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# PRICE INSTABILITY AND TRANSMISSION IN MAJOR WHOLESALE TOMATO MARKETS OF TAMIL NADU: EVIDENCE FROM THE VAR APPROACH

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**ABSTRACT:**
Tomato is a highly perishable vegetable crop with high price volatility and market uncertainty throughout the season. Knowledge of price behaviour and price dynamic transmission between wholesale markets is very important for market efficiency and to minimize marketing risks. The weekly wholesale price data of the major four wholesale tomato markets of Tamil Nadu (Coimbatore, Chennai, Dindigul, and Krishnagiri) for 2022–25 was analyzed through this study to understand the price behaviour, price instability, and dynamic price transmission of the tomato market. The Seasonal Index was used to examine the seasonal price behaviour, the Cuddy-Della Valle Instability Index (CDVI) to measure the price instability, and the Augmented Dickey-Fuller (ADF) test, Vector Auto regression (VAR), Granger causality, Impulse Response Function (IRF), and Forecast Error Variance Decomposition (FEVD) were applied for analysis of the dynamic price relationships. The findings showed strong seasonal price variation and high price instability in all the selected markets. All the price series were found to be stationary at level [I(0)] in the ADF test, which justifies the use of VAR model. The results from the VAR, Granger causality, IRF and FEVD analyses showed strong short-run price transmission with Coimbatore and Chennai being the most important price-discovery markets. The results indicate the requirement of reinforced implementation of post-harvest infrastructure, better market information system, and regular market arrival to minimize price volatility and improve the efficiency and resilience of the tomato marketing system in Tamil Nadu.

**KEYWORDS:** Tomato Price Instability; Seasonal Price Behaviour; Price transmission; Vector Autoregression

## 1. INTRODUCTION

The tomato (*Solanum lycopersicum L.*) is one of the most grown and economically important vegetable crops in the world, due to its nutritional content, wide consumption and the significant contribution to the agricultural sector's income and employment. It is rich in vitamins, minerals, dietary fibre, antioxidants and lycopene and is a crucial food item as well as being a raw material for the food processing industry. India produced around 21.32 million tonnes of tomatoes during 2023-24 which makes India the second biggest tomato producer in the world. The crop has an important contribution to the horticulture economy with significant production states making a substantial contribution to the country's production including Andhra Pradesh, Madhya Pradesh, Karnataka and Tamil Nadu. Although tomato is an economically important crop, it is one of the most price volatile agricultural commodities, due to its high perishability, seasonal production, climatic variability, occurrence of pests and diseases, poor post-harvest infrastructure, and variable market arrivals and consumer demand (1). In the period of high harvest, overproduction normally leads to a rapid downward price trend, which leads farmers to sell their crops at less than production costs or to carry out distress sales. When the adverse impact of climate or supply is felt during production, it results in a substantial rise in prices, which can have a negative impact on consumers and negatively contribute to food inflation (2). The volatility leads to uncertainties over farm income, affects marketing and production decisions, and affects the efficiency of agricultural markets. The impact of price adjustments that develop in one wholesale market to other markets is fundamental for assessing the efficiency of agricultural marketing systems (3). Efficient price transmission allows markets to adjust quickly to variations in supply and demand, allows spatial arbitrage, better allocates resources to market participants and reduces regional price differences by timely dissemination of market information (4). Well connected markets can help to quickly transmit price signals from large production and consumption centers to neighbouring markets, which helps to enhance marketing efficiency and facilitate good decision-making in the entire value chain (5). Most of the studies on the tomato markets in India focused on either price volatility or price transmission and relied on monthly observations, a narrow geographical scope and a long-run equilibrium model (6). Few studies, however, have had the flexibility to take into account the seasonal price behaviour, price instability, and short-term dynamic price transmissions using recent high frequency weekly data, especially for the big tomato wholesale markets of Tamil Nadu. In addition, the growing use of digital market information systems, the upgrading of transportation facilities, and changes in the supply chain networks require a reassessment of price relationships at the largest wholesale markets in the state (7). The current research aims to examine the price behaviour, price instability and dynamic price transmission between four major tomato markets (Coimbatore, Chennai, Dindigul and Krishnagiri) in Tamilnadu during the period 2022-2025 using the weekly data of the wholesale price. The results give empirical evidence of the price dynamics of tomatoes and hence these results would provide useful information for the reinforcement of market information system, efficiency of the tomato supply chain and the formulation of policies for reducing the instability in the tomato price in Tamil Nadu (8).

## 2. MATERIAL AND METHODS

### Data and Methodology

The study utilized daily tomato price data obtained from the Tamil Nadu Agricultural Marketing Department for the period from January 2022 to December 2025, which were converted to weekly data for all analysis. A total of four major markets namely Dindigul, Coimbatore, Chennai and Krishnagiri were selected for the analysis owing to their importance in the tomato marketing system of Tamil Nadu for tomato production, market arrivals, trading activities, etc. Both the production and consumption markets were included to examine the price behaviour, price instability and dynamic price transmission along the tomato supply chain on a seasonal basis. The collected data was cleaned and standardized for consistency and reliability before proceeding with the analysis, which was done in Indian Rupees per kilogram (Rs/kg). The Seasonal Index method was used to analyze the seasonal price behaviour, and the Cuddy–Della Valle Instability Index (CDVI) was used to assess the price instability. A first step was to investigate the stationarity of the price series using the Augmented Dickey–Fuller (ADF) test, and then to assess short-run dynamic relationships between the markets using a Vector Auto regression (VAR) model. In addition, the direction, persistence, and relative importance of the price transmission was further explored through the application of Granger causality, Impulse Response Functions (IRF) and Forecast Error Variance Decomposition (FEVD).

### Analytical Framework

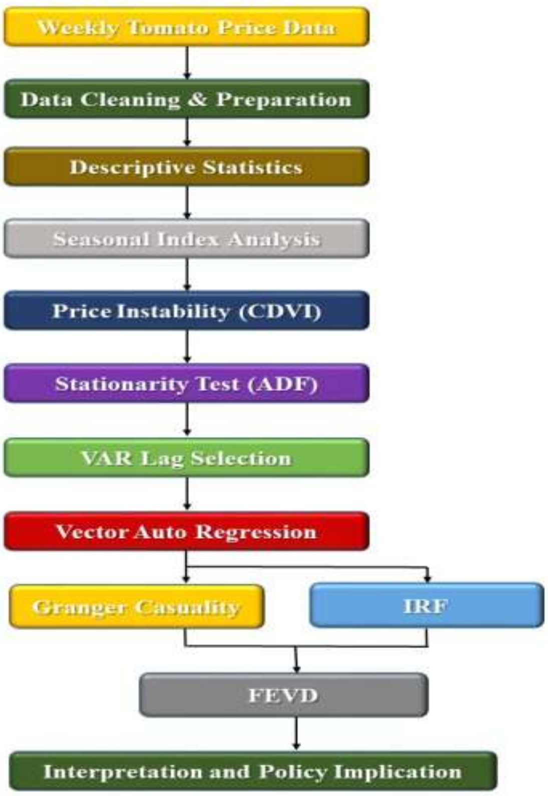


**Figure 1: Analytical Framework of Research**

Figure 1 represents the analytical framework in the study. The analysis comprised seasonal price analysis, price instability and dynamic price transmission analysis using VAR, Granger causality, IRF, and FEVD. The results were used to interpret market price dynamics and formulate policy implications.

### Seasonal Price Analysis

Seasonal price analysis was conducted to understand the regular weekly variation in tomato prices and to determine the tomato market price trend levels (9). The seasonal pattern was determined by use of the Simple Average Method which involves comparing the average price for each week to the average price for the entire study period. This gives a price

index for the season which gives an appreciation of relative prices for each week, and helps in recognizing the weeks which may have gluts or shortages in the markets (10).
The Average weekly price was calculated as

$$\bar{P}_w = \frac{\sum_{i=1}^{n} P_{iw}}{n}$$

Where, $P_w$= average price of the $w^{th}$ week, $P_{iw}$= observed tomato price in the $w^{th}$ week for year i, and n= total number of years considered in the study.
The Overall average price was computed as

$$\bar{P} = \frac{\sum_{w=1}^{52} \bar{P}_w}{12}$$

Where, P= grand average price across all weeks.
The Seasonal Index for each week was then estimated using the following expression

$$SI_w = \frac{\bar{P}_w}{\bar{P}} \times 100$$

Where, $SI_w$= seasonal index for the $w^{th}$ week, $P_w$= average price of the respective week, and P= overall average price.
A seasonal index greater than 100 indicates that tomato prices during that week are above the annual average, whereas an index below 100 suggests below-average prices, generally associated with higher market arrivals and increased supply. An index equal to 100 reflects price levels close to the annual average.

**Price Instability**

Price instability is a phenomenon of commodity prices changing over time and is a key indicator of market uncertainty and market risk in agricultural markets (11). Price instability was calculated as price instability index (CDVI) developed by Cuddy and Della Valle in the present study (12). CDVI adjusts the coefficient of variation for long-term trends using the coefficient of determination ($R^2$), providing a more reliable measure of instability (13).
The first step in estimating price instability was the calculation of the Coefficient of Variation (CV), expressed as:

$$CV = \frac{\sigma}{\bar{X}} \times 100$$

Where, CV = Coefficient of Variation (%); σ = Standard deviation of weekly tomato prices; and X= Mean weekly tomato price.
To account for the long-term trend in prices, a linear trend equation was estimated using ordinary least squares regression:

$$Y_t = a + bt + e_t$$

Where, $Y_t$= Weekly tomato price at time t; a = Intercept; b = Trend coefficient; t = Time period (week); and $e_t$= Random error term.
The coefficient of determination ($R^2$) obtained from the above regression was subsequently used to compute the Cuddy–Della Valle Instability Index as follows:

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

Where, CDVI = Cuddy–Della Valle Instability Index (%); CV = Coefficient of Variation (%); and $R^2$ = Coefficient of determination obtained from the trend regression.
The estimated CDVI values were interpreted using the following classification commonly adopted in agricultural economics studies:
CDVI < 15%: Low price instability
CDVI = 15–30%: Moderate price instability
CDVI > 30%: High price instability
Higher CDVI values indicate greater price instability, while lower values indicate relatively stable prices. The CDVI being used is therefore very powerful and price variation sensitive, and is very appropriate for describing the instability for the weekly tomato price in various wholesale markets, taking into account the trend of prices over the past few weeks.

**Stationarity Test**

The stationarity properties of the time-series data were examined before analyzing dynamic price transmission and short-run interactions among the selected wholesale tomato markets. The Augmented Dickey-Fuller (ADF) test proposed by Dickey and Fuller (14) was used to check for the existence of a unit root in the tomato price series (15).
The ADF Model is specified as:

$$\Delta Y_t = \alpha + \beta t + \delta Y_{t-1} + \sum_{i=1}^{p} \gamma_i \Delta Y_{t-i} + \varepsilon_t$$

Where, $Y_t$= Weekly wholesale tomato price at time t, $\Delta Y_t$= first difference of the series $Y_t Y_{t-1}$, α= intercept term, βt= deterministic time trend, δ= coefficient of the lagged price variable, $\gamma_i$= coefficients of lagged differences, p= optimal lag length, and $\varepsilon_t$= white noise error term.

The null hypothesis (H0: $\delta = 0$) indicates the presence of a unit root, implying that the series is non-stationary, whereas the alternative hypothesis (H1: $\delta < 0$) indicates that the series is stationary. The ADF test statistic was used to evaluate the null hypothesis. The null hypothesis is rejected when the p-value is less than 0.05.

**Lag Length Selection**

The present study adopted four widely accepted information criteria, namely Akaike Information Criterion (AIC), Schwarz Bayesian Information Criterion (BIC), Hannan–Quinn Information Criterion (HQIC) and Final Prediction Error (FPE), to find the optimum lag length (16). These criteria assess alternative VAR specifications, giving weight to the goodness-of-fit while keeping the specifications from being under or over-fitted (17).

The Akaike Information Criterion (AIC) is expressed as:

$$AIC = \ln|\Sigma| + \frac{2k}{n}$$

Where, AIC = Akaike Information Criterion; $|\Sigma|$= Determinant of the estimated residual covariance matrix; k = Number of estimated parameters; n = Number of observations.

The BIC is calculated as:

$$BIC = \ln|\Sigma| + \frac{k\ln(n)}{n}$$

Where, BIC = Schwarz Bayesian Information Criterion; $|\Sigma|$= Determinant of the estimated residual covariance matrix; k = Number of estimated parameters; n = Number of observations.

For the HQIC equation:

$$HQIC = \ln|\Sigma| + \frac{2k\ln(\ln n)}{n}$$

Where, HQIC = Hannan–Quinn Information Criterion; $|\Sigma|$= Determinant of the estimated residual covariance matrix; k = Number of estimated parameters; n = Number of observations.

The Final Prediction Error (FPE) criterion is expressed as:

$$FPE = \left(\frac{n+k}{n-k}\right)^m |\Sigma|$$

Where, FPE = Final Prediction Error; n = Number of observations; k = Number of estimated parameters; m = Number of endogenous variables; $|\Sigma|$= Determinant of the estimated residual covariance matrix.

**Vector Auto Regression**

A Vector Autoregression (VAR) model was used to analyze the dynamic interrelationship among the wholesale tomato prices in the selected markets. The VAR framework enables the examination of how price shocks originating in one wholesale market are transmitted to other markets over time, thereby providing valuable insights into market interactions and the price discovery process (18).

The general form of the VAR (p) model is expressed as:

$$Y_t = c + A_1Y_{t-1} + A_2Y_{t-2} + \cdots + A_pY_{t-p} + \varepsilon_t$$

Where, $Y_t$= Vector of endogenous variables (weekly tomato prices of Coimbatore, Chennai, Dindigul, and Krishnagiri) at time t; c = Vector of intercept terms; $A_1, A_2, \ldots, A_p$= Coefficient matrices corresponding to each lag; p = Optimal lag length; $\varepsilon_t$= Vector of white-noise error terms.

If the coefficient is positive and statistically significant, then an increase in the lagged price of a market is associated with an increase in the current price of the same or another market; if the coefficient is negative and statistically significant, then an increase in the lagged price of a market is associated with a decrease in the current price of the market. The magnitude of the coefficient reflects the strength of price transmission, while the statistical significance (p-value) determines whether the estimated relationship is meaningful. The large own-lag coefficients suggest price persistence, while the significant cross-market lag coefficients indicate short-run price transmission and dynamic interactions among the selected wholesale markets (19).

**Diagnostic Tests of the VAR Model**

Diagnostic tests were conducted to assess residual normality and model stability.

**Residual Normality Test (Jarque-Bera Test)**

The Jarque–Bera test, proposed by Jarque and Bera, was used to examine whether the residuals of the estimated VAR model followed a normal distribution (20).

The Jarque–Bera statistic is expressed as:

$$JB = \frac{n}{6}\left(S^2 + \frac{(K-3)^2}{4}\right)$$

Where, JB = Jarque–Bera statistic; n = Number of observations; S = Sample skewness; K = Sample kurtosis.

The hypotheses tested were:

$H_0$: Residuals are normally distributed.

$H_1$: Residuals are not normally distributed.
A p-value of less than 0.05 resulted in rejection of the null hypothesis, thus the residuals were not normally distributed.

**Stability Test (Characteristic Roots)**

The stability of the estimated VAR model was assessed using the characteristic roots. The estimated VAR model was considered dynamically stable when the modulus of all characteristic roots exceeded one (21).
The stability condition is represented by the characteristic polynomial:

$$|I - A_1 z - A_2 z^2 - \cdots - A_p z^p| = 0$$

Where, I = Identity matrix; $A_1, A_2, \ldots, A_p$= Estimated coefficient matrices of the VAR model; z = Characteristic root; p = Optimal lag length.
The VAR model is considered stable when all characteristic roots satisfy the stability condition

**Granger Causality Test**

The Granger causality test suggested by Granger was used in this study to analyse the direction of price transmission between the selected tomato markets (22).
The Granger Causality Model is specified as:

$$Y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i Y_{t-i} + \sum_{j=1}^{q} \beta_j X_{t-j} + \varepsilon_t$$

$$X_t = \gamma_0 + \sum_{i=1}^{p} \gamma_i X_{t-i} + \sum_{j=1}^{q} \delta_j Y_{t-j} + \mu_t$$

Where, $X_t$ and $Y_t$ represent tomato prices in two different markets at time t, $X_{t-j}$ and $Y_{t-I}$ denote lagged price values, p and q represent the optimal lag lengths, $\alpha_i$, $\beta_j$, $\gamma_i$, and $\delta_j$ are model coefficients, while $\varepsilon_t$ and $\mu_t$ are random error terms.
The Null Hypothesis for the 1st equation is

$$H_0: \beta_1 = \beta_2 = \cdots = \beta_q = 0$$

Indicating that market X does not Granger-cause market Y.
The Null Hypothesis for the 2nd equation is

$$H_0: \delta_1 = \delta_2 = \cdots = \delta_q = 0$$

Indicating that market Y does not Granger-cause market X.
The null hypothesis was rejected when the probability value was less than the chosen level of significance, indicating that past prices in one market significantly contributed to explaining current prices in another market. Depending on the results, the relationship may be unidirectional, bidirectional, or absent.

**Impulse Response Function**

After the estimation of the Vector Autoregression (VAR) model, the Impulse Response Function (IRF) was used to study the reaction of the tomato price in a market to a single shock in the same market or another market (8). The IRF, developed within the VAR framework by Sims, traces the magnitude, direction, and duration of the effect of an unexpected innovation (shock) in one endogenous variable on the current and future values of all endogenous variables in the system.
The Impulse Response Function is mathematically represented as:

$$Y_t = \mu + \sum_{i=0}^{\infty} \Psi_i \varepsilon_{t-i}$$

Where, $Y_t$= Vector of endogenous variables (weekly tomato prices of the selected markets) at time t; $\mu$ = Vector of intercept terms; $\Psi_i$= Impulse response coefficient matrix at the $i^{th}$ period; $\varepsilon_{t-i}$= Innovation (shock) or error term at lag i.
A one standard deviation shock was introduced to each market, and responses were traced over the forecast horizon. A response that steadily approaches zero is a sign of a dynamically stable market, with temporary price disturbances fading over time, while a long-lasting response or a spreading out response suggests that the market is disturbed, with a slower response (23).

**Forecast Error Variance Decomposition**

Forecast Error Variance Decomposition (FEVD) was used to quantify the relative contribution of shocks from each market to the forecast error variance for prices of tomato at various forecast horizons, complementing the Impulse Response Function analysis (24). FEVD was derived from the estimated VAR model (25).
The forecast error variance decomposition is expressed as:

$$VD_{ij}(h) = \frac{\sum_{k=0}^{h-1} (\psi_{ij,k})^2}{\sum_{k=0}^{h-1} \sum_{j=1}^{n} (\psi_{ij,k})^2} \times 100$$

Where, $VD_{ij}(h)$= Percentage contribution of shocks from market j to the forecast error variance of market i at forecast horizon h; $\psi_{ij,k}$= Impulse response coefficient measuring the effect of a one-unit shock in market j on market i after k periods; h = Forecast horizon; n = Number of endogenous variables (markets).
FEVD estimates the percentage contribution of own-market and cross-market shocks to forecast error variance. Markets contributing a larger proportion of forecast variance were considered price-leading markets.

## 3. RESULTS AND DISCUSSION

### 3.1 Descriptive Statistics

**Table 3.1: Descriptive Statistics**

| Market | Observations | Mean | Median | Minimum | Maximum | Std Dev |
|---|---|---|---|---|---|---|
| Coimbatore | 208 | 21.77 | 17.00 | 4.00 | 98.00 | 16.91 |
| Chennai | 208 | 28.14 | 24.17 | 8.33 | 122.50 | 17.22 |
| Dindigul | 208 | 26.00 | 21.33 | 5.83 | 110.00 | 17.04 |
| Krishnagiri | 208 | 23.45 | 19.00 | 6.14 | 98.00 | 16.13 |

Table 3.1 represents the descriptive statistics of weekly wholesale tomato prices across the four selected markets. All markets consisted of 208 weekly observations. Chennai recorded the highest mean price (₹28.14/kg), followed by Dindigul (₹26.00/kg), Krishnagiri (₹23.45/kg), and Coimbatore (₹21.77/kg). The standard deviation ranged from ₹16.13 to ₹17.22/kg, indicating considerable price fluctuations across all markets. Chennai also exhibited the highest maximum price (₹122.50/kg), reflecting relatively greater price variability, whereas Coimbatore recorded the lowest average price during the study period. The relatively higher average price at Chennai may be explained by the fact that the city is a consuming and distribution centre which has strong demand for the product and the city also has a dependency on supplies from the producing areas, which results in relatively higher wholesale prices. However, the relatively lower average price in Coimbatore is likely related to its close proximity to the production areas and the larger number of market arrivals during the harvest period. The wide price range recorded in all the markets can be attributed to the perishability of tomato, fluctuations in the production, weather induced variability in supply and change in market arrivals indicating the volatility in tomato markets of Tamil Nadu.

### 3.2 Seasonal Index

**Table 3.2: Seasonal indices of Weekly Prices in Selected Wholesale Markets**

| Market | Minimum Seasonal Index | Week | Maximum Seasonal Index | Week | Average Seasonal Index |
|---|---|---|---|---|---|
| Coimbatore | 36.40 | 12 | 185.45 | 29 | 100.00 |
| Chennai | 54.53 | 12 | 186.59 | 30 | 100.00 |
| Dindigul | 40.86 | 12 | 186.23 | 29 | 100.00 |
| Krishnagiri | 44.46 | 12 | 176.84 | 30 | 100.00 |

The seasonal indices of weekly tomato prices are presented in Table 3.2 and Figure 3.1. The average seasonal index for each market was 100, confirming the correctness of the seasonal adjustment procedure. The results revealed pronounced seasonal variation in tomato prices across all four markets, with seasonal indices ranging from 36.40 to 185.45 for Coimbatore, 54.53 to 186.59 for Chennai, 40.86 to 186.23 for Dindigul, and 44.46 to 176.84 for Krishnagiri. The lowest seasonal indices were observed around Week 12, whereas the highest indices occurred during Weeks 28–31, indicating that tomato prices follow a distinct seasonal pattern associated with fluctuations in market arrivals and supply conditions. Lower prices during week 12 were likely associated with peak harvesting period, it increases the arrivals creates excess supply and leads to reduction in wholesale prices. In contrast the higher prices during Week 29-30 were likely due to reduced market arrivals caused by seasonal production gaps, weather problems and constant consumer demand. These findings indicate that seasonal supply fluctuation plays a major role in tomato price behaviour, which emphasize the importance of production planning, market information and post-harvest management to reduce seasonal price instability. The present findings are consistent with Kumar et al. (26), who also reported pronounced seasonal fluctuations in tomato prices driven by seasonal production cycles and market arrivals.

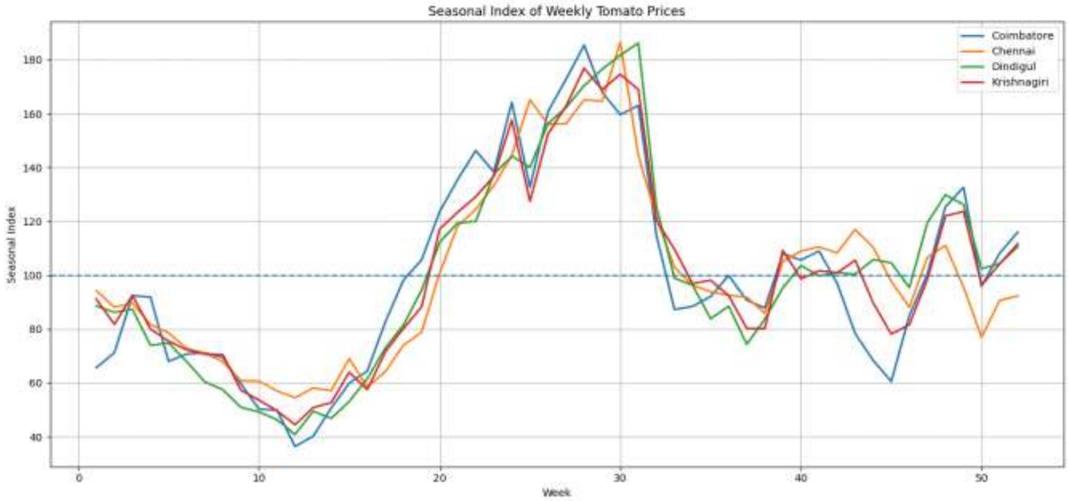


**Figure 3.1: Seasonal Index of Weekly Tomato Prices**

### 3.3 Cuddy-Della Valle Instability Index

**Table 3.3: CDVI values of Selected Markets**

| Market | Mean Price | CV (%) | $R^2$ | CDVI (%) | Instability |
|---|---|---|---|---|---|
| Coimbatore | 21.77 | 37.31 | 0.1110 | 35.18 | High |
| Chennai | 28.14 | 32.64 | 0.1126 | 30.75 | High |
| Dindigul | 26.00 | 36.98 | 0.1871 | 33.34 | High |
| Krishnagiri | 23.45 | 34.60 | 0.1297 | 32.28 | High |

Table 3.3 and Figure 3.2 show the Cuddy – Della Valle Instability Index values of the tomato prices. The price instability was very high in all four markets with CDVI between 30.75% to 35.18%. Coimbatore had the maximum instability (35.18%), Dindigul (33.34 %), Krishnagiri (32.28 %) and Chennai (30.75 %). The relatively low $R^2$ values indicate that long-term price trends explained only a small proportion of the overall price variation, suggesting that short-term market factors were the primary drivers of price fluctuations. The major reasons for the high price instability in all the selected markets are the highly perishable nature of tomato, seasonal fluctuation in production, irregular market arrival, weather related production shocks and less storage facility. Coimbatore being a major production and assembly centre, the comparatively higher instability may be linked to its seasonal gluts and sudden changes in arrivals of raw materials, which leads to greater price fluctuations. In contrast, Chennai exhibited relatively lower instability, possibly due to its function as a major consumption market with more stable demand and continuous inflow of produce from multiple production regions. Based on these results, it is clear that there is a need for better post-harvest infrastructure, efficient market intelligence systems and improved supply chain management to minimize price volatility and improve income stability of the tomato growers. Similarly, high price instability were reported by Guleria et al. (3), who observed considerable volatility in tomato markets due to perishability, seasonal arrivals and supply fluctuations.

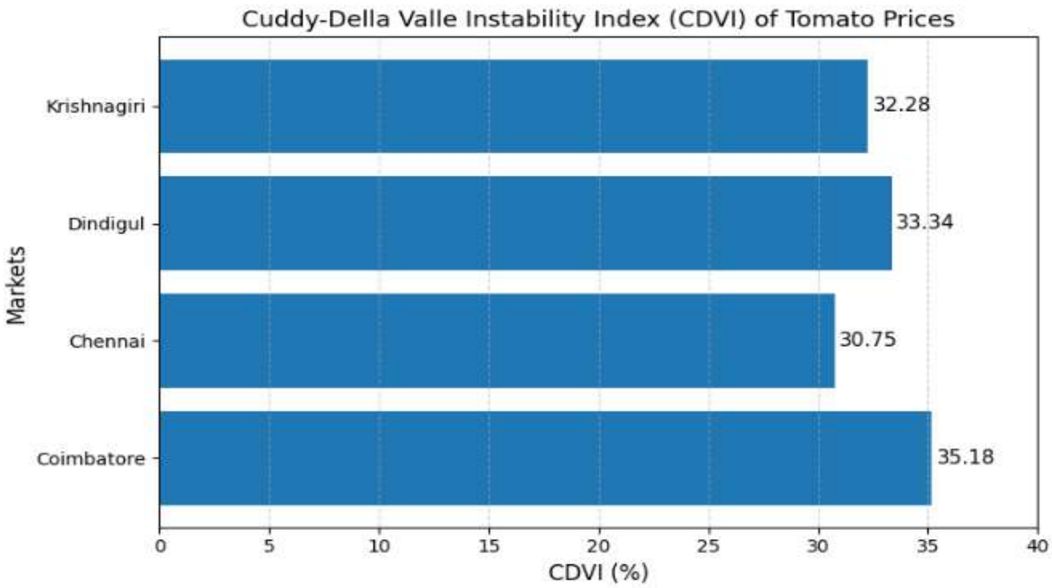


**Figure 3.2 CDVI for Weekly Tomato prices in selected markets**

### 3.4 Augmented Dickey Fuller Test

**Table 3.4: Stationarity of Weekly Wholesale Tomato Prices using ADF Test**

| Market | ADF Statistic | P-value | Order of Integration | Decision |
|---|---|---|---|---|
| Coimbatore | -6.215 | <0.001 | I(0) | Stationary |
| Chennai | -6.607 | <0.001 | I(0) | Stationary |
| Dindigul | -5.537 | <0.001 | I(0) | Stationary |
| Krishnagiri | -6.418 | <0.001 | I(0) | Stationary |

The stationarity of weekly wholesale tomato prices is tested by Augmented Dickey–Fuller (ADF) test and the result is presented in Table 3.4. The ADF statistics were between −5.537 and −6.607; all p-values were less than 0.001, which led to the rejection of the null hypothesis for the presence of a unit root for all four markets. The results indicate that the price series of Coimbatore, Chennai, Dindigul and Krishnagiri are stationary at level [I(0)], which means that the weekly price movements in the price series fluctuate around a stable mean but do not show a stochastic trend. Hence the data were considered stationary and thus a direct estimation of the Vector Autoregression (VAR) model was made to look into the interaction between different markets in the short run and the price transmission. Tomato prices at the market are fairly stationary, indicating that the prices have not changed permanently in response to short-term shocks, such as changes in market arrivals, seasonal supply or temporary changes in market demand. On the contrary, prices adjust towards their long-term equilibrium over time and it is a sign of efficient market adjustment in the selected wholesale markets. As all the price series were stationary at level, co-integration analysis and Vector Error Correction Model (VECM) were not necessary, so VAR was used to analyze the dynamic market relationship of the price series. The stationarity results agree with Guleria et al. (3), who also confirmed the suitability of tomato price series for econometric analysis following unit root testing.

**Auto-Correlation Function and Partial Auto-Correlation Function**

The weekly wholesale tomato prices are shown on the Autocorrelation Function (ACF) graph and the Partial Autocorrelation Function (PACF) graph in figure 3.3. The plots of the autocorrelations confirm that the weekly price changes are persistent, with strong positive autocorrelations at the first lags gradually decreasing towards zero. The PACF plots reveal a strong first lag partial autocorrelation followed by relatively smaller partial autocorrelations on the other lags. The results show that the price series has short-run temporal dependence, and that the dynamic relationships are mostly in the first lags. The information criteria suggested that a model of the second order of lag was the most suitable choice for analysing price transmission between the markets selected, and this is supported graphically. These findings support the selection of a VAR (2) model for analysing short-run price transmission among the selected markets.

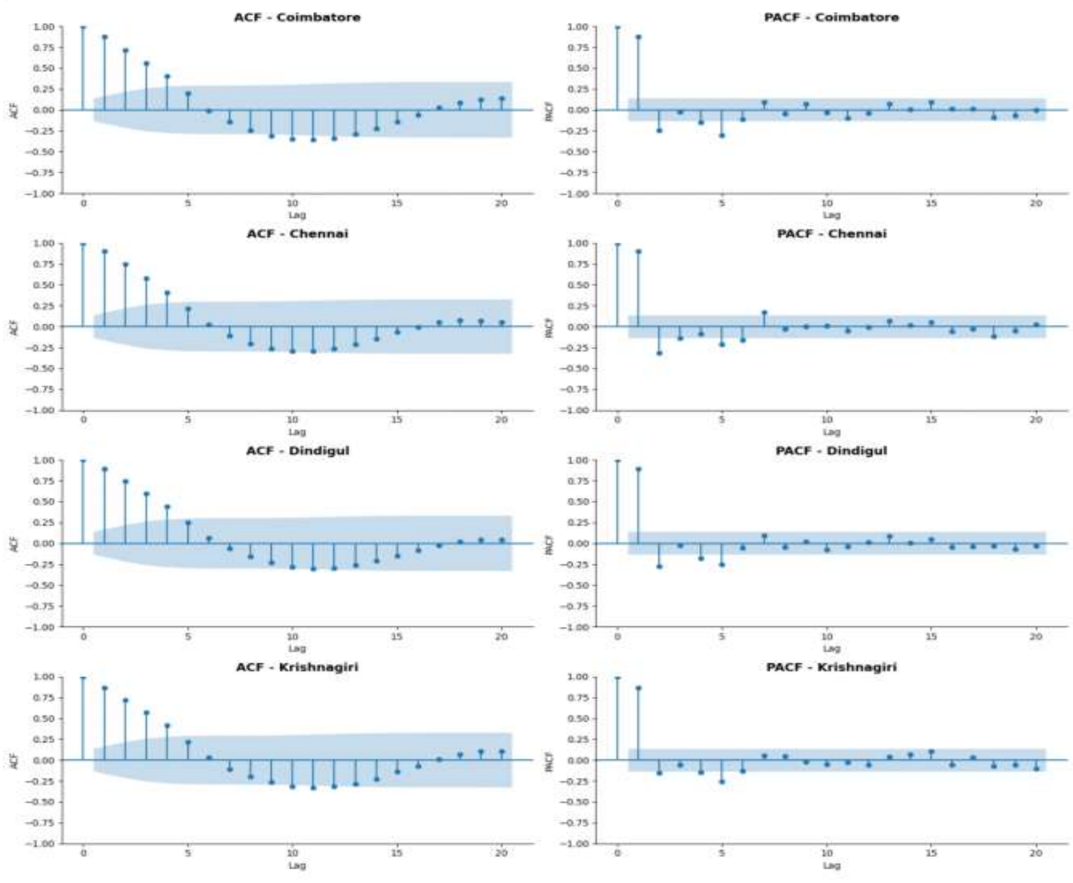


**Figure 3.3: ACF and PACF of Weekly Wholesale Tomato Prices**

Note: The Shaded region indicate 95% Confidence Levels

### 3.5 VAR Lag Selection

**Table 3.5: Optimal Lag determined by AIC, BIC, HQIC and FPE results**

| Lag | AIC | BIC | HQIC | FPE | Selected |
|---|---|---|---|---|---|
| 0 | 15.06 | 15.13 | 15.09 | $3.482 \times 10^6$ | |
| 1 | 12.44 | 12.77 | 12.57 | $2.521 \times 10^5$ | BIC |
| 2 | 12.28 | 12.88 | 12.53 | $2.157 \times 10^5$ | AIC, HQIC, FPE |
| 3 | 12.36 | 13.23 | 12.71 | $2.341 \times 10^5$ | |

The optimal lag length of the Vector Autoregression (VAR) model was determined using the Akaike Information Criterion (AIC), Schwarz Bayesian Information Criterion (BIC), Hannan–Quinn Information Criterion (HQIC) and Final Prediction Error (FPE) and is presented in Table 3.5. The AIC (12.28), HQIC (12.53) and FPE ($2.157 \times 10^5$) indicated lag order 2 as the best specification, while the BIC gave the answer as lag order 1. A Var (2) model was chosen for analysis because AIC, HQIC and FPE are usually preferred for capturing dynamic relationships in finite samples. The two lags suggest that the price of tomatoes the previous week, as well as adjustments over the previous two weeks, affect the weekly price of tomatoes. This lag structure is suitable to describe the price transmission and market interactions between the selected wholesale markets in the short run and is suitable for further VAR, Granger causality, Impulse Response Function (IRF) and Forecast Error Variance Decomposition (FEVD) analysis.

### 3.6 Vector Auto-Regression Model

**Table 3.6: Significant coefficients of the estimated VAR (2) model for weekly tomato prices**

| Dependent Market | Influencing Market | Lag | Coefficient | p-value | Economic Implication |
|---|---|---|---|---|---|
| Coimbatore | Coimbatore | 1 | 1.076 | <0.001 | Strong own-price persistence |
| | Chennai | 1 | 0.633 | <0.001 | Positive short-run price transmission |
| | Krishnagiri | 1 | −0.475 | 0.010 | Short-run price correction (inverse relationship) |
| | Chennai | 2 | −0.375 | <0.001 | Delayed market adjustment |
| Chennai | Chennai | 1 | 0.989 | <0.001 | Strong own-price persistence |
| | Coimbatore | 1 | 0.402 | 0.008 | Positive short-run price transmission |
| | Chennai | 2 | −0.233 | 0.024 | Delayed own-price adjustment |
| Dindigul | Dindigul | 1 | 0.649 | <0.001 | Strong own-price persistence |
| | Chennai | 1 | 0.650 | <0.001 | Positive short-run price transmission |
| | Coimbatore | 1 | 0.413 | 0.002 | Positive short-run price transmission |
| | Krishnagiri | 1 | −0.338 | 0.036 | Short-run price correction |
| | Chennai | 2 | −0.263 | 0.004 | Delayed market adjustment |
| Krishnagiri | Chennai | 1 | 0.708 | <0.001 | Positive short-run price transmission |
| | Coimbatore | 1 | 0.624 | <0.001 | Positive short-run price transmission |
| | Dindigul | 1 | 0.242 | 0.024 | Positive short-run price transmission |
| | Chennai | 2 | −0.268 | 0.005 | Delayed market adjustment |

Note: Only statistically significant coefficients ($p < 0.05$) are reported. Lag 1 and Lag 2 denote one-week and two-week lagged price effects, respectively.

The estimated Var(2) model showed that there were significant short-run dynamic relationships between the selected wholesale tomato markets (Table 3.6). Coimbatore, Chennai and Dindigul show strong and statistically significant own-lag coefficients, meaning that the current prices are strongly dependent on the prices over the last week in these markets and are highly price-stable. The significant positive first-lag effect of the markets of Chennai and Coimbatore on the other markets indicates a short-run price transmission, which indicates efficient information flow over the tomato marketing chain. In comparison, the high negative coefficients in the Coimbatore and Dindigul equations suggest that short-run price adjustments after a short-term shock in the market. The strong presence of the cities of Chennai and Coimbatore in terms of their influence can be explained based on their importance in the tomato supply chain of Tamil Nadu. Chennai is a consumption and distribution centre and Coimbatore is a production and assembling centre. Thus, price fluctuations from these markets are quickly passed on to other wholesale markets via trader's arbitrage, frequent market entries and marketing networks. The dominant influence of Coimbatore and Chennai observed in the present study supports the findings of Shubham et al. (8), who reported that major production and consumption markets play a leading role in transmitting price information across tomato markets. The fact that the price changes in Chennai had a significant second lag effect also indicates that prices started in this market had a long lag period (up to 2 weeks) before the effect diminishes in other markets. In general, the VAR results show that the selected tomato markets have good short-run price transmission and dynamic market linkages, thus forming a solid basis for the subsequent Granger causality, Impulse Response Function (IRF), and Forecast Error Variance Decomposition (FEVD).

**Residual Normality Test**

**Table 3.7 Jarque–Bera Normality Test for VAR Residuals**

| Market | JB Statistic | p-value | Decision |
|---|---|---|---|
| Coimbatore | 15.1455 | 0.0005 | Residuals not normally distributed |
| Chennai | 64.8505 | 0.0000 | Residuals not normally distributed |
| Dindigul | 49.1747 | 0.0000 | Residuals not normally distributed |
| Krishnagiri | 9.8873 | 0.0071 | Residuals not normally distributed |

To check the normality of the residuals from the estimated VAR model, the Jarque–Bera (JB) test was applied, with the results presented in Table 3.7. All four markets had a significant JB statistic ($p < 0.05$) and the null hypothesis of normally distributed residuals was rejected. These results show that the residuals are not normally distributed among the selected wholesale tomato market. The non-normality observed in the agricultural commodity price series was not surprising, because the tomato price series may be affected by seasonal production cycles, rapid shifts in market supply, weather-related market shocks, and demand shocks, causing asymmetric price movements and extreme observations. Since the estimated VAR model satisfied the stability condition and was used primarily to analyse dynamic price relationships rather than statistical prediction, the deviation from normality does not invalidate the subsequent analysis.

**Stability Test**

**Table 3.8. Stability Test of the VAR Model**

| Root | Modulus |
|---|---|
| 1 | 10.1723 |
| 2 | 5.8614 |
| 3 | 5.8614 |
| 4 | 3.7017 |
| 5 | 2.0522 |
| 6 | 2.0522 |
| 7 | 1.3115 |
| 8 | 1.3115 |

The stability of the estimated VAR model was determined by examining the characteristic roots of the system and the results are shown in Table 3.8. The VAR model is stable as all the characteristic roots had modulus higher than one. This shows that the estimated system is dynamically stable and appropriate for short-term analysis of the interactions between the selected wholesale tomato markets. The stability of the VAR model indicates that temporary price shocks do not generate explosive price behaviour but gradually diminish over time as market prices adjust towards equilibrium. This implies that any price disturbances caused by variations in market arrivals, seasonal supply or temporary variations of demand are taken up by normal market adjustment processes. The estimated VAR model therefore serves as a good basis to understand the results of the Granger causality, Impulse Response Function (IRF), and Forecast Error Variance Decomposition (FEVD).

**3.7 Granger Causality Test**

**Table 3.9. Granger Causality Test Results among Selected Tomato Markets**

| Direction of Causality | F-statistic | p-value | Decision |
|---|---|---|---|
| Chennai → Coimbatore | 26.1449 | <0.001 | Significant |
| Dindigul → Coimbatore | 4.2699 | 0.0153 | Significant |
| Krishnagiri → Coimbatore | 0.8544 | 0.4271 | Not Significant |

| | | | |
|---|---|---|---|
| Coimbatore → Chennai | 10.7492 | <0.001 | Significant |
| Dindigul → Chennai | 8.8286 | 0.0002 | Significant |
| Krishnagiri → Chennai | 5.8134 | 0.0035 | Significant |
| Coimbatore → Dindigul | 7.3495 | 0.0008 | Significant |
| Chennai → Dindigul | 36.3305 | <0.001 | Significant |
| Krishnagiri → Dindigul | 6.4161 | 0.0020 | Significant |
| Coimbatore → Krishnagiri | 7.1622 | 0.0010 | Significant |
| Chennai → Krishnagiri | 34.4108 | <0.001 | Significant |
| Dindigul → Krishnagiri | 10.9984 | <0.001 | Significant |

The Granger causality test was used to analyse the direction of price transmission among the selected wholesale tomato markets, with the results shown in Table 3.9. There were significant causal relationships between most market pairs, suggesting that the degree of short-run market interaction is high. There was a bidirectional causal relationship between Coimbatore and Chennai, indicating that both markets have influences on each other in regards to price information exchange. Coimbatore and Chennai were significantly influenced by Dindigul whereas Krishnagiri significantly influenced Chennai and Dindigul, but not Coimbatore. Moreover, Krishnagiri was heavily affected by the market prices of Coimbatore, Chennai and Dindigul, which has led to the relatively higher dependency of the market on other markets. The findings indicated that the causal relationship that was observed indicated that there was an efficient transfer of information and good marketing linkage between the selected wholesale markets. The bidirectional causalities between Coimbatore and Chennai reflect the complementary role of both in tomato value chain, with Coimbatore as a significant production/assembling centre and Chennai as a significant consumption/distribution market. It can be inferred that Krishnagiri is price-following market as compared to Coimbatore and Chennai which is more active in price discovery as it is mostly dependent on the price signal from the other markets. Overall, the results suggest that there is a more integrated marketing system, with information about prices moving quickly throughout markets allowing for efficient responses to price changes and elimination of some of the persistent regional price differences. The bidirectional and unidirectional causal relationships identified among the selected markets are consistent with the findings of Shubham et al. (8) and Guleria et al. (3), who also reported significant information flow between major tomato markets.

**3.8 Impulse Responsive Function Analysis**

The Impulse Response Functions (IRFs) were estimated to examine the dynamic responses of wholesale tomato prices to one standard deviation shocks over a 10-week forecast horizon (Figure 3.3). The price shock effects in the own-markets of Coimbatore, Chennai, Dindigul and Krishnagiri were initially positive and then moved closer to zero indicating short duration of the shock effect. There were also mostly positive cross-market responses, higher for shocks from Coimbatore and Chennai. In contrast, Krishnagiri showed relatively weak and slow responses prior to equilibrium. As all impulse response curves approach zero that suggests that temporary price disturbances dissipate over time because of normal market adjustment mechanisms. These findings are consistent with Shubham et al. (8), who also reported that price shocks in major tomato markets gradually diminished over time, indicating efficient market adjustment and stable price transmission. The relatively greater influence of Coimbatore and Chennai indicate the significance of these markets in transmitting prices in the tomato marketing system, whereas the comparatively less responsiveness in Krishnagiri imply that the price signals were more relied on from other markets. The overall IRF results suggest that markets have a stable, well connected nature since the short-term supply and demand shocks have a non-persistent effect on wholesale tomato prices across the markets.

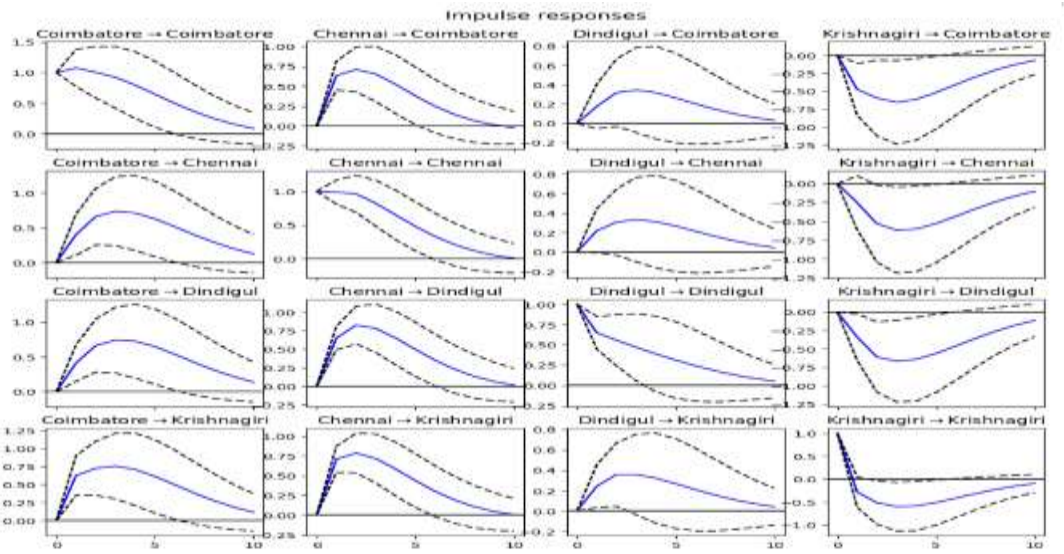


**Figure 3.4: Impulse Response Functions of Tomato Prices among Selected Markets**

Note: The solid blue line represents the estimated impulse response, while the dashed lines denote the 95 per cent confidence intervals. The responses are traced over a 10-week forecast horizon.

### 3.9 Forecast Error Variance Decomposition

The Forecast Error Variance Decomposition (FEVD) results for the selected wholesale tomato markets are presented in Figure 3.4. The decomposition showed that the forecast error variance for Coimbatore was mainly due to its own innovations (77.47 %), followed by the innovations of Chennai (16.49 %), Krishnagiri (4.32 %) and Dindigul (1.73 %). Meanwhile, innovations from Coimbatore (65.46%) and Chennai (25.64%) had the most significant impact on the forecast error variance of Krishnagiri; in total, however, innovations from only a small proportion of the group (6.43%) had a sizable effect on the forecast error variance. In a similar fashion, Coimbatore (57.04%) and Chennai (27.48%) accounted for the majority of forecast uncertainty in Dindigul, suggesting significant cross-market effects. The FEVD results show that Coimbatore and Chennai are the predominant market centres in the price discovery process of the selected tomato markets. Coimbatore is a major production and assembling centre that sends price signals strongly impacting neighbouring wholesale markets while Chennai is a major consumption and distribution centre that plays a major role in passing price information as a result of demand. The external market shocks responded relatively strong in both Dindigul and Krishnagiri markets, indicating that these markets are price-following markets. The analysis of FEVD shows that Coimbatore and Chennai are the main markets influencing the wholesale price of tomatoes in Tamil Nadu, indicating high degree of market linkages and quick price information flows in the regional marketing system. The FEVD results further confirmed the dominant role of Coimbatore and Chennai in price discovery, which is in agreement with Shubham et al. (8), who identified major producing and consuming markets as the principal sources of price transmission in the tomato marketing system.

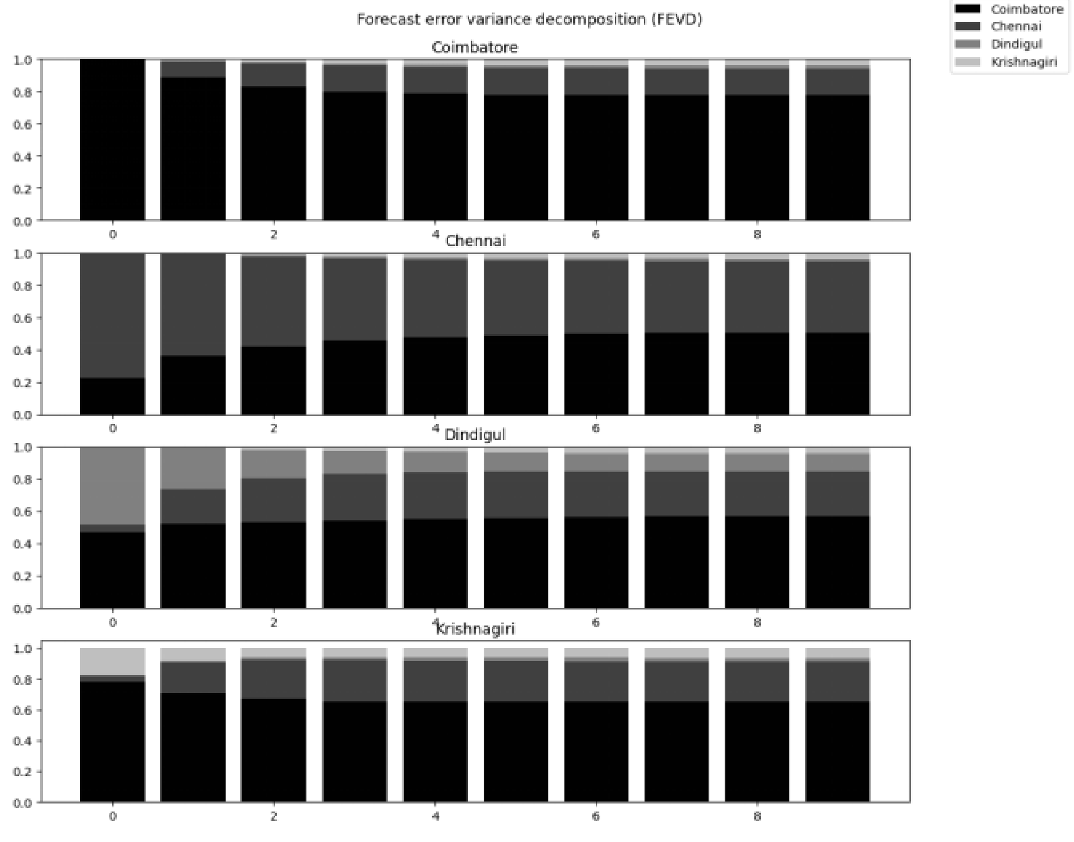


**Figure 3.5: Forecast Error Variance Decomposition (FEVD) of Tomato Prices among Selected Markets**

Note: The stacked bars represent the proportion of forecast error variance explained by shocks originating from Coimbatore, Chennai, Dindigul and Krishnagiri over a 10-week forecast horizon.

## 4. CONCLUSION

This study analysed the seasonal price behaviour, price instability, and dynamic price relationships among the major wholesale tomato markets of Coimbatore, Chennai, Dindigul, and Krishnagiri using weekly price data from 2022–2025. The findings indicated significant seasonal price variations, high price instability which is mainly attributed to the seasonality of tomato production, market arrivals and perishability of tomato. The VAR, Granger causality, IRF and FEVD analyses showed high price transmission and market tightness between the selected markets, where Coimbatore and Chennai were found to act as the price-discovery markets which affected the price movements in the region. While the short-term price adjustment is found to be efficient in selected markets, tomato producers still face challenges in terms of price volatility in the short-run. Hence, enhancing the post-harvest infrastructure, market information system, market co-ordination by Farmer Producer Organizations (FPOs) and increasing the processing infrastructure would help minimize price volatility and enhance efficiency and resilience of the tomato marketing chain in Tamilnadu. Future research may extend the present study by incorporating market arrivals, weather variables, transportation costs, and policy interventions to better understand the factors influencing tomato price dynamics and improve price forecasting and market management strategies.

## 5. POLICY IMPLICATIONS

It reveals that the wholesale price of tomato in the markets studied has a strong seasonal trend, with low prices during high harvests and high prices during low harvests, suggesting that seasonal supply is the most important determinant of price behaviour. The findings suggest several policy implications for improving tomato market efficiency and reducing price instability. Improved market intelligence systems, which deliver up-to-the-minute information on price and market arrivals, could help farmers make better harvesting and marketing decisions. Investment in cold stores, pack houses, grading centres and effective transportation system would minimize post-harvest losses and dampen the price volatility. The promotion of staggered planting dates and farmer producer organizations (FPOs) to coordinate the market arrivals may help to reduce gluts in the season and enhance the bargaining power of farmers. As Coimbatore and Chennai are the price leading markets, enhancing digital price dissemination and market information services based on these markets would help enhance price transparency and effective price transmission to neighbouring markets. In addition, increasing the capacity of processing units for excess tomato production during the peak production seasons would help to meet market arrivals and minimize distress sales and hence increase the income stability for tomato growers. All of these interventions would help build a more resilient, integrated and efficient tomato marketing system in Tamil Nadu.

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