcing a pattern of relative price homogeneity in early months. Also, outliers are most prominent from June to November, suggesting intermittent price spikes (Figure 6). The spread of the data (IQR) is not uniform across months, with highest variability particularly in June-September. For market stabilization, these insights can guide intervention timing, such as minimum support pricing or procurement in June-August while for producers, this provides a temporal window for maximizing returns, whereas for consumers and policymakers, it emphasizes months of heightened price risk.

The pronounced seasonal patterns exhibited by the monthly tomato price series make it highly suitable for modelling

applications, such as the utilization of SARIMA models to explicitly capture and account for these observed seasonal dynamics. Some years (e.g., 2017) exhibit relatively stable prices throughout the year, while others, particularly post-2020, show steep increase and decrease, reflecting greater instability and unpredictability in prices post-2020 (Figure 5). Furthermore, both the trend component in decomposition plot in Figure 4 and the seasonal plot in Figure 5 suggests the presence of an increasing long-term trend in the series, with tomato prices gradually rising over the years. The trend suggests a steady increase in prices over time, which accelerates post-2020. The analysis of the monthly tomato price series reveals a statistically significant upward trend, as demonstrated by a fitted linear trend model. A linear regression model was employed to estimate the trend, specified as:

$$\hat{y} = \frac{56.6295}{(71.7024)} + \frac{10.4172}{(0.7873)} t$$

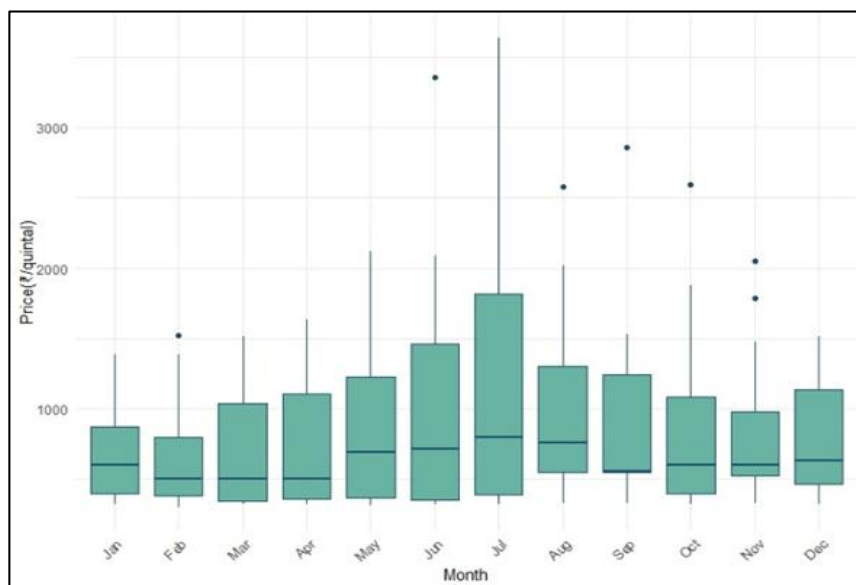


Fig 6: Boxplot depicting intra-annual price dispersion and central tendency

Table 3: Summary of linear regression results for linear trend model fit on monthly tomato prices

Metric	Value	Standard Error	T-Statistic	P-Value
Intercept	56.63	71.7024	0.79	0.431
Slope	10.42	0.7873	13.23	$< 2.2 \times 10^{-16}$
Multiple R-squared	0.5304		-	-
F-statistic	175.1		-	$< 2.2 \times 10^{-16}$
Residual Standard Error	447.1 (155 DF)		-	-

The results of the regression in Table 3 show the Intercept as 56.63 ($p = 0.431$), indicating that the initial value of the price series is not statistically significant and Slope as 10.42 ($p < 2 \times 10^{-16}$), suggesting a highly significant upward trend with an average increase of approximately Rs. 10.42 per quintal per month, translating to an annual increase of Rs. 125.04 per quintal. The F-statistic of 175.1 ($p < 2.2 \times 10^{-16}$) on 1 and 155 df further underscores the significance of the overall model. Although the linear trend model offers ease of interpretation particularly through its slope coefficient which reflects the average monthly rate of change it fails to adequately capture the underlying seasonality & variability in the tomato price series. The coefficient of determination (R^2) from the linear trend model stands at 0.5304, indicating that

only approximately 53% of the variation in prices is explained by the linear trend, leaving a substantial proportion unaccounted for. This is further established by the high Cuddy-Della Valle Index (CDVI) in Table 5, which adjusts for the loss of degrees of freedom and suggests a weak explanatory power of the model and high instability in the price series. To improve model performance, higher-order polynomial trend models such as quadratic and cubic models were fitted as shown in Figure 7. However, the corresponding increases in the R^2 values, 0.5504 for the quadratic model and 0.5599 for the cubic model are marginal improvements over linear trend model and insufficient to meaningfully improve the explanatory power of the deterministic trend models.

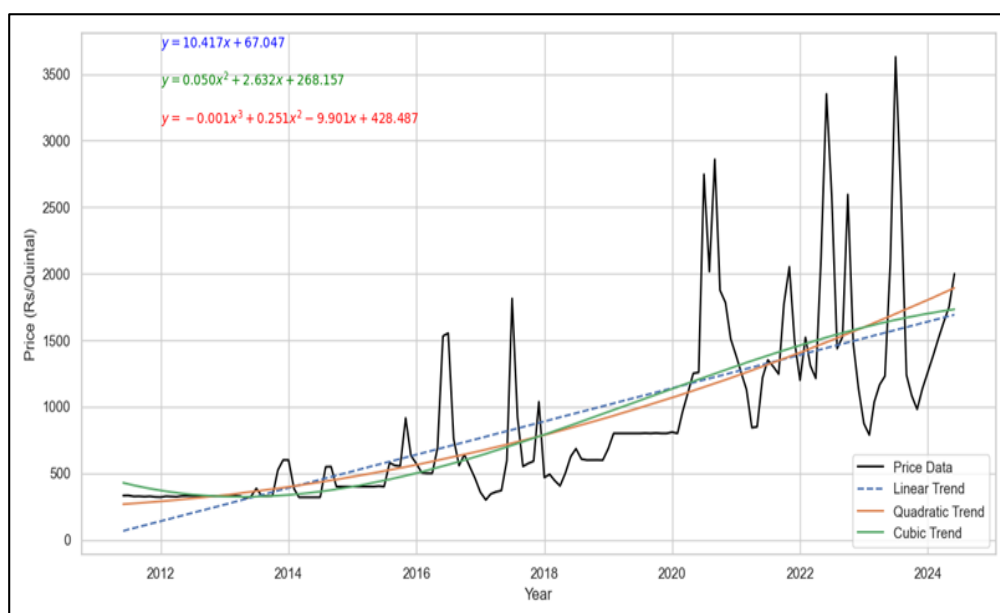


Fig 7: Visualisations of the fit of linear, quadratic and cubic trend models to tomato price series data

These findings highlight the limitations of deterministic trend models in capturing the complexity and stochastic nature of price dynamics, particularly in the context of agricultural commodities that are subject to supply shocks, demand fluctuations, and seasonal patterns. Consequently, this justifies the shift towards stochastic modeling frameworks such as ARIMA that account for both deterministic trends and random disturbances. Additionally, the Compound Annual Growth Rate (CAGR) of tomato prices was also estimated based on the following exponential growth model, which allows for an interpretation of growth on a multiplicative scale specified as

$$P_t = 267.43(1.01232)^t$$

This functional form ensures that the percentage growth rate is more accurately captured, particularly when the data exhibit exponential-like behaviour over time. The log transformation linearizes exponential growth, making the coefficient of time interpretable as a monthly growth rate, which translates to approximately 15.83% annually for tomato price series as shown,

$$\text{Compound Annual Growth Rate} = (e^{0.146968} - 1) \times 100 \approx 15.83\%$$

Table 4: Summary of log-linear regression for the exponential growth model

Metric	Value	Standard Error	T-Statistic	P-Value
Intercept	5.5889	0.0541	103.30	$< 2.2 \times 10^{-16}$
Slope (t)	0.0122	0.0006	20.62	$< 2.2 \times 10^{-16}$
Multiple R-squared	0.7328	-	-	-
F-statistic	425	-	-	$< 2.2 \times 10^{-16}$
Residual Standard Error	0.3373 (155 DF)	-	-	-

Given the statistically significant coefficients (Table 4), both Intercept (5.5888700, p value < 0.001) and Slope (0.0122473, p value < 0.001) of the corresponding log-lin form of the specified model, high adjusted R^2 (0.7311), and lowest residual error as well as low instability indicated by low CDVI value (Table 5), the log-linear trend model is most appropriate for modeling the deterministic growth trend as well as efficiently proving the robustness of log transformation for tomato price for reducing instability in the time series effectively, which is central to economic and policy analyses.

To investigate the presence of structural breaks in the time series of monthly tomato prices in Jabalpur district of India, Bai-Perron multiple breakpoint test was employed. This method detects multiple endogenous breakpoints in a time

series by minimizing the residual sum of squares (RSS) across various segmentations. To ensure robustness and account for potential non-linearities in the price trajectory, three model specifications of increasing complexity were considered i.e. Mean Shift Model, Linear Trend Model and Quadratic Trend Model. The optimal number of breakpoints for each specification was identified as the one which minimised the BIC value. The results of the Bai-Perron test have been enlisted in Table 6.

Table 5: CDVI evaluations for various Model Specifications

Model Specifications	CDVI (%)
Linear Trend Model	50.66
Log-Lin model (Log transformed data)	5.13

Table 6: Results of the Bai Perron test for structural breaks detection in tomato price series

Model Specification	Optimal Number of Breakpoints	Break Dates (Year-Month)	RSS	BIC
Mean Shifts	2	2015-07, 2020-04	24,921,906	2356
Linear Trend	1	2020-04	24,929,008	2356
Quadratic Trend	2	2020-05, 2022-04	21,469,206	2363

The presence of a common breakpoint around April-May 2020 (Figure 8) across all three specifications is particularly noteworthy. This period coincides with the onset of the COVID-19 pandemic and the imposition of nationwide lockdowns in India, which severely disrupted agricultural supply chains (Rajpoot *et al.*, 2021) ^[11] and likely caused a regime shift in the price determination mechanism for perishable commodities such as tomatoes. The second break identified under the trend models (April 2022) may reflect post-pandemic normalization or structural adjustments in the market (e.g., changes in production practices, logistics, or demand patterns). The earlier breakpoint identified by the mean shift model (July 2015) could correspond to volatility arising from climatic events, supply shocks, or changes in government procurement or distribution systems.

Conclusion

This study investigates the temporal dynamics of wholesale tomato prices in Jabalpur, emphasizing the critical need for accurate pattern detection due to the commodity's inherently high volatility. Seasonal analysis of tomato prices via seasonal indices reveals peaks in June-July due to high perishability, low shelf life and monsoon disruptions,

followed by stabilization from August to November, and lowest prices during December-February caused by post-harvest effects. These patterns highlight the need for targeted interventions to reduce price volatility and protect stakeholders. Various deterministic trend models were fitted to the price data wherein fitted linear trend model indicated a significant upward average price increase of about ₹10.42 per quintal monthly (₹125.04 per quintal annually). Though, quadratic and cubic models provided only marginal improvements in fit compared to linear model, all of them exhibited poor fit to tomato price data underscoring the limitations of deterministic trend models in capturing the complex and stochastic nature of agricultural prices. The Compound Annual Growth Rate of approximately 15.83% in tomato prices was estimated through fitted log linear model confirming substantial long-term growth as well as the need of Logarithmic transformation to cater to the high variance of the tomato price series in Jabalpur.

Notably, structural breaks were detected using Bai Perron structural breaks test around April-May 2020, coinciding with the COVID-19 pandemic lockdowns, and again in April 2022, likely reflecting market adjustments. Given the high variance

inflation in the linear model and the superior variance stabilization with log transformations, these findings support employing stochastic models like ARIMA framework over

deterministic ones for accurate forecasting of prices in the volatile tomato market.

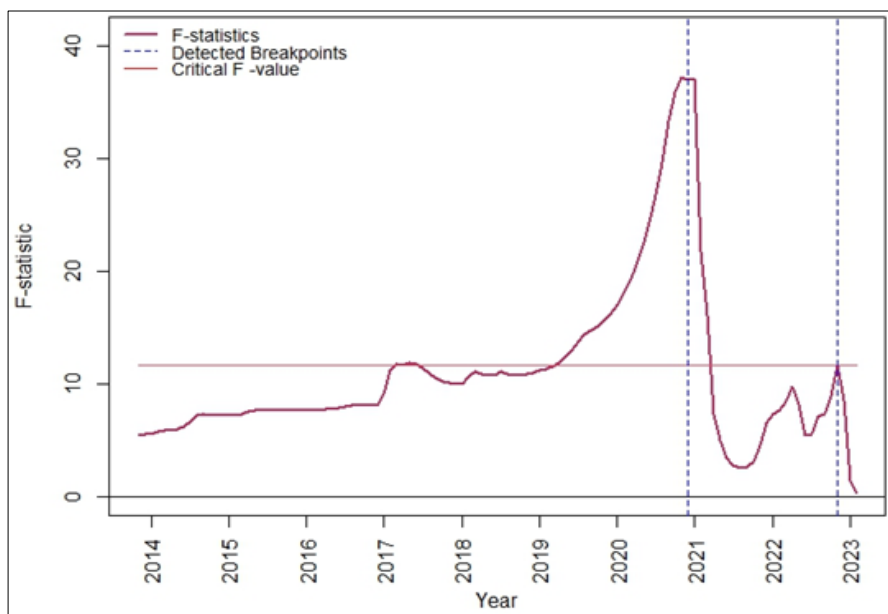


Fig 8: F-Statistics plot for detecting the significance of the structural breaks detected in Tomato price data

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